C-band radar data and in situ measurements for the monitoring of wheat crops in a semi-arid area (center of Morocco)

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Abstract. A better understanding of the hydrological functioning of irrigated crops using remote sensing observations is of prime importance in the semi-arid areas where the water resources are limited. Radar observations, available at high resolution and revisit time since the launch of Sentinel-1 in 2014, have shown great potential for the monitoring of the water content of the upper soil and of the canopy. In this paper, a complete set of data for radar signal analysis is shared to the scientific community for the first time to our knowledge. The data set is composed of Sentinel-1 products and *in situ* measurements of soil and vegetation variables collected during three agricultural seasons over drip-irrigated winter wheat in the Haouz plain in Morocco. The *in situ* data gathers soil measurements (time series of half-hourly surface soil moisture, surface roughness and agricultural practices) and vegetation measurements collected every week/two weeks including above-ground fresh and dry biomasses, vegetation water content based on destructive measurements, cover fraction, leaf area index and plant height. Radar data are the backscattering coefficient and the interferometric coherence derived from Sentinel-1 GRDH (Ground Range Detected High resolution) and SLC (Single Look Complex) products, respectively. The normalized difference vegetation index derived from Sentinel-2 data based on Level-2A (surface reflectance and cloud mask) atmospheric effects-corrected products is also provided. This database, which is the first of its kind made available in open access, is described here comprehensively in order to help the scientific community to evaluate and to develop new or existing remote sensing algorithms for monitoring wheat canopy under semi-arid conditions. The data set is particularly relevant for the development of radar applications including surface soil moisture and vegetation parameters retrieval using either physically based or empirical approaches such as machine and deep learning algorithms.

The database is archived in the DataSuds repository and is freely-accessible via the DOI: https://doi.org/10.23708/8D6WQC (Ouaadi et al., 2020a).

1 Introduction

The south-Mediterranean region has been identified as a hot spot of climate change (Giorgi, 2006; Giorgi and Lionello, 2008; IPCC, 2014) that may worsen the water shortage already affecting the region. Up to 90% of available water is dedicated to irrigation (Ministre de l'agriculture et peche maritime du develpement rurale et des eaux et forets, 2018). Indeed, the predicted temperature rise that could reach 3°C by 2050 combined to precipitation decrease and increased evapotranspiration could drastically increase the irrigation requirements. The demand for water is also already increasing in response to an ever-growing population and to changes of agricultural practices-intensification, conversion to cash crops, rise of irrigated areas (Ducrot et al., 2004; Fader et al., 2016; Jarlan et al., 2016). The monitoring of irrigated crops and the optimization of water use is therefore of prime importance for the sustainability of the water resources in the Mediterranean region. This requires the implementation of methods to monitor the crop water status and the underlying soil moisture (Wang et al., 2012).

Within this context, the observations from active spaceborne sensors in the microwave domain (radar) have shown great potential for the monitoring of crops (Mattia et al., 2003; Ouaadi et al., 2020b; Picard et al., 2003). The potential of radar data for monitoring irrigated crops originates from their high sensitivity to the water status of the surface including the water content of the above ground biomass and the moisture of the upper soil layer (Ulaby and Dobson, 1986). It is also sensitive to the structural properties of the observed target including the size and orientation of the canopy elements (leaves, steams, trunks) and the soil roughness. A key advantage of radar observations for monitoring crops, especially those crops growing during the rainy season such as wheat, is also that it is not prone to atmospheric perturbations. Sentinel-1 provides for the first time since 2014 backscattering coefficients at a resolution of 10 m and a revisit time of 6 days compatible with the high dynamic of annual crops at the field scale paving the way to an operational use of C-band radar data for crop monitoring.

Nevertheless, radar signal is a complex mix of backscattering from the soil and from the canopy that are often difficult to disentangle. The impact of any changes of the canopy structure such as the appearance of the heads during the heading stage of wheat (Brown et al., 2003; El Hajj et al., 2019; Ulaby et al., 1986) or of the soil roughness may also drastically impact the backscattering response. These processes are not fully understood and not always properly reproduced by the backscattering models.

The sensitivity of the backscattering coefficient to the surface soil moisture (SSM) is widely documented in the literature for bare or covered soils (Ezzahar et al., 2020; Ouaadi et al., 2020c, 2020b; Ulaby and Dobson, 1986; Zribi et al., 2014). Several retrieval approaches based on the inversion of a radiative transfer models (Bai et al., 2017; Gherboudj et al., 2011; El Hajj et al., 2016; Li and Wang, 2018; Ouaadi et al., 2020b) or based on linear or non-linear empirical regression (Gorrab et al., 2015; Ouaadi et al., 2020b) have been developed. The SSM derived from radar observations are also used to estimate RZSM (root zone soil moisture), a key variable in agronomy, through the combination with a land surface model (Cho et al., 2015; Das et al., 2008; Dumedah et al., 2015; Ford et al., 2014; Rodell et al., 2004; Sabater et al., 2006; Sure and Dikshit, 2019).

64 The presence of a canopy above the soil results in two more contributions to the backscattered signal: the volume scattering
65 and the attenuated signal by the canopy. The water content of vegetation influences the dielectric properties, that in turn
66 influence the radar backscatter from the vegetation (Ulaby et al., 1982). Based on these findings, some studies are focused on
67 the retrieval of vegetation parameters from SAR (Synthetic Aperture Radar) data such as above-ground biomass (Hosseini
68 and McNairn, 2017; Periasamy, 2018; Taconet et al., 1994) or even grain yield (Fieuzal et al., 2013; Patel et al., 2006). In
69 addition to the backscattering coefficient, the polarization ratio and the interferometric coherence have demonstrated
70 potentialities for the characterization of the vegetation including height (Blaes and Defourny, 2003; Engdahl et al., 2001),
71 vegetation cover fraction (Wegmuller and Werner, 1997), fresh above-ground biomass (Mattia et al., 2003; Veloso et al.,
72 2017), above-ground biomass (Ouaadi et al., 2020b) and vegetation water content (Ouaadi et al., 2020b). Other studies
73 acknowledge the sensitivity of coherence to soil moisture (De Zan et al., 2014; Scott et al., 2017). Recent research suggests
74 that radar observations could also provide valuable information on the canopy water status (Van Emmerik et al., 2015;
75 Ouaadi et al., 2020d) for crop stress detection.

76 In situ measurements of vegetation and soil characteristics are always needed to improve our understanding of the radar
77 response, to develop and calibrate radiative transfer models and to propose generic retrieval methods for the inversion of soil
78 or vegetation variables. Nevertheless, in situ data set dedicated to these objectives are really specific in the sense that, for
79 instance, soil roughness is only of interest for understanding the physical principle of observations in the microwave domain.
80 Likewise, above-ground biomass is often measured by agronomist for crop modeling for instance but the partition between
81 dry and wet matter, a key variable for radar acquisition, is hardly ever done. Indeed, the latter relies on heavy destructive
82 measurements consisting in cutting all the vegetation elements within squares sample in the field and a double weighting
83 before and after drying the samples in an oven. In this paper, a recent, multi-year and complete database composed of
84 processed Sentinel-1 SAR data (the backscattering coefficient and the interferometric coherence), Sentinel-2 NDVI and
85 measured variables on the soil, on the vegetation and on the agricultural practices are made available. The in situ data
86 include automatic measurements as well as observations carried out during measurement campaigns once or twice every 15
87 days throughout the growing season. This database covers 3 wheat seasons (2016-2017 to 2018-2019) of 3 different irrigated
88 fields (Ouaadi et al., 2020b). It is a unique and valuable data set that can be used for vegetation and soil moisture monitoring
89 applications including from radar observations. In addition, the multiyear database can be useful for multiyear time series
90 analysis. In the next section, an overview of the field-location and a detailed description of the variables, including field
91 measurements and remote sensing data processing, are presented. In Section 3, the variables are experimentally and
92 physically analyzed to assess the consistency of the dataset. Conclusions are provided in Section 4.

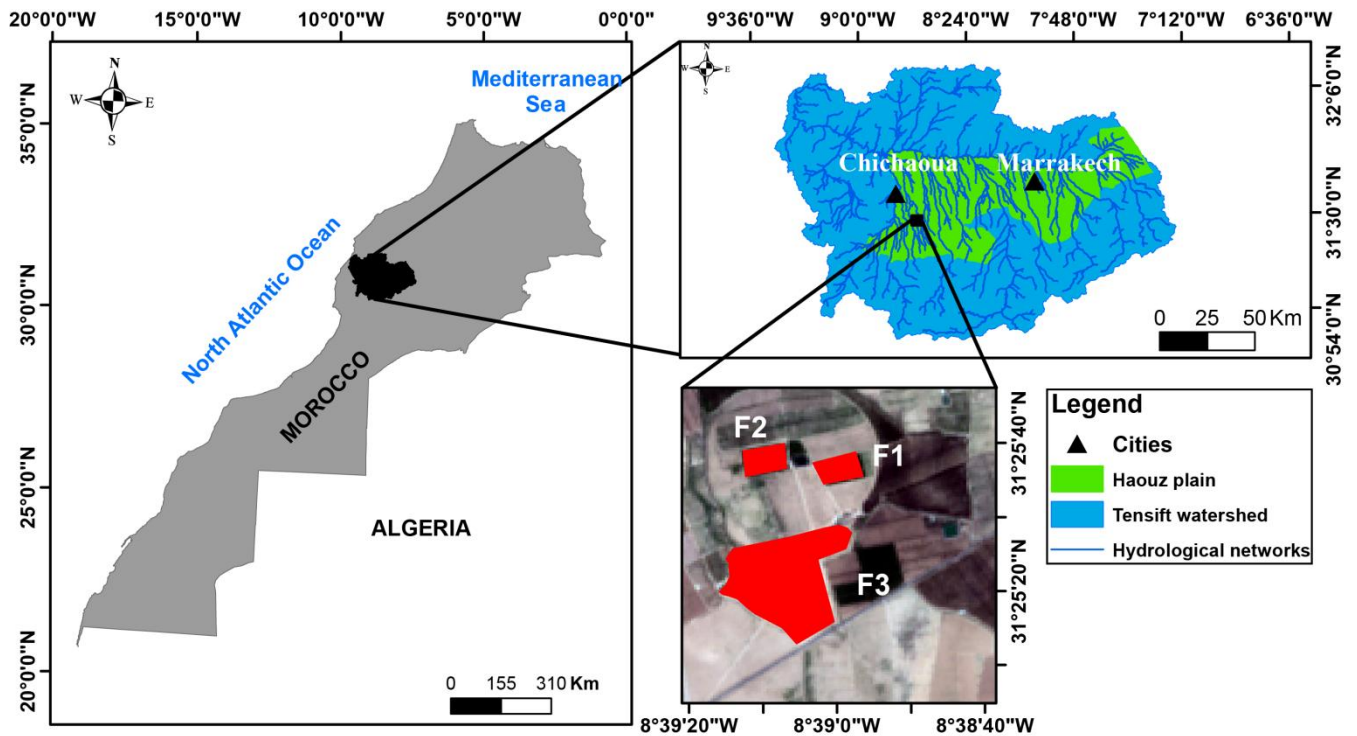
2 Study area and experimental sites

2.1 Study area

The database described in this paper is collected in the Haouz plain in the Tensift watershed, center of Morocco (Fig. 1). This plain is one of the most important plains in Morocco located at 550 m above sea level and covers about 6000 km^2 of which 2000 km^2 are irrigated. The climate in the region is Mediterranean semi-arid, with an annual average precipitation of about 250 mm. The distribution of precipitations highlights a wet season with around 85% of annual precipitations between October and April, and a dry season from May to September. The maximum average of temperature occurs during summer in July-August (about 35°C) and the minimum in January (about 5°C) (Abourida et al., 2008). The average air humidity is about 50% and the reference evapotranspiration ET0 is around 1600 mm/year (Jarlan et al., 2015), which is greatly exceeding the annual rainfall. The agricultural production in the plain is not very diverse, focusing on cereals (51% of the irrigated areas), olive trees (30% of the irrigated area), 9% of fodder production and 2% of market gardening for cattle breeding while the non-irrigated part of the plain is cropped with rainfed wheat (Abourida et al., 2008). Wheat is usually sown between November and January depending on precipitation distribution, even for irrigated field, and on cultivar. Harvest usually occurs in May or June.

2.2 Experimental sites

The database concerns three irrigated fields (F1, F2 and F3) located within a private farm in the province of Chichaoua located 65 Km west of Marrakech city (Fig. 1). F1 and F2 are monitored during two successive growing seasons (2016-2017 and 2017-2018) while F3 is monitored during the season 2018-2019. The fields are sown using an automatic seed drill. They are irrigated using the drip technique. For all the fields, the wheat is cropped once a year during winter-spring (see Table 1 for sowing and harvest dates). After harvest, the fields are generally used for cattle grazing until mid-July when the plowing works started. Table 1 summarizes some general information about the fields. Please note that during the 2017-2018 season, wheat in F2 is affected by specific growing conditions: i) the development of adventices belonging to the wild thistles family characterized by a horizontal structure, ii) the seeding density is higher than in F1, and iii) the seeding is a mixture of barley and wheat within F2. This resulted in very long stems: 146 cm in F2 compared to 110 cm in F1 in April 2018. Finally, these long stems in F2 are laid down by the wind from April 12, 2018. A picture of F2 during 2017-2018 is provided in appendix A (Fig. A1). Although such exceptional growing conditions are not very likely, it has been chosen to include this crop season in the data set to cover different conditions of growth.

120

121
122 **Figure 1. Location of the study fields: F1, F2 and F3 are drip-irrigated wheat plots in a private farm ("Domaine Rafi") near**
123 **Chichaoua city in the Haouz plain, center of Morocco.**

124 **Table 1. General information about the three fields**

Field	Area (ha)	Season	Sowing date	Harvest date	Irrigation	Sand (%)	Clay(%)
F1	1.5	2016-2017 & 2017-2018	Nov 25, 2016	May 16, 2017	Drip technique	32.5	37.5
F2	1.5		Nov 27, 2017	June 08, 2018			
F3	12	2018-2019	Nov 04, 2018	June 06, 2019			

125 **3 Database**

126 **3.1 Field datasets**

127 The field datasets consist of automatic measurements of soil moisture and weather data in addition to punctual surveys for
128 surface roughness, biomass, vegetation water content, canopy height, green leaf area index and cover fraction. Table A1 in

129 the appendix summarizes the details of the 26, 18 and 16 field campaigns carried out during 2016-2017, 2017-2018 and
130 2018-2019 seasons, respectively.

3.1.1 Soil moisture

132 SSM is automatically measured every 30 min using Time Domain Reflectometry sensors (TDR), (Campbell Scientific
133 CS616) using two sensors buried at a depth of 5 cm: one under the drippers and another one between. The average is
134 computed in order to get a representative SSM value of the field. In addition, similar sensors are buried for RZSM measuring
135 at 25 and 35 cm of depth over F1 and F3 while one sensor is buried at 30 cm over F2 by lack of additional sensor. Figure 2a
136 illustrates an example of TDR sensors at different depths.

137

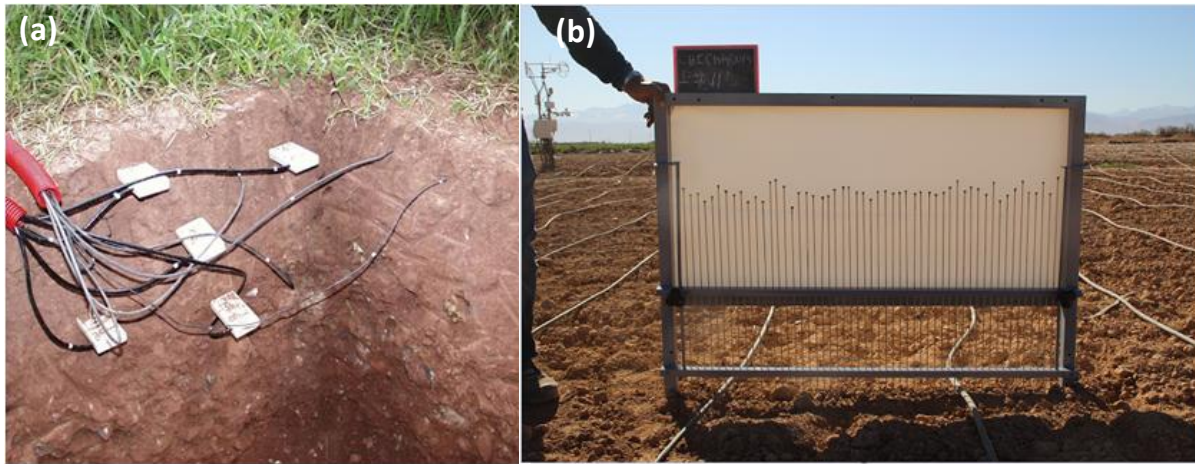



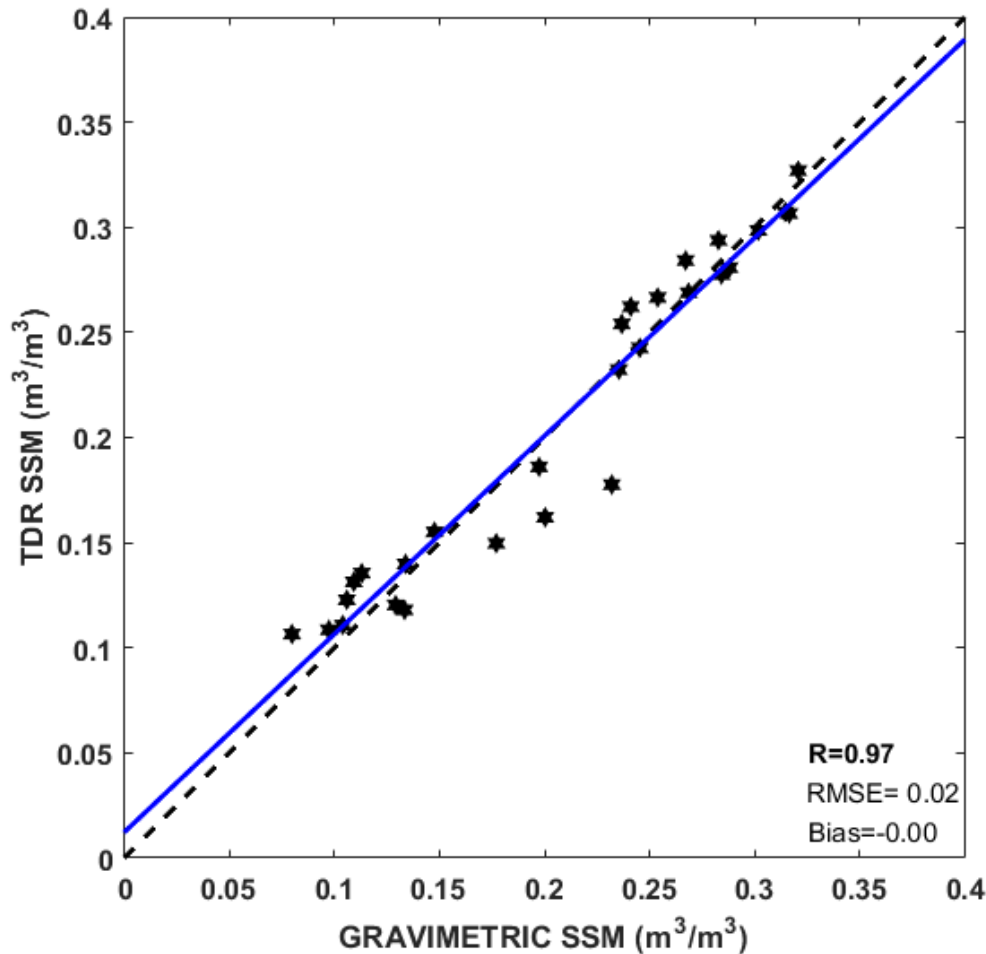
Figure 2. Examples of (a) TDR sensors installed at different depths and b) a pin profiler picture taken over one of the ploughed
field with drip irrigation tubes installed.

140 TDR sensors are calibrated using the gravimetric technique. The calibration is done during 2016-2017 season using samples
141 taken from the first 5 cm from both fields F1 and F2 and then the calibrated equation is applied to F1, F2 and F3 data as the
142 soil characteristics are similar and the same sensors are used. For that purpose, an aluminum core of 392.5 cm^3 is used to
143 collect samples at the TDR installation depths. Three samples are collected per day and per field during five days chosen
144 with different soil moisture conditions in order to cover a wide range of values (0.08 to 0.33 m^3/m^3). A linear regression is
145 established between the volumetric water content and the square root of the TDR time response (named τ in second) as
146 follow:

$$SSM = a_{TDR} * \sqrt{\tau} + b_{TDR} \tag{1}$$

148 The calibrated values using data of both fields are $a_{TDR} = 0.275 \, \text{m}^3/\text{m}^3/\text{s}^{0.5}$ and $b_{TDR} = -1.154 \, \text{m}^3/\text{m}^3$. Figure 3
149 illustrates the calibration results with all the samples displayed. The statistical metrics are: correlation coefficient R = 0.97,
150 Root Mean Square Error RMSE = 0.018 m^3/m^3 and no Bias. When considering both fields separately, the results for (F1,
151 F2) are R = (0.90, 0.94), RMSE = (0.023, 0.01) m^3/m^3 and Bias = (-0.002, 0.003) m^3/m^3.

152   The calibrated equation is also applied for the RZSMs assuming that the soil properties are the same at different depths.

153   Figure A2 in appendix A illustrates an example of an RZSM time series over F1.

154

155   **Figure 3. Surface soil moisture measured by TDR versus gravimetric measurements using samples collected over both fields F1**

156   **and F2 during 2016-2017 growing season. The blue solid line is the linear regression and the dashed line is Y=X.**

157   **3.1.2 Surface roughness**

158   Surface roughness characterizes the micro variation of the ground surface elevation within a given area/field (Allmaras et al.,

159   1966). It ~~is a parameter that affect~~ affects particularly the SAR signal and to a lesser extent the visible and near infrared

160   (Girard and Girard, 1989). The two parameters that characterize the surface roughness are the root mean square height (h_{rms})

161   and the correlation length (L). h_{rms} provides a vertical descriptor of ground roughness by measuring the elevation of the

162   surface along one or more observation lines and calculating the standard deviation of the recorded values. The second

163   parameter (L) corresponds to the distance between measurements from which the heights between points are statistically

164 independent. This parameter provides a horizontal description of the ground surface roughness, more specifically the

165 organizational structure and spatial continuity of the microtopography (Nolin et al., 2005). Over the 3 studied fields,

166 measurements of the surface roughness are taken during the first stage of wheat (from emergence to early tillering) when the

167 ground is not totally covered by the canopy. We used a pin profiler of 1 m length, composed of a set of 53 metal needles of

168 equal length every 2 cm (Fig. 2b). 16 sample pictures are taken per field and per date including eight pictures parallel and

169 eight pictures perpendicular to the rows direction. The pictures are taken using Canon 6EOS 600D equipped with TAMRON

170 lens (Model A14).

171 The images are processed in MATLAB based on the detection of the top position of each needle. h_{rms} and L are computed

172 from the auto-correlation function and then the average per direction, per field and per date is computed. For illustration, Fig.

173 4 shows the time series of h_{rms} and L parameters computed separately for each direction for F1 and F2 during the season

174 2017-2018 while the average value per season are summarized in Table 2 for F1, F2 and F3.

175 **Table 2. Average values of the roughness parameters (8 samples are gathered per field and per direction).**

		F1		F2		F3	
		h_{rms} (cm)	L (cm)	h_{rms} (cm)	L (cm)	h_{rms} (cm)	L (cm)
2016-2017	Parallel	0.92	5.02	1.19	5.77		
	Perpendicular	1.34	5.88	1.19	5.8		
	Average	1.13	5.45	1.19	5.78		
2017-2018	Parallel	0.89	5.44	1.1	5.88		
	Perpendicular	1.16	7.4	1.12	6.6		
	Average	1.02	6.42	1.11	6.24		
2018-2019	Parallel					0.83	6.54
	Perpendicular					0.96	7.32
	Average					0.89	6.93

176

177 Based on the range of h_{rms} measurements (0.83< h_{rms} <1.35), it can be clearly seen that the fields are characterized by a

178 slightly rough or smooth surface, which is the general case of disk tilling fields. After sowing, a slight change is observed at

179 there is no soil work and hence the change of h_{rms} and L are limited apart from the beginning the start of the crop season

180 (December 28, 2017, see Fig. 4). At that time, the soil has just been prepared for sowing and rows are directly exposed to

181 rain. The fact that the rows are still clearly visible in the field also explaining the differences observed between both

182 directions early in the season. This anisotropy disappeared quickly with irrigation, rainfall and plant growth. h_{rms} and L are

183 almost constant from early January onwards. Indeed, it has been shown that after sowing, roughness is affected by very

184 limited temporal variations (Bousbih et al., 2017) as no soil works occur after sowing. It is usually kept constant during the

185 crop season (El Hajj et al., 2016; Gherboudj et al., 2011; Gorrab et al., 2015; Ouaadi et al., 2020).

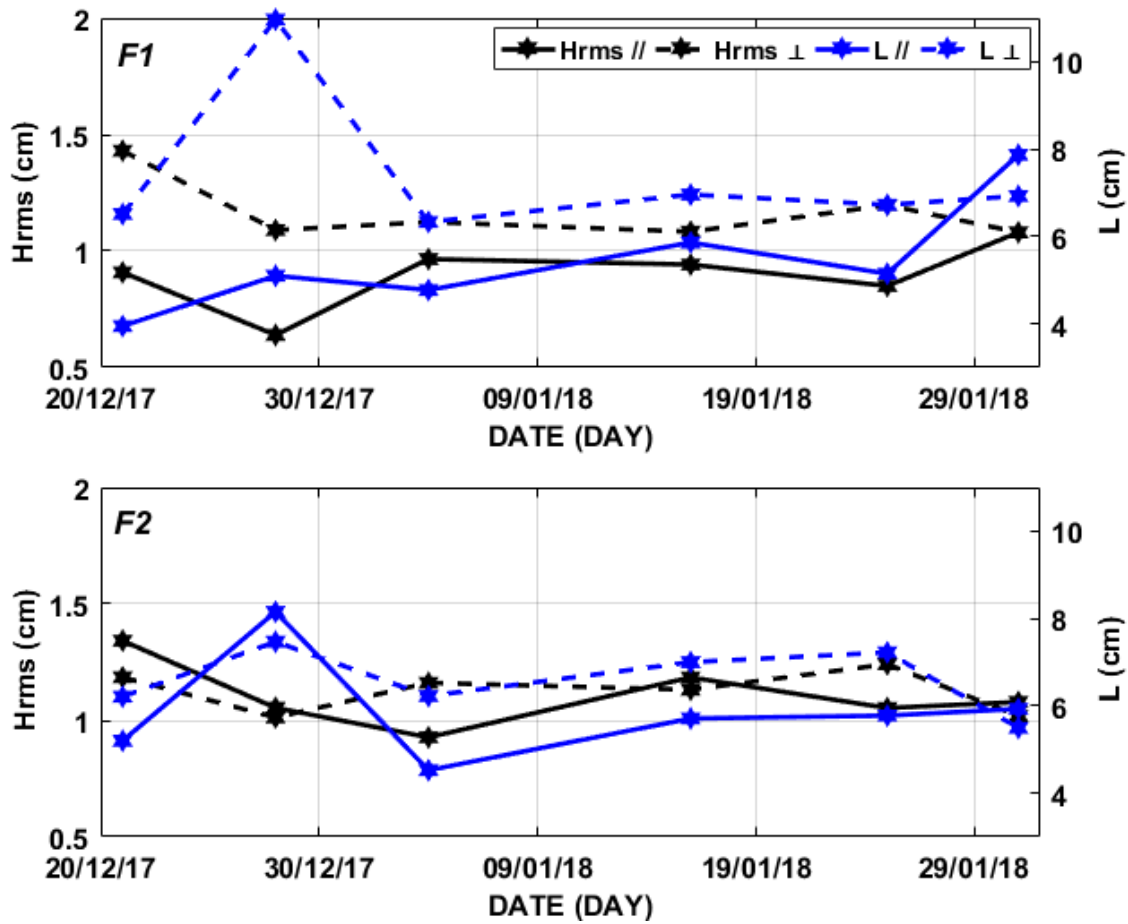



Figure 4. Time series of h_{rms} and L computed from parallel and perpendicular measurements separately for F1 and F2 during the season 2017-2018.

3.1.3 Biomass and water content

Biomass and water content are two biophysical parameters of crucial importance in different agricultural applications including particularly plant stress monitoring, radar backscattering response, crop yield and evapotranspiration modeling. Within each field, eight samples are collected once a week/two weeks during the growing season. The samples are chosen randomly so that the average is representative of the plot. A quadrates of an area of 0.0625 m^2 is used for the sampling (Fig. 5). The samples are weighed first in the field to get fresh above-ground biomass (FAGB). The corresponding above ground biomass (AGB) expressed in kg of dry matter by m^2 is determined at the laboratory by drying the samples in an electric oven at 105°C for 48 hours. The vegetation water content (VWC) is thus computed as the difference between FAGB and AGB (Gherboudj et al., 2011).

198

Figure 5. Photo taken during a measurement campaign illustrating a sample of above-ground biomass measurement.

200 **3.1.4 Canopy height, green leaf area index and cover fraction**

201 Canopy height (H), green leaf area index (GLAI) and cover fraction (F_C) are measured every week during the growing
202 season. Values from eleven different places are averaged and considered as a representative measure of the field. H is simply
203 measured using a measuring tape while GLAI and Fc are computed by processing hemispherical photos (Fig. 6b) using
204 MATLAB software following the method described in Duchemin et al. (2006) and Khabba et al. (2009). The eight photos
205 per date and per field are taken using a camera Canon 6EOS 600D with SIGMA 4.5 mm F2.8 EXDC circular fisheye HSM
206 (Fig. 6a). Photos are taken in optimal lighting conditions to avoid shadow effects and over-exposure phenomena which make
207 classification more difficult. The algorithm is based on the binarization of the hemispherical images by thresholding a
208 greenness index. Next, the useful part of the images is extracted by masking the operator and the high viewing angles (> 75°)
209 (Fig. 6c). Finally, the ground-covered area is extracted on concentric rings associated with fixed viewing angles and the
210 average of all pictures is the field GLAI. Using the same process, Fc is calculated as the ratio of the vegetation pixels number
211 to the pixels total number.

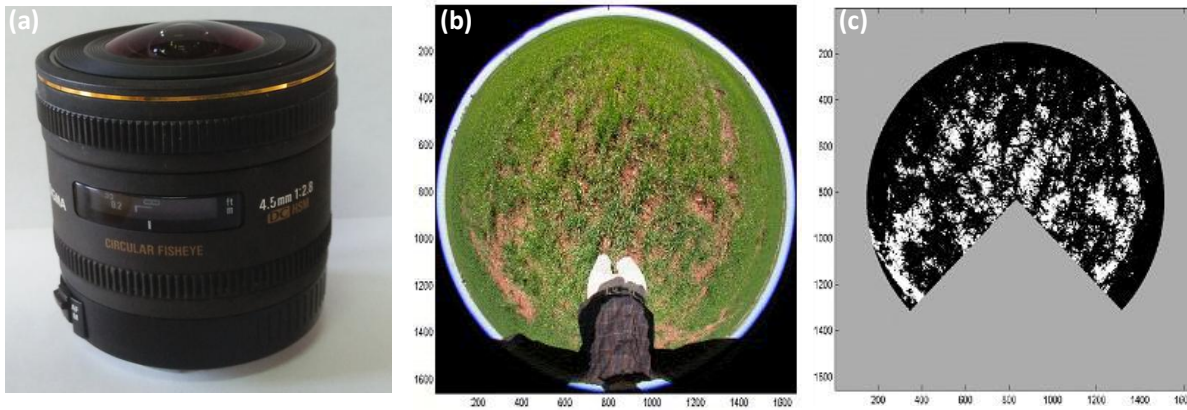



Figure 6. (a) the 4.5 mm F2.8 EXDC circular fisheye HSM, (b) hemispherical photo and (c) result of the processing after binarization and after masking the operator and the high viewing angles (> 75°).

3.1.5 Irrigation and weather data

F1, F2 and F3 are irrigated using the drip technique. Irrigation quantities are determined by the farmer by estimating the daily ~~potential~~ evapotranspiration under standard conditions (ETc) in the region computed using the FAO-56 model simple approach (Allen et al., 1998)~~. Irrigation is then planned on the basis of each period by giving the cumulative ET$_p$ during that period~~. The cumulative ET$_c$ for a given period (usually one week) is applied during one or more events per week depending on the farmer's constraints (e.g. availability of workforce) and on the weather conditions (e.g. occurrence of rain). The irrigation pipes are spaced by 0.7 m while the distance between the drippers along the pipe is 0.4 m. Over F1 and F2, the flowrate of each dripper is 7.14 mm/hour. The irrigation takes place about 105 min (12.53 mm). A flowmeter mounted downstream of a valve allowed an accurate collection of irrigation volumes. F2 and F3 are irrigated according to FAO recommendations while F1 is stressed voluntarily. The stress involved in F1 is during the first season (2016-2017) only. By contrast, the 2017-2018 season was wet so that there is no clear stress observed on the field. The irrigation dates and amounts over F1 and F2 during both seasons are made available throughout this database while irrigation over F3 are not available.

The weather data including precipitation, air temperature, relative humidity, solar radiation, wind speed and direction are collected by an automatic weather station installed over an alfalfa field near the studied fields (Fig. 7). The weather station provides continuously meteorological data every 30 min. The sensor Campbell CS215 is used to measure the air temperature and the relative humidity (Fig. 7). The global solar radiation and the wind direction and speed are measured using Campbell SKP215 and Campbell windsonic4, respectively. The precipitation are measured using the Rain Gauge (Campbell SBS500) shown in Fig. 7.

234

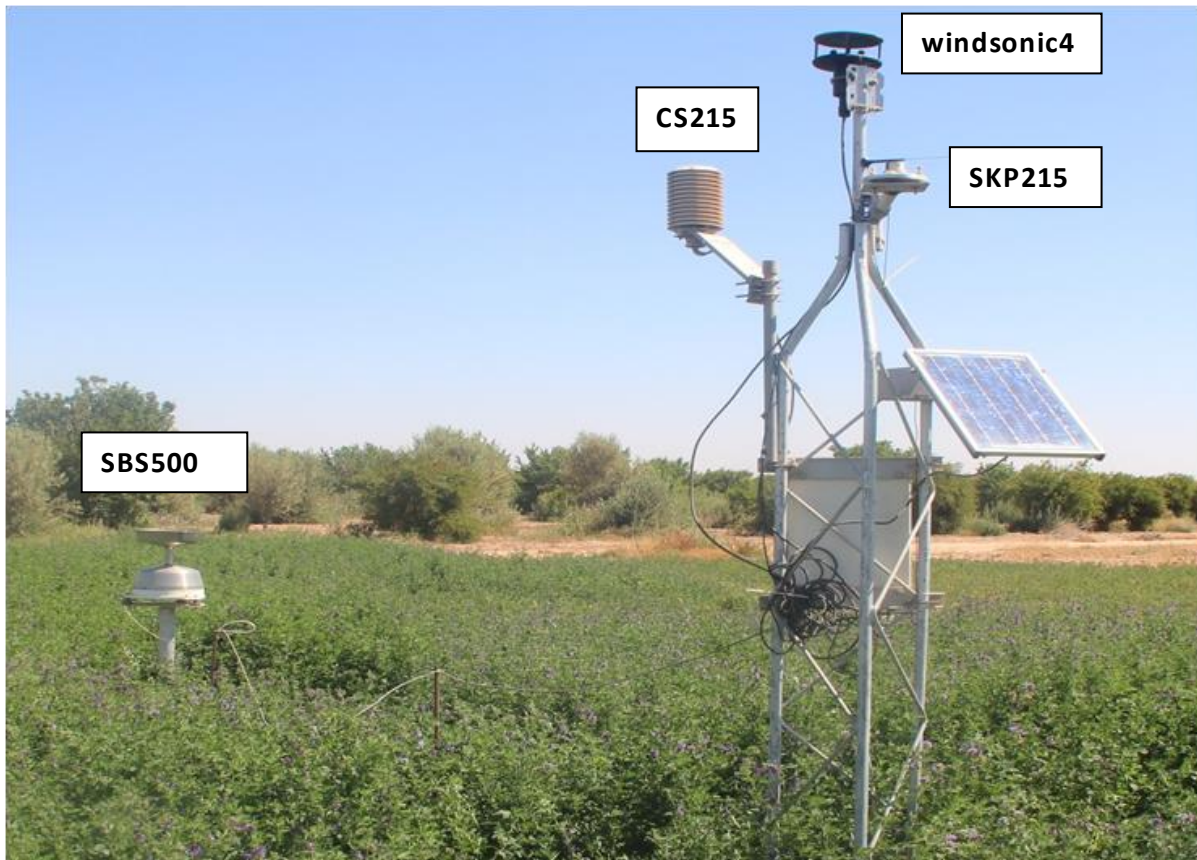



Figure 7. Automatic weather station installed over an alfalfa field near F1, F2 and F3.

236 **3.2 Remote sensing datasets**

237 **3.2.1 Sentinel-1**

238 Sentinel S1A and S1B are earth observation satellites developed for the Copernicus initiative and launched by the European

239 Space Agency on April 2014 and 2016, respectively. During full operation, S1A and S1B are maintained in the Near-polar

240 Sun-synchronous orbit at 693 km altitude, phased 180°, providing a revisit time of six days (Torres et al., 2012). S1 is a

241 synthetic aperture radar operating at C-band with a frequency of 5.33 GHz, mapping the entire world in 175 orbits per cycle.

242 The main operational imaging mode is the Interferometric Wide-swath mode (IW). IW acquires data with a wide swath of

243 250 km with high geometric (azimuth resolution 20 m and ground range resolution 5 m) and radiometric resolution (Mission

244 and Services, 2012). IW mode supports operation in single and dual polarization (HH, VV, HH/HV and VV/VH) and covers

245 a range of incidence angles between 31° and 46°. The product is composed of three Sub-Swath acquired in TOPSAR

246 imaging technique which significantly reduces the scalloping effect (Zan and Guarnieri, 2006).

247 Level 1 products are systematically processed and available within 24 hours, free of charge from the Sentinel-1 Data Hub

248 website (https://scihub.copernicus.eu). The website provides data under two types of products: GRDH (Ground Range

249 Detected High resolution) and SLC (Single Look Complex).

250 In this database, 561 GRDH and SLC products are processed (Table 3). Among them, 124 images are acquired over F3

251 during 2018-2019 growing season and 437 over F1 and F2 from October 01, 2016, to July 31, 2018, along the ascending

252 #118 (221 images) and descending #52 (216 images) relative orbits. This period includes two agricultural seasons in addition

253 to the summer period.

254 **Table 3. Characteristics of the sentinel-1 products processed over the three fields for the monitored periods**

Field	Season	Relative Orbit Number	Incidence angle	Relative Orbit	Overpass time	Product	Number of images
F1 and F2	October 2016 - July 2018	118	45,6°	Ascending	18:30	GRDH	112
						SLC	109
		52	35,2°	Descending	06:30	GRDH	110
						SLC	106
F3	November 2018 - May 2019	118	45,6°	Ascending	18:30	GRDH	32
						SLC	31
		52	35,2°	Descending	06:30	GRDH	31
						SLC	30

255 *Backscattering coefficient*

256 GRDH products are provided by ESA with a square pixel size and contains only the intensity information. The

257 backscattering coefficients are extracted using the Orfeotoolbox (CNES, 2018). The processing procedure consists of three

258 steps (Frison and Lardeux, 2018) :

259 1. *Thermal noise removal*: SAR product contains not only the useful signal but also the unwanted noise disturbing the

260   information contained in the intensity images, especially when the backscattered power is low. The thermal noise is

261   an additive noise. The compensation of this noise can be performed by subtracting the scaled noise power using the

262   calibrated noise vectors provided by ESA.

263 2. *Calibration*: The "calibration" step aims to convert the digital accounts into a physically interpreted parameter: the

264   backscattering coefficient. A calibration vector included in the GRDH products contains the necessary information

265   to convert the digital values to the backscattering coefficient.

266 3. *Terrain correction*: S1-SAR data are sensed with viewing angle greater than zero which induces distortion in the

267   products because of the lateral viewing geometry. The "Terrain corrections" module is used to compensate these

268   distortions and get as much possible images with the real geometric representation. The images are projected on the

269   Earth's surface using a Digital Elevation Model (DTM). The DTM SRTM (Shuttle Radar Topography Mission) of

270   30 m of resolution is used according to the method described in Small and Schubert (2008).

271 SAR images are affected by the speckle noise, which is mainly due to the relative phase of individual scatters within a

272 resolution cell. Many filters have been developed to remove the speckle noise although the best filter is the spatial average.

273 The presented database is generated using a simple average per field of. 120, 121 and 1100 pixels for F1, F2 and F3,

274 respectively with a mean standard deviation of around 1.55 dB. In order to visualise data dynamics, backscattering

275 coefficients are converted into dB.

276 *Interferometric coherence*

277 Sentinel-1 SLC products are provided in slant-range geometry. It contains three sub-swath images IW1, IW2 and IW3. Each

278 sub-swath is composed by nine bursts with black-fill demarcation. By contrast with GRD, both intensity and phase

279 information are kept. The phase information is used for the computation of interferometric coherence. SAR interferometry

280 consists of correlating two images acquired from two positions in space slightly separated from each other (with two radars

281 mounted on the same platform) or at different times by exploiting repeated orbits of the same satellite such as for Sentinel-1.

282 Thanks to its high temporal resolution (six days per orbit), the interferometric coherence is computed from two consecutive

283 acquisitions of the same orbit.

284 The interferometric coherence, given by the Eq. (2), for a local neighborhood of N pixels, is generated by cross multiplying,

285 pixel by pixel, the first SAR image z_i with the complex conjugate $z_i^{'*}$ of the second (Bamler and Hartl, 1998; Touzi et al.,

286 1999).

287

288
$$\rho = \frac{\sum_{i=1}^{N} z_i \cdot z_i^{'*}}{\sqrt{\sum_{i=1}^{N} |z_i|^2 \cdot \sum_{i=1}^{N} |z_i'|^2}}$$
(2)

289 The interferometric coherence $|\rho|$ varies between zero (incoherence) and one (perfect coherence). The interferometric

290 coherence is related to the movements of the scatterers within a given canopy. It decreases (loss of coherence) in the case of

291 dense vegetation while high values are obtained over bare soils. Loss of coherence could be caused by temporal interval

292 between acquisitions, orbit errors, vegetation development/movement or processing errors. The random dislocation of

293 scatters because of the weather (wind and rain) or the plants growth is the main cause of the temporal decorrelation.

294 Sentinel application platform SNAP is used to compute the interferometric coherence from S1-SLC products in five steps

295 (Veci, 2015):

296   1. *Apply-Orbit-file*: This module is applied for a better estimation of the position and speed of the satellite using the

297   orbit state vector. Preliminary, a predicted orbit state vector is contained in the metadata but it is not accurate. The

298   precise orbit is made available one month after data acquisition at the later. For this reason, the automatic download

299   in SNAP is used in order to update the orbit state vectors.

2. *Back-geocoding*: The two images need to be co-registered. One of the images is the master and the other is the slave. This step ensures that each pixel of the slave image is aligned with the corresponding pixel in the master image so that both pixels contain contributions from the same target. The DEM is required for "*Back-geocoding"* step, SNAP allows either to enter it manually or to download it automatically.

3. *Coherence*: This module in SNAP allows the computation of the interferometric coherence between the two images for a given local neighborhood. In order to get a square pixel of 13.95 m, azimuth* range are fixed to 3*15 in the processing.

4. *TOPSAR-Deburst*: The black-fills in between bursts are deleted separately for both polarization images (VV and VH).

5. *Terrain-Correction*: Finally, the processed images are projected on the earth surface using a DEM.

3.2.2 Sentinel-2 NDVI

Sentinel-2 optical satellites S2A and S2B are launched by ESA in June 2015 and March 2017, respectively. They are placed in opposition on the same orbit at an altitude of 800 km. Sentinel-2 provides data every 5 days with a width of 290 km and a resolution of 10 to 60 m according to spectral bands (13 bands) ranging from visible to the medium infrared. The National Centre for Space Studies (CNES) provides Level-2A products atmospherically corrected free of charge via the PEPS platform (https://peps.cnes.fr/) or the Theia website (https://theia.cnes.fr/). Data are corrected from atmospheric effects by the Center for the Study of the Biosphere from Space (CESBIO) using the MAJA chain (Hagolle et al., 2015). The atmospheric corrections are performed in three steps:

1. The satellite top-of-atmosphere (TOA) reflectances are corrected from the absorption by the atmospheric gas molecules using the absorption part of the Simplified Model for Atmospheric Correction (SMAC) method by Rahman et al., 1994. The concentrations of the ozone, the oxygen and the water vapor are obtained from satellite data (ozone) and meteorological data (water vapor, pressure).

2. The detection of the clouds (and cloud's shadows) is based on the multi-temporal cloud detection method proposed by Hagolle et al., 2010 .

3. The estimation of the aerosol optical thickness (AOT) relies on a hybrid method merging the criteria of a multi-spectral method with the multi-temporal technique developed initially for the VENµS satellite mission by Hagolle et al., 2010. The AOT is used along with the surface altitude, the viewing geometry and the wavelength in the parameterization of look-up tables for the conversion of TOA reflectances already corrected in step "1" into surface reflectances. The look-up tables are provided by the successive orders of scattering code (Lenobel et al., 2007) used in the modeling of molecular and aerosol scattering effects. A different look-up table is computed for each aerosol model.

Data are downloaded from the Theia site. Among the available products, only the products non-covered with clouds are used corresponding to ten, twenty-five and twenty-six images for 2016-2017, 2017-2018 and 2018-2019 agricultural seasons, respectively. Please note that during the season 2016-2017, only S2A was in the orbit which explaining the limited number of images (10). Next, the Normalized Difference Vegetation Index (NDVI) corresponding to each pixel is computed from band 4 and 8. An average per field is used to compute the time series of each field.

4   Data analysis

4.1 Vegetation variables

In this section, the relationships between the different variables (GLAI, FAGB, AGB, VWC and H) that characterize the vegetation growth and development are firstly investigated. These relationships are extensively used for different applications such as the calibration of backscattering models and the development of retrieval approaches (Chauhan et al., 2018). Several land surface or crop model relies on empirical relationships to predict Fc or H as well (Bigeard et al., 2017; Castelli et al., 2018). Other agricultural models compute AGB from GLAI using linear or polynomial relationships (Major et al., 1986; Petcu et al., 2003). Figure 8 displays the resulting relationships using data from F1 by selecting only the 2016-2017 season for illustration purposes. These relationships are computed separately based on the data recorded before and after the peaks of GLAI and FAGB.

The nature of the relationship changes depending on the structure (biomass variables) or on the greenness of the plant (GLAI). The biomass variables (FAGB, AGB and VWC) and H increase up to the biomass peak. Afterwards, a reverse evolution can be observed characterized in particular, by a decorrelation between FAGB/VWC and AGB. This is mainly related to the senescence process of the vegetation; the leaves begin to dry progressively with the start of the grain filling, so that the Sapflow (water, carbohydrates, proteins and mineral salts) migrates to the heads at the top of the plant (Farineau and Morot-Gaudry, 2018). Indeed, VWC and AGB are highly correlated until vegetation peak (the correlation coefficient R = 0.94 before the peak and R = -0.20 afterwards) while FAGB being dominated by the plant water content is highly correlated with VWC during the whole crop season (R=0.99 before the peak and R = 0.98 afterwards). Likewise, H is highly correlated to FAGB, VWC and AGB until vegetation peak (R > 0.97) when H remains at its maximum value while AGB continue to increase with grain filling and VWC and FAGB decrease because of the vegetation drying. The relationship of these variables (FAGB, AGB, VWC and H) with GLAI and Fc is quite different. The curves are of a parabolic shape with a maximum reached around the GLAI peak. A timing shift between the peaks of GLAI and FAGB is observed. This is probably related to the senescence of the lower leaves, which leads to an earlier drop of GLAI than of FAGB. Between the peaks of GLAI and FAGB, GLAI decreases while i) AGB and H increase and ii) FAGB increases slightly while VWC is almost constant. After the FAGB peak, AGB goes on increasing due to grain filling while the VWC decreases due to drying of the plant. FAGB which is the sum of AGB and VWC is almost constant.

362

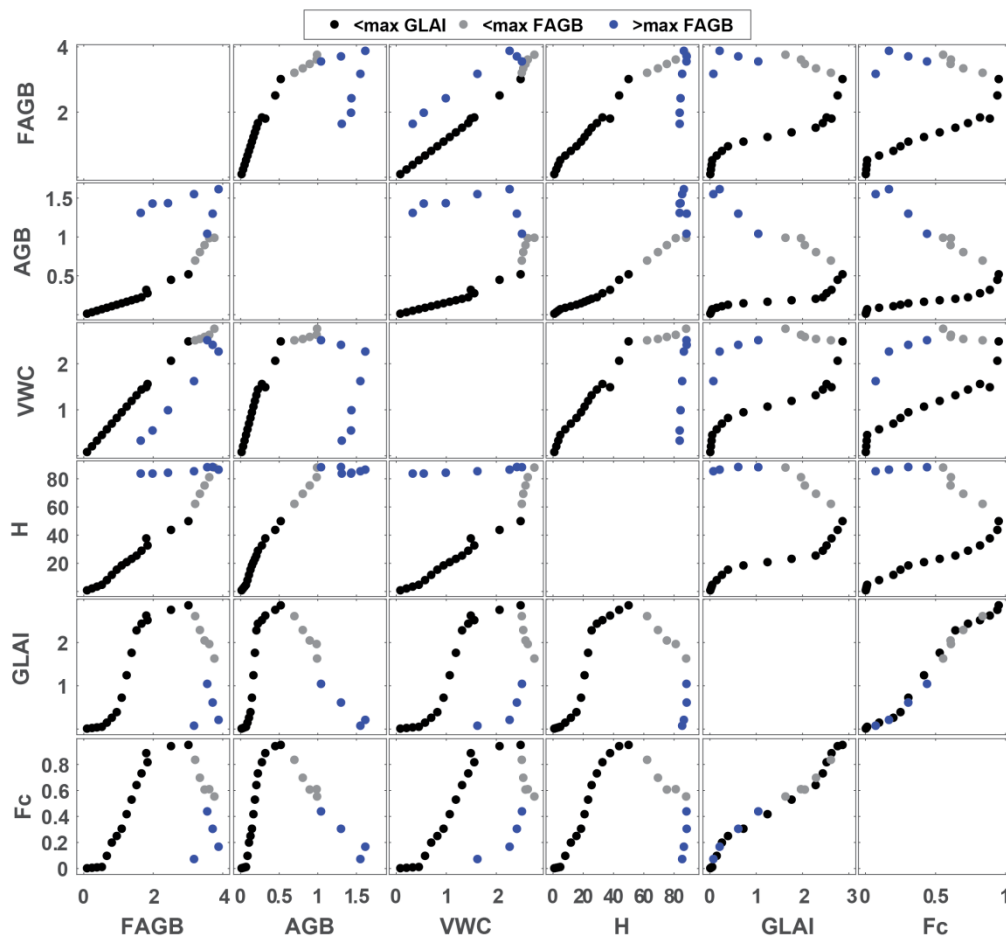



Figure 8. Scatterplots of the relationships between wheat measured variables: FAGB, AGB, VWC, H, GLAI and Fc. Data are
presented separately using the maximum of GLAI and FAGB as thresholds: data <max GLAI are in black, data < max FAGB
(and > max GLAI) are in grey and data > max FAGB (and > max GLAI) are in blue.

4.2 Radar data

The time series of the backscattering coefficient, the polarization ratio and the interferometric coherence are analyzed here
for two agricultural seasons and a summer period on F1 and F2 and at two incidence angles (35.2° and 45.6°).

4.2.1 The backscattering coefficient

Figure 9 displays the time series at 45.6° over F2 for illustration purposes: a) backscattering coefficient at VV polarization
(σ^0_{VV}); b) backscattering coefficient at VH polarization (σ^0_{VH}) as well as wheat phenological stages; c) SSM, air temperature,

372 irrigation and rainfall. Figures A3- A5 in appendix A show the same time series over F1 and F2 at 35.2° and F1 at 45.6°,

373 respectively. The backscattering coefficients reveal a strong seasonal signal with two cycles. The first cycle takes place from

374 sowing to the heading stage and the second from heading to harvest with the minimum reached around the heading stage.

375 The highest values at 35.2° are observed in the first cycle, while at 45.6°, σ° is higher on the second peak. The maximum

376 values of σ_{VV}^0 reached the same value for F1 and F2 while higher values are observed on F2 at VH. σ_{VV}^0 is more sensitive to

377 soil moisture variation until mid-January, corresponding to the tillering stage, when the soil is not yet fully covered by

378 vegetation. Although it is agreed that the signal during this period is governed by the dynamics of soil moisture, its behavior

379 differs from one site to another giving the difference in soil hydric conditions and surface roughness. After this period, the

380 signal behavior is similar to the profiles obtained by Cookmartin et al. (2000), El Hajj et al. (2019), Nasrallah et al. (2019)

381 and Veloso et al. (2017). ~~The~~ It ~~signal hereafter~~ decreases gradually from the early tillering until the heading stage (around

382 March 13) by about 10 dB on F2 and 5 dB on F1 because of the attenuation by the canopy during the development of the

383 stems (extension stage) (Cookmartin et al., 2000; Mattia et al., 2003; Picard et al., 2003; Wang et al., 2018). Obviously, the

384 attenuation is more important at VV polarization because of the vertical structure of wheat (stems) in line with the results of

385 (Fontanelli et al., 2013; Picard et al., 2003; Wang et al., 2018). The response of σ_{VH}^0 to SSM variation and canopy attenuation

386 is lower than for σ_{VV}^0. After the heading stage, the signal starts to increase again. This is clearer on F2 than F1 and at 45.6°

387 than at 35.2°. The heading stage is the phenological stage of wheat when the spike or head starts emerging out from the leaf

388 sheath. This change of the structure of the canopy shield the stems for the radar signal through the appearance of a thick, wet

389 top layer composed of the heads. The C-band wavelength penetrates this layer only, resulting in increased volume scattering,

390 while attenuation becomes low. This effect- is stronger for F2 than for F1, at VH than at VV and at 45.6° than at 35.2°. This

391 increase was first reported by Ulaby and Batlivala (1976). Subsequently, Ulaby et al. (1986) suggested that an additional

392 term must be added to the traditional three-term model (vegetation volume diffusion, soil attenuation, and soil-vegetation

393 interaction) to properly represent wheat backscattering after heading. Later on, similar behaviour has been observed and

394 attributed to the appearance of the heads followed by the grain by numerous authors (Brown et al., 2003; El Hajj et al., 2019;

395 Mattia et al., 2003; Patel et al., 2006; Veloso et al., 2017). ~~This effect is stronger for F2 than for F1, at VH than at VV and at~~

396 ~~45.6° than at 35.2°.~~ The exceptional growing conditions on F2 during S2 is at the origin of the observed plateau of the

397 backscattering coefficient which remains quite stable until harvest. This is due to a significant contribution of volume

398 scattering which is a behavior that characterize a crop developing a random canopy structure in relation to the numerous and

399 dense adventices as already highlighted (cf. picture Fig. A1 at appendix A).

400 The low variation observed on F1 during the 2016-2017 season is mainly related to the limited development of vegetation

401 because of the triggered water stress. Likewise, the difference between the two seasons over F2 is related to a higher density

402 of grown seeds and wetter conditions in the 2017-2018 season compared to 2016-2017 (the amount of rainfall during the

403 growing season-from sowing to harvest-reached 167.23 mm in 2017-20118 while only 69.94 mm is recorded in 2016-2017).

404 With the drying of the head layer, the backscattering decreases again at the end of the season to reach the lower observed

values. Indeed, as the head layer dries, the vegetation becomes transparent to the signal. The soil is also dry at the end of the season because irrigation is stopped. These low values remained until the first deep ploughing on July 11, when a sharp increase is observed because of a drastic change of soil roughness. Hereafter, the signal is again stable until the seedling preparation work for the next 2017-2018 season (November 22).

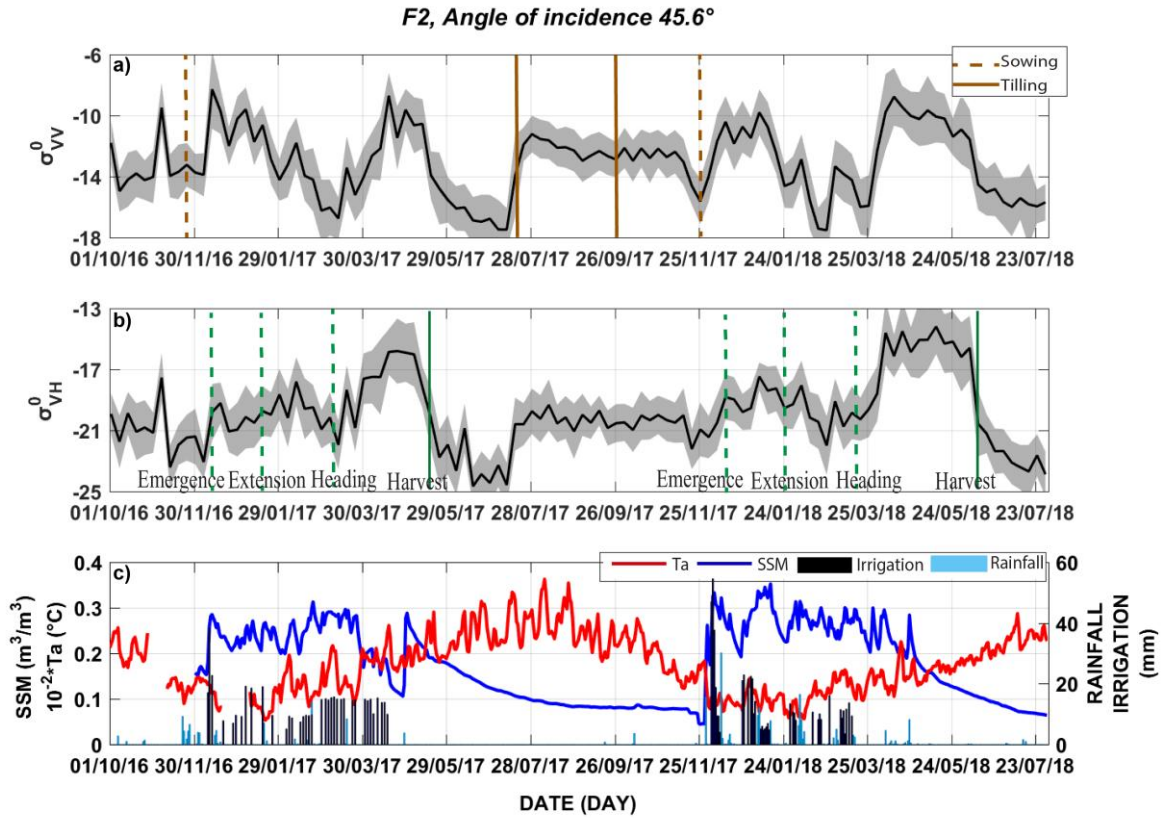



Figure 9. Time series of the backscattering coefficient at VV (a) and VH (b) polarizations on F2 at 45.6° of incidence angle during the period from October 01, 2016 to July 31, 2018. The tilling works and phenological stages of wheat are superimposed on subplots (a) and (b), respectively. The air temperature, surface soil moisture (SSM), irrigation and rainfall are displayed on subplot (c).

4.2.2 The interferometric coherence and the polarization ratio

Figure 10 displays the time series at 45.6° over F2 of: a) interferometric coherence at VV (ρ_{VV}) and VH (ρ_{VH}) polarizations together with sowing and tilling dates; b) polarization ratio (PR $= \sigma^0_{VH}/\sigma^0_{VV}$), as well as wheat phenological stages; c) Sentinel-2 NDVI and measured GLAI; d) Measured FAGB, AGB, VWC and H. Likewise, Fig. A6- Fig. A8 in appendix A display the time series over F1 and F2 at 35.2° and F1 at 45.6°, respectively. The time series of ρ_{VV} and ρ_{VH} follows a similar evolution. Before sowing, coherence is at its highest value corresponding to 0.9 for ρ_{VV} and 0.7 for ρ_{VH} (Fig. 10a). These values express a dominance of coherent scattering, corresponding to response of bare soils composed of big rocks.

421 Indeed, during the summer, the plots are subjected to deep ploughing which yields big clods that resist any change in surface
422 structure caused by climatic factors such as wind or rain. The second tilling breaks up the clods for the next seeding. Soil
423 works and farming activities induce a large decrease in coherence in line with the observation of Wegmuller and Werner
424 (1997). The surface roughness is a main parameter that influences not only the amplitude at C-band but also the phase.
425 Indeed, abrupt drops are observed around each sowing events and tilling works (brown vertical lines on Fig. 10a).

426 After sowing, the evolution is similar to the profiles obtained by Blaes and Defourny (2003) and Engdahl et al. (2001). The
427 interferometric coherence increases from 0.15 to 0.7 and then starts to decrease slightly from the emergence of wheat,
428 becoming almost constant after stem extension with values < 0.3 corresponding to the noise level. Indeed, using the ERS–
429 Envisat Tandem mission, Santoro et al., (2010) demonstrated that coherence measurements of vegetated fields are always
430 below the level of bare soils coherence. Actually, the interferometric coherence is known to decrease exponentially with
431 wheat growth (Lee et al., 2012). Vegetation growth and random dislocation of scatters cause a degradation of coherence
432 (Blaes and Defourny, 2003; Engdahl et al., 2001; Wegmuller and Werner, 1997), especially under wind and rain effects.
433 Between sowing and emergence, the observed variation is assumed to be related to the installation of irrigation drippers that
434 took place up to two weeks after sowing. The changes that occur between the harvest and the first tilling could be attributed
435 to livestock grazing, a common practice in the region after wheat harvest, which could change the surface roughness.

436 The polarization ratio (PR) is closely related to the biomass dynamic. Both are increasing from emergence to heading and
437 then start to decrease until harvest. The maximum timing is around middle of April. The significant differences in
438 biophysical parameters between F1 and F2 is due to irrigation, as already highlighted for the backscattering coefficient time
439 series. Likewise, the difference between the two seasons over F2 is related to a higher sowing density and wetter conditions
440 in the 2017-2018 season compared to 2016-2017. As shown above (Fig. 8), the time series of FAGB and VWC are in line
441 with AGB and H up to the peak of FAGB and then decrease together while AGB continues to increase and H remains at its
442 maximum value. FAGB and VWC are dropping at the same time but 50 days after when compared to GLAI and NDVI and
443 about 15 days before the backscattering coefficient.

F2, Angle of incidence 45.6°

444

445

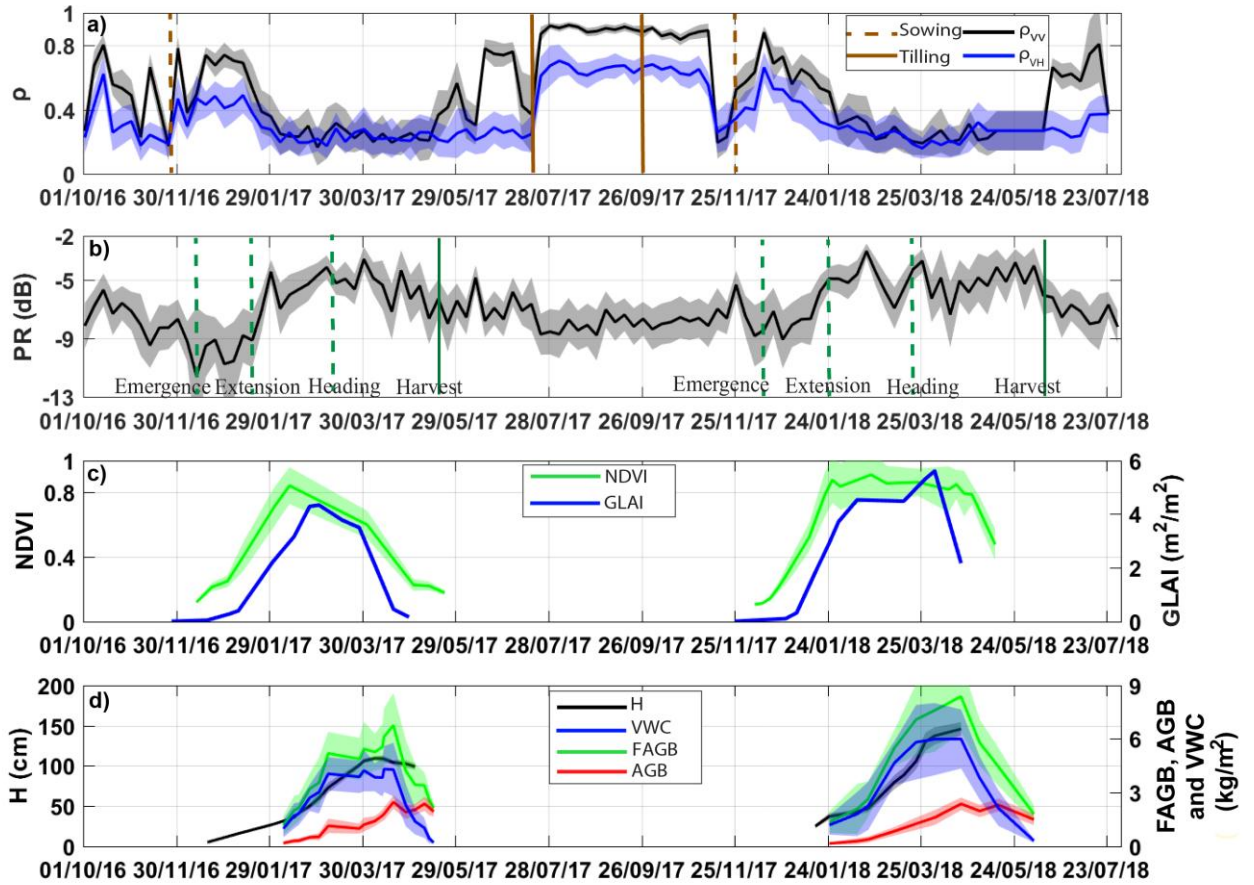
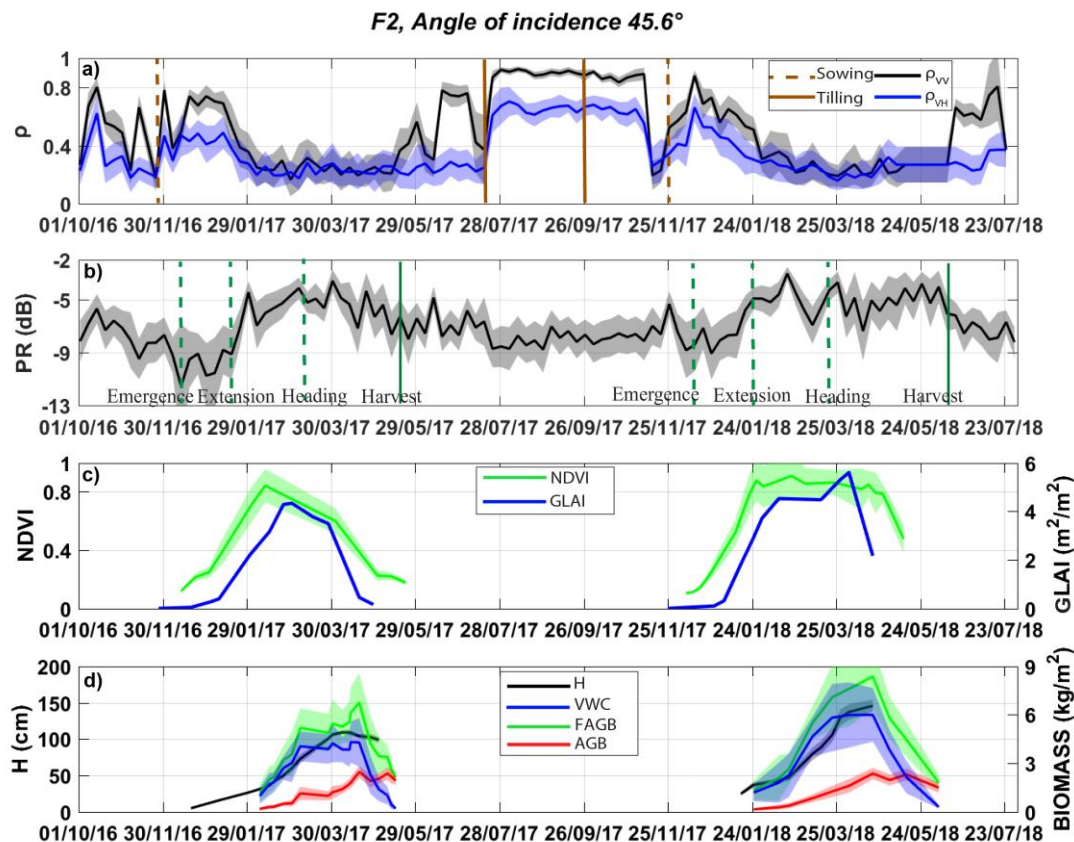



Figure 10. Time series of the interferometric coherence at VV and VH polarizations (a) and the polarization ratio (b) on F2 at 45.6° of incidence angle during the period from October 01, 2016 to July 31, 2018. The tilling works and phenological stages of wheat are superimposed on subplots (a) and (b), respectively. NDVI and measured GLAI are displayed in subplot (c). Measured H, FAGB, VWC and AGB are plotted in subplot (ed). Time series are presented by mean values (solid lines) and standard deviations (filled fields surrounding the solid lines).

4.3 Relationship between SAR data and vegetation variables

The polarization ratio and the interferometric coherence have been shown to be related to vegetation growth. In this section, the relationships between PR, ρ_{VV} and ρ_{VH} and vegetation variables, including AGB, VWC, H, GLAI and NDVI are analyzed. Figure 11 displays the results at 35.2° of incidence angle and Fig. A9 in appendix A displays the results at 45.6°. H is used to illustrate the vegetation growth because its evolution is monotonic, so that data corresponding to before and after maximum development can be easily separated. The determination coefficient R^2 and the Spearman rank correlation Rs are superimposed on the subplots together with the fitting equations using the whole database. Overall, a good correlation has been found between SAR variables (PR, ρ_{VV} and ρ_{VH}) and AGB, VWC, GLAI and H. A hysteresis behavior is obviously observed for the vegetation variables with a non-monotonic dynamic (VWC, NDVI and GLAI). Using PR, the relationships are more scattered and characterized by lower saturation value. Although the range of variation of ρ_{VH} is limited with

461 regards to PR, the statistical metrics of the relationships between interferometric coherences and the vegetation variables are
462 better than those obtained using PR. ρ_{VV} exhibited better correlation to the vegetation variables than ρ_{VH}. With the exception
463 of NDVI, Rs is always greater than 0.67. The best fit is obtained between ρ_{VV} and H (Rs = 0.78 and R^2 = 0.65) with higher
464 saturation value than the other relationships (~55% of H range which is about 77 cm). By contrast, a visual inspection of the
465 Fig. 11 (d, i and n) shows that relationships with NDVI are poorer when using data of the whole growing season. The
466 dispersion is strong along the season. Data before and after the maximum development can be distinguished, particularly,
467 using ρ_{VV} and to a lesser extent ρ_{VH}. Figure 11 (i and n) shows that a linear relationship exists between NDVI and SAR data
468 using data before maximum development only, i.e. when the vegetation is still green. During the beginning of the season, the
469 slope of ρ_{VV}-NDVI and ρ_{VH}-NDVI is low compared to the other vegetation variables. This is because the NDVI increases
470 faster around the emergence of wheat while ρ_{VV} is steel high because of the low vegetation cover fraction at this time. The
471 hysteresis effect observed after the maximum of vegetation development is due to the senescence of the leaves when NDVI
472 starts decreasing while ρ_{VV} and ρ_{VH} are stable at low values.

473 When considering SAR data at 45.6° of incidence angle (Fig. A9), a similar behavior to Fig. 11 is observed with AGB,
474 VWC, H and NDVI. Same hysteresis and scattering are observed for NDVI although higher correlations are obtained.
475 Similarly, ρ_{VV} is better correlated to vegetation parameter than ρ_{VH} and PR. By contrast, GLAI is better correlated with SAR
476 variables than H. The PR-GLAI relationship is more scattered than at 35.2° while ρ_{VV}-GLAI has the best metrics (Rs = 0.82
477 and R^2 = 0.73) with a higher saturation value around 50% of the GLAI range (3 m^2 m^{-2}).
478 Unlike PR, the metrics at both 35.2° and 45.6° are stable for the relationships between ρ_{VV} with AGB, VWC and H. By
479 contrast, PR-GLAI is more stable than ρ_{VV}-GLAI at both incidence angles.

480

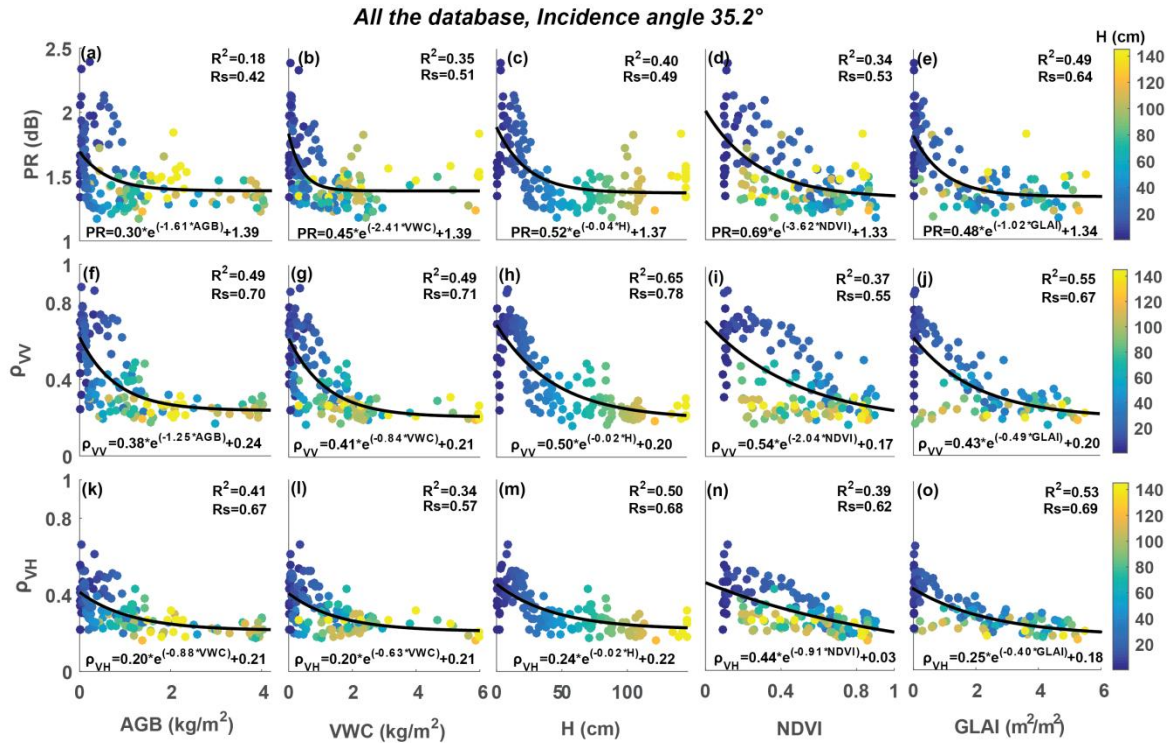
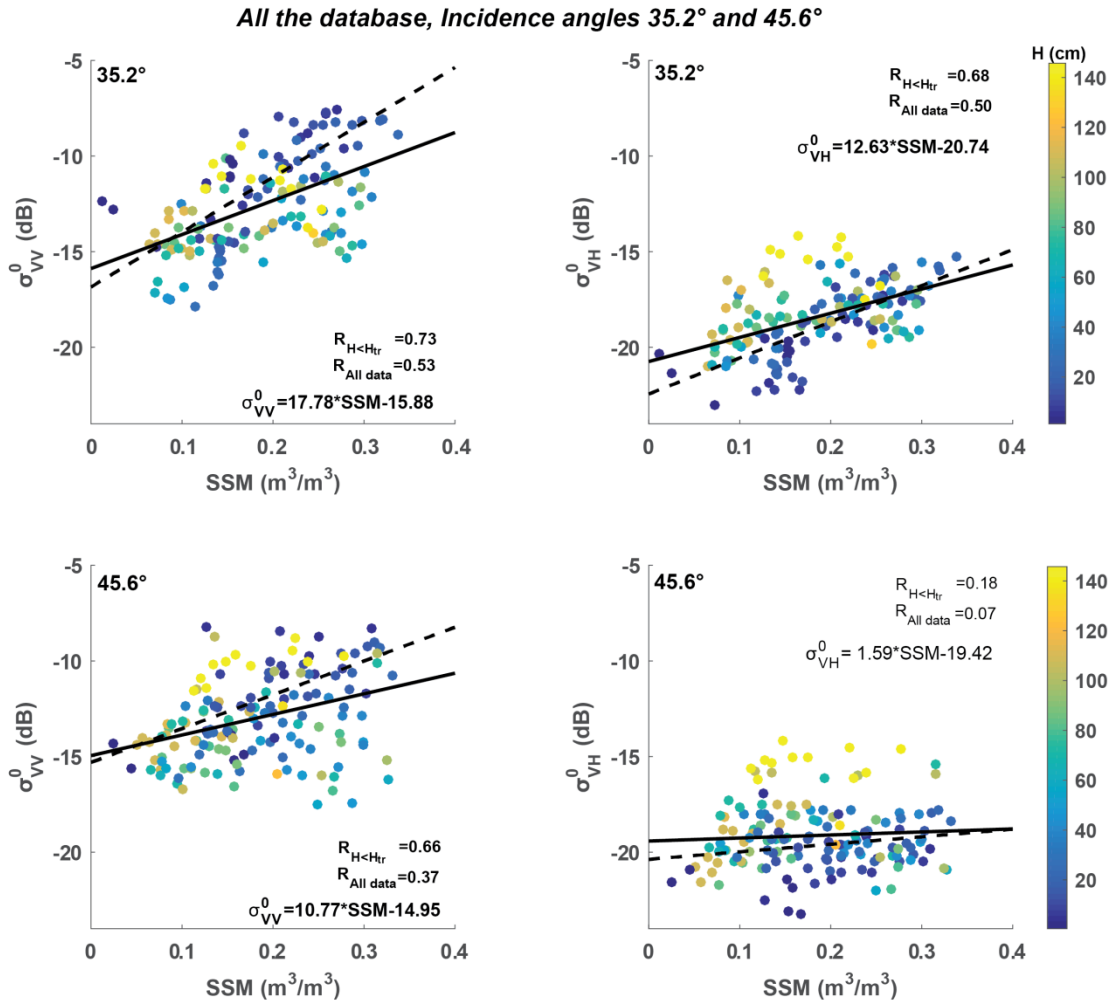



Figure 11. Scatter plots of the relationships between PR, ρ_{VV} and ρ_{VH} and AGB, VWC, H, NDVI and GLAI at 35.2° angle of incidence. The entire database is used from the three fields (F1, F2 and F3). H is used to monitor the evolution during the growing season. All the determination coefficient R^2 and the Spearman rank correlation Rs are significant at 99%.

4.4 Relationship between backscattering coefficient and SSM

Figure 12 displays the relationships between σ^0 and SSM using the entire database at 45.6° and 35.2° of incidence angles. H is used as an indicator of vegetation growth. The correlation coefficient is computed separately for the entire database and for data corresponding to H lower than a threshold value (H_{tr}) correspond to GLAI < 1.5. This value of GLAI correspond to wheat not fully covering the soil (Ouaadi et al., 2020b). H_{tr} is about 23.5 cm, 23.5 cm, 32.9 cm and 26 cm for F1 and F2 during 2017-2018, for F2 during 2016-2017 and for F3. Overall, σ^0_{VV} is obviously better correlated to SSM than σ^0_{VH} in line with the results of numerous studies (Holah et al., 2005; Li et al., 2014; Ulaby and Batlivala, 1976). Likewise, metrics at 35.2° are better than those obtained at 45.6°. This is expected as the contribution of vegetation is dominant at higher incidence angles and at VH polarization. The relationships are scattered when using data from the whole season. This is attributed to the presence of vegetation and mainly to the attenuation of the soil signal backscattered by the wheat. The sensitivity of σ^0 to SSM decreases progressively during the growing season as shown by the decreasing slope of the relationships with the vegetation development. By considering the early season data only, when the soil is not yet covered by

496 vegetation, a better fitting is obtained between σ^0 and SSM. Indeed, the correlation coefficient using data with H < H_{tr} is
497 improved whatever the polarization and the incidence angle. Obviously, the highest correlation is obtained at VV
498 polarization and 35.2° of incidence angle (R = 0.73) and to a lesser extent at VV at 45.6° and VH at 35.2° with R ≥ 0.66.

499
500 **Figure 12. Scatter plots of the relationships between σ^0_{VV} and σ^0_{VH} and SSM at 45.6° and 35.2 2° angles of incidence. The entire**
501 **database is used from the three fields (F1, F2 and F3). H is used to monitor the evolution during the growing season. The**
502 **significant correlation coefficients are in bold. The solid and the dashed lines correspond to all database and data with GLAI < 1.5,**
503 **respectively.**

5 Conclusion

This paper presents a 3-year database of C-band radar data and all necessary ancillary ground measurements to improve our understanding of the radar signal and to develop inversion methods for land surface parameters retrieval. The data are collected from three heavily monitored wheat fields under semi-arid conditions in the center of Morocco. The database offers a complete set of data for radar applications on wheat monitoring. The measured parameters include fresh and dry above ground biomass, canopy height, leaf area index, cover fraction, surface soil moisture, root zone soil moisture and surface roughness, in addition to the normalized difference vegetation index and SAR data (the backscattering coefficient and the interferometric coherence). The irrigation and meteorological data are also provided. This database opens the opportunity to use remote sensing together with measured parameters to understand and investigate the behavior of wheat crops and thereafter for vegetation parameters and soil moisture retrieval. The database analysis presented in this paper demonstrates the potentialities of SAR data for wheat monitoring by addressing the well-known sensitivity of SAR to surface soil moisture and vegetation variables. The obtained relationships between SAR measurements including backscattering coefficient, polarization ratio and interferometric coherence can be used for the application of several backscattering models, the retrieval of biophysical variables and for yield prediction in crop models. They can also be useful for land surface models relying on accurate estimation of vegetation height such as the energy balance models (i.e. TSEB -Two Source Energy Balance- Norman et al., 1995). The dataset illustrates also the complex signal acquired by C-band radar over wheat crops that is not yet fully understood as it mix the responses from highly dynamic contributions of soil and vegetation elements. The unique dataset provided in this paper should contribute through future studies to improve our understanding of the response of C-band radar observations over annual crops.

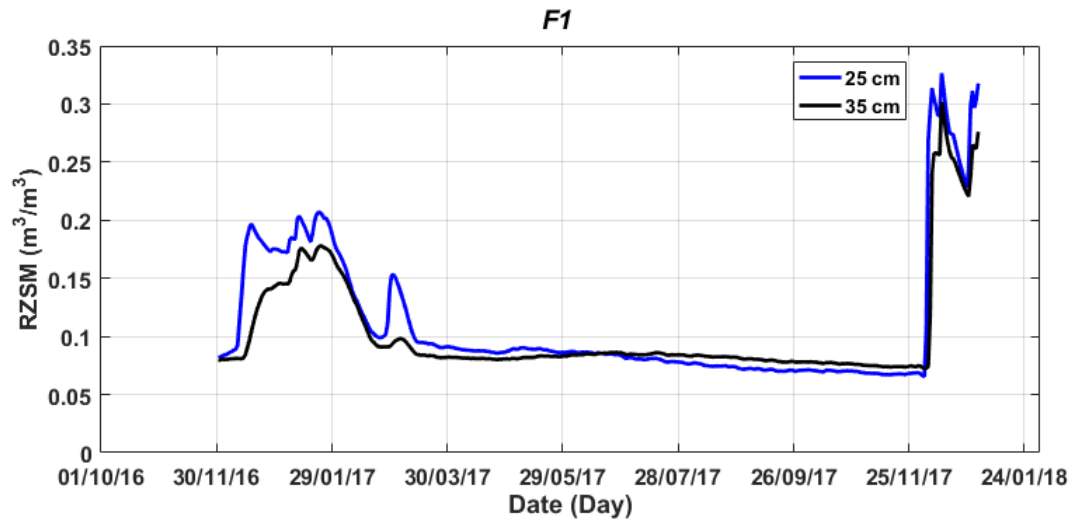
6 Database availability

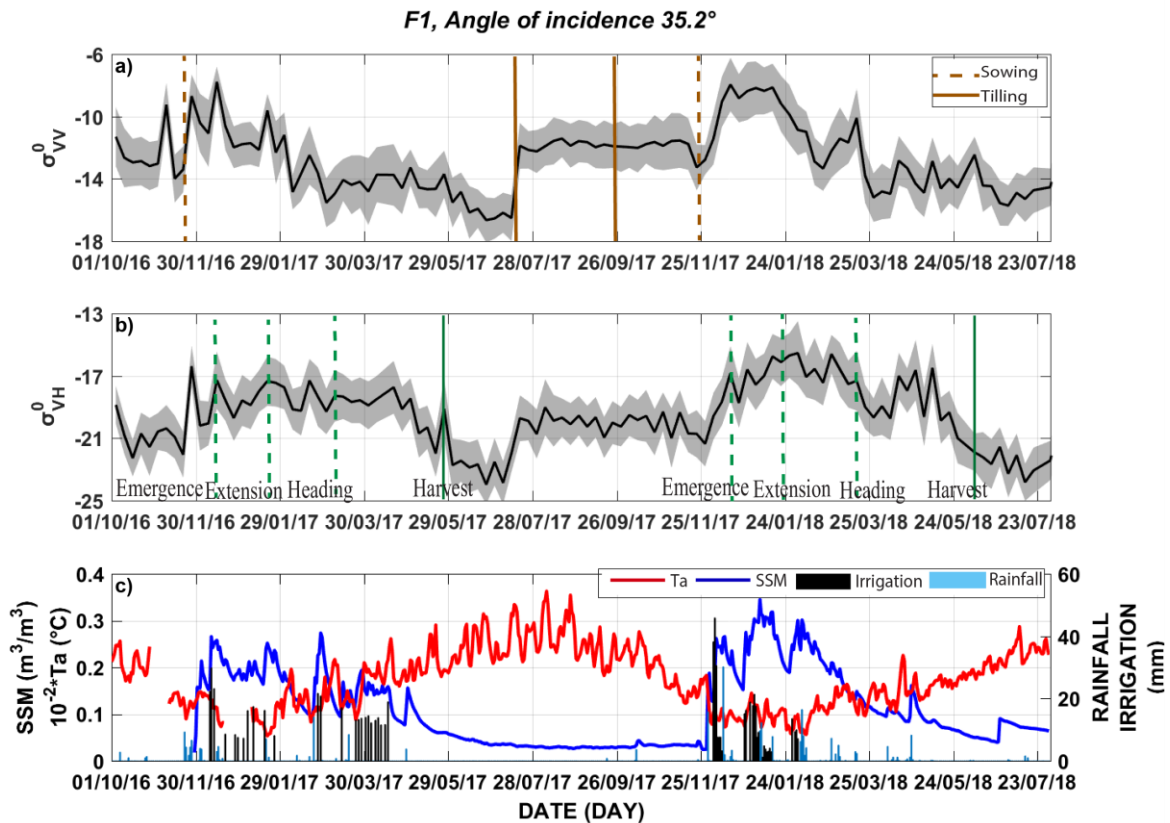
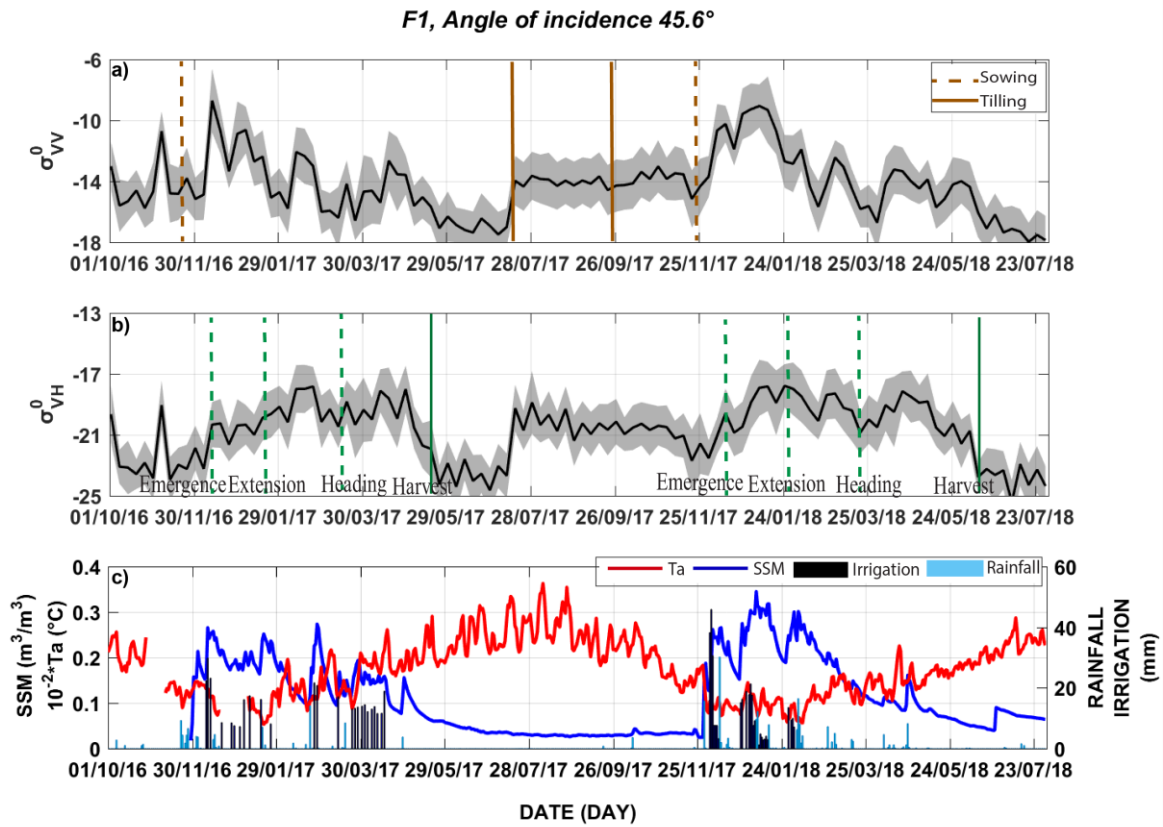
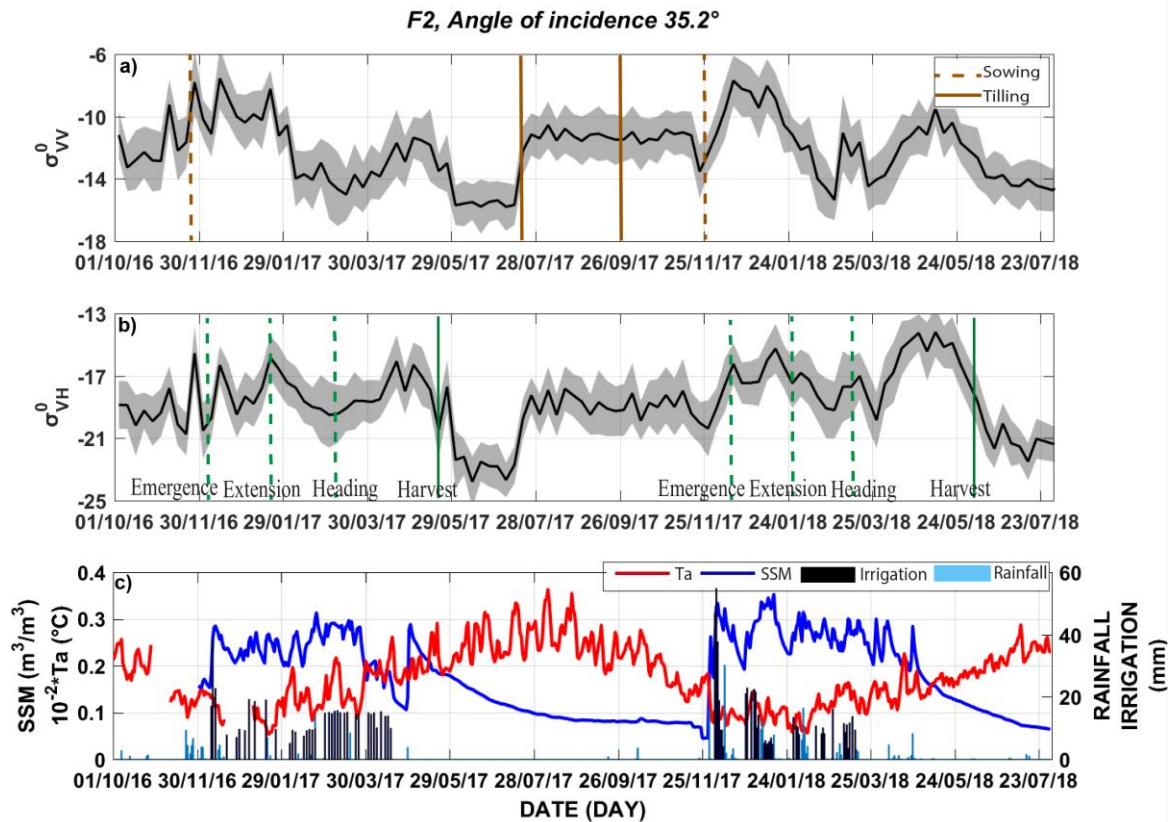
This database is archived in DtaSuds repository of the French National Research Institute for Sustainable Development (IRD). The database is accessible free of charge with "CC-BY" licence at https://doi.org/10.23708/8D6WQC (Ouaadi et al., 2020a). It can be downloaded as xlsx files accompanied by a variable dictionary containing the variable names and units. The files are also accompanied by a metadata including a description of the database, time coverage, keywords and other general information.

530   **Appendix A: Complimentary figures**

531

532   **Figure A1~~13~~. Picture taken over F2 during 2017-2018 growing season (14/05/2018) illustrates the specific growing conditions**
533   **(adventices and stems laid down by wind).**

534

535

536 **Figure A2. Time series of root zone soil moisture (RZSM) at 25 and 35 cm of depth measured over F1 from December 01, 2016 to**
537 **December 31, 2017.**

538
539 **Figure A3. Time series of the backscattering coefficient at VV (a) and VH (b) polarizations on F1 at 35.2° of incidence angle during**
540 **the period from October 01, 2016 to July 31, 2018. The tilling works and phenological stages of wheat are superimposed on**
541 **subplots (a) and (b), respectively. The air temperature, Surface soil moisture (SSM), irrigation and rainfall are displayed on**
542 **subplot (c).**

543
544 **Figure A4. Time series of the backscattering coefficient at VV (a) and VH (b) polarizations on F1 at 45.6° of incidence angle during**
545 **the period from October 01, 2016 to July 31, 2018. The tilling works and phenological stages of wheat are superimposed on**
546 **subplots (a) and (b), respectively. The air temperature, Surface soil moisture (SSM), irrigation and rainfall are displayed on**
547 **subplot (c).**

548
549 **Figure A5. Time series of the backscattering coefficient at VV (a) and VH (b) polarizations on F2 at 35.2° of incidence angle during**
550 **the period from October 01, 2016 to July 31, 2018. The tilling works and phenological stages of wheat are superimposed on**
551 **subplots (a) and (b), respectively. The air temperature, Surface soil moisture (SSM), irrigation and rainfall are displayed on**
552 **subplot (c).**

553

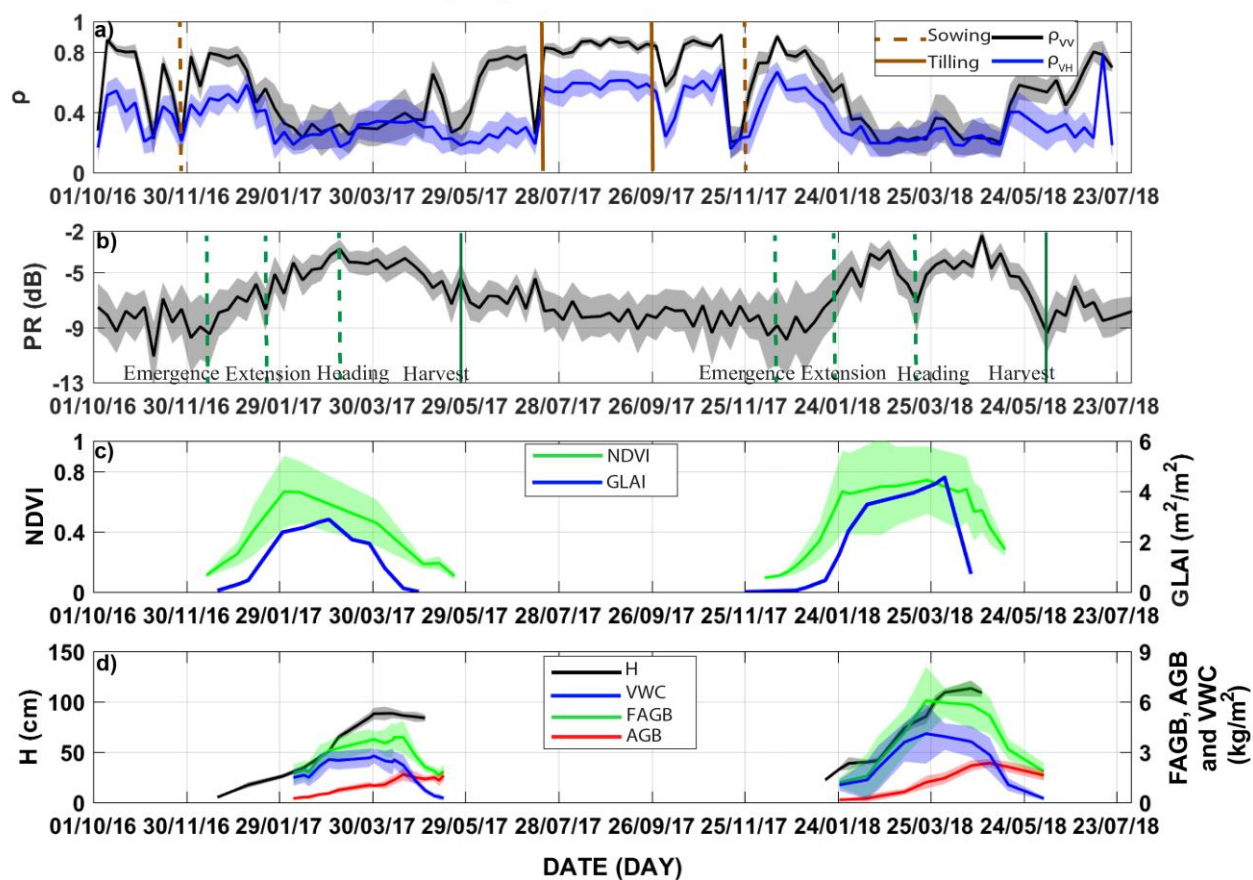
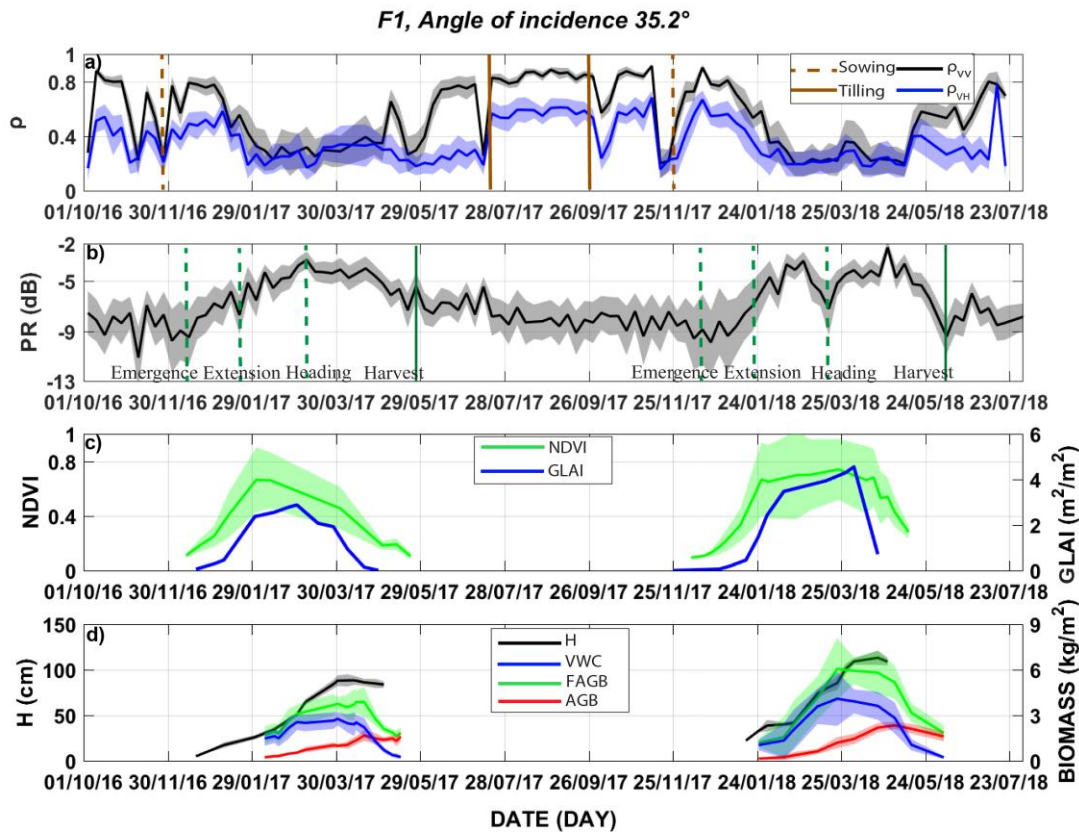



Figure A6. Time series of the interferometric coherence at VV and VH polarizations (a) and the polarization ratio (b) on F1 at 35.2° of incidence angle during the period from October 01, 2016 to July 31, 2018. The tilling works and phenological stages of wheat are superimposed on subplots (a) and (b), respectively. NDVI and measured GLAI are displayed in subplot (c). Measured H, FAGB, VWC and AGB are plotted in subplot (ed). Time series are presented by mean values (solid lines) and standard deviations (filled fields surrounding the solid lines).

F1, Angle of incidence 45.6°

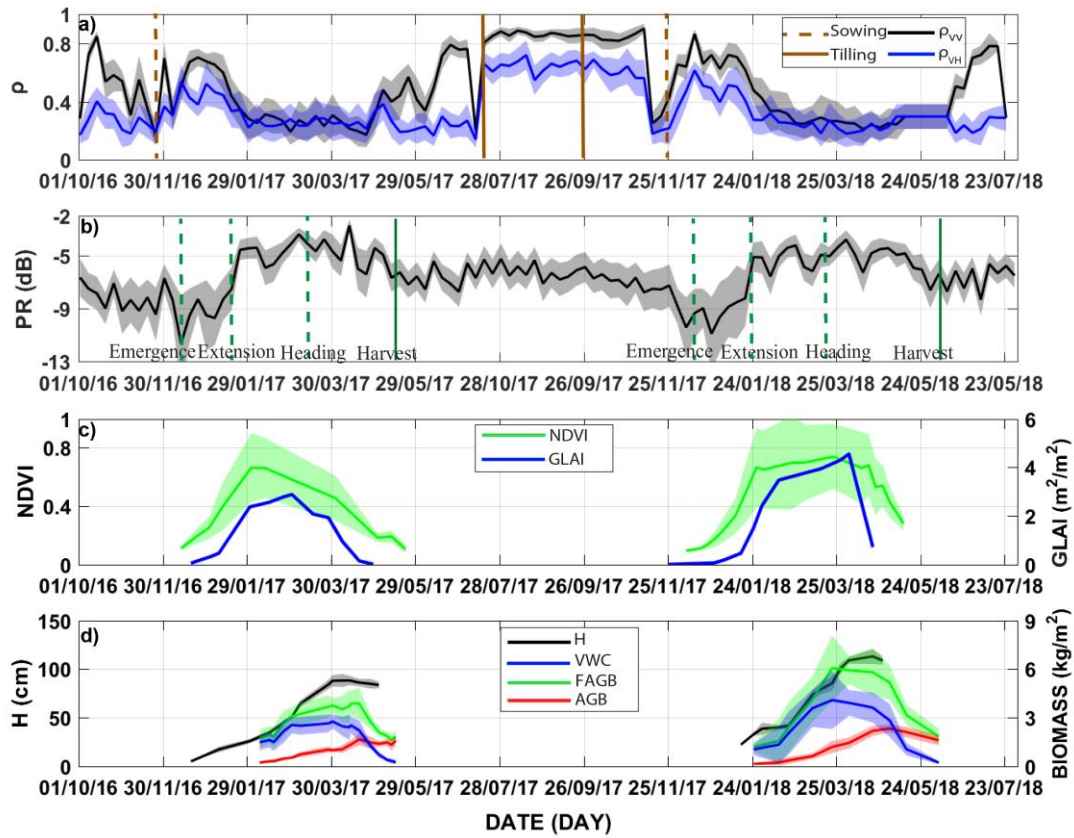
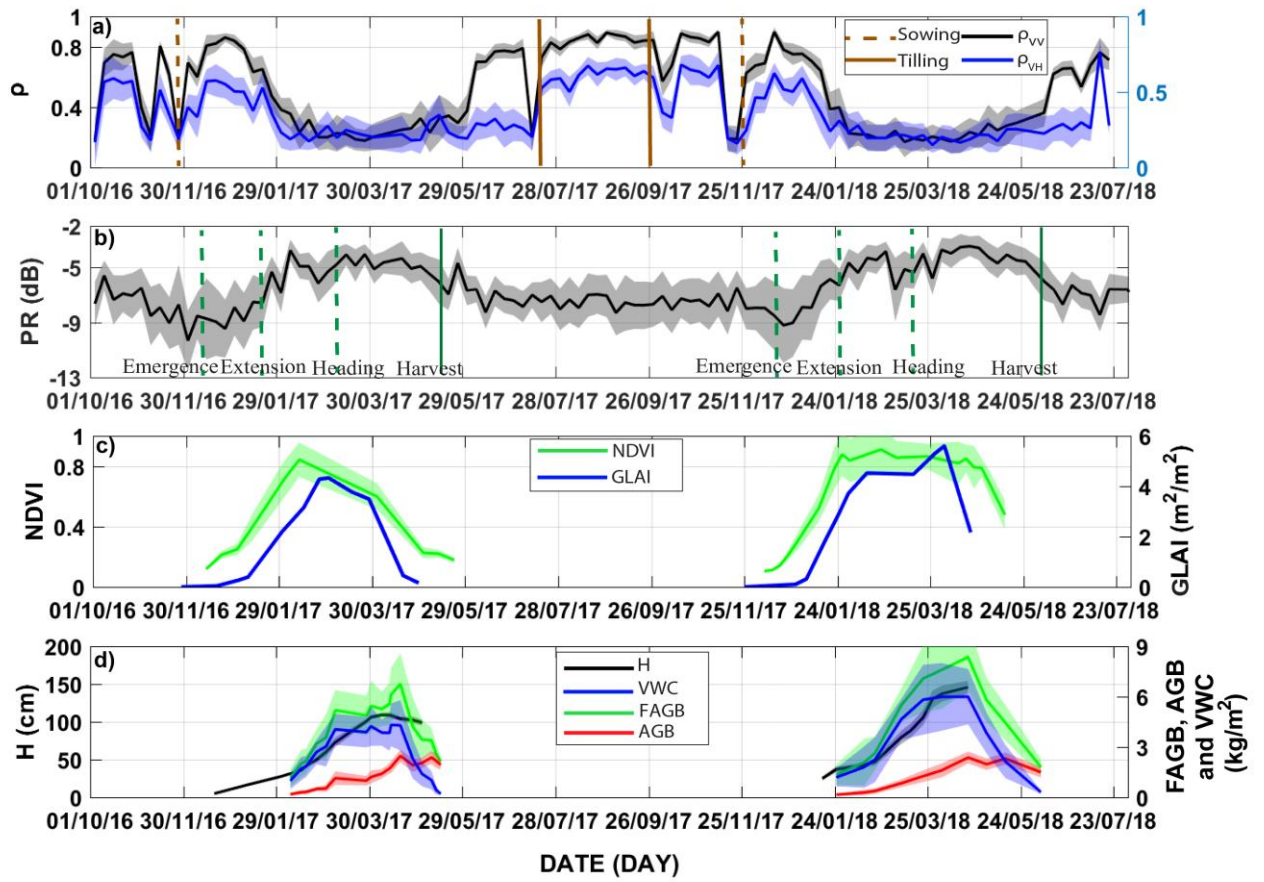
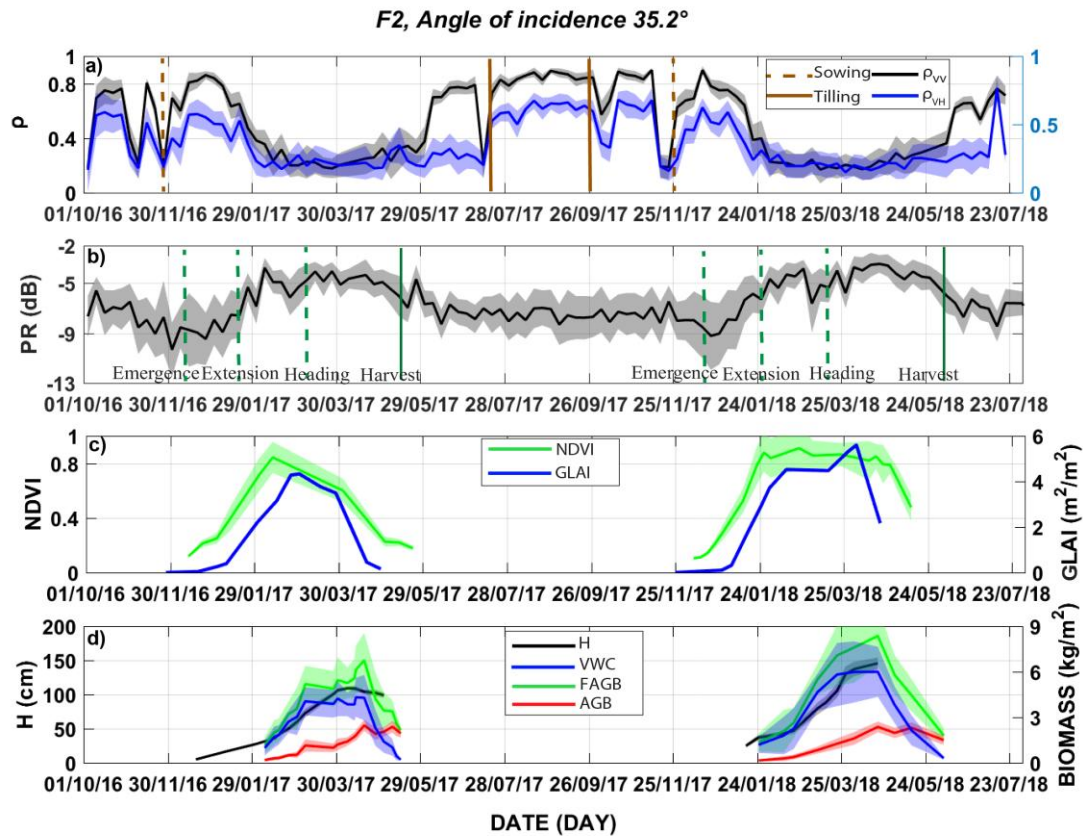



Figure A7. Time series of the interferometric coherence at VV and VH polarizations (a) and the polarization ratio (b) on F1 at 45.6° of incidence angle during the period from October 01, 2016 to July 31, 2018. The tilling works and pheneological stages of wheat are superimposed on subplots (a) and (b), respectively. NDVI and measured GLAI are displayed in subplot (c). Measured H, FAGB, VWC and AGB are plotted in subplot (ed). Time series are presented by mean values (solid lines) and standard deviations (filled fields surrounding the solid lines).

568
569 **Figure A8. Time series of the interferometric coherence at VV and VH polarizations (a) and the polarization ratio (b) on F2 at**
570 **35.2° of incidence angle during the period from October 01, 2016 to July 31, 2018. The tilling works and phenological stages of**
571 **wheat are superimposed on subplots (a) and (b), respectively. NDVI and measured GLAI are displayed in subplot (c). Measured**
572 **H, FAGB, VWC and AGB are plotted in subplot (ed). Time series are presented by mean values (solid lines) and standard**
573 **deviations (filled fields surrounding the solid lines).**

574

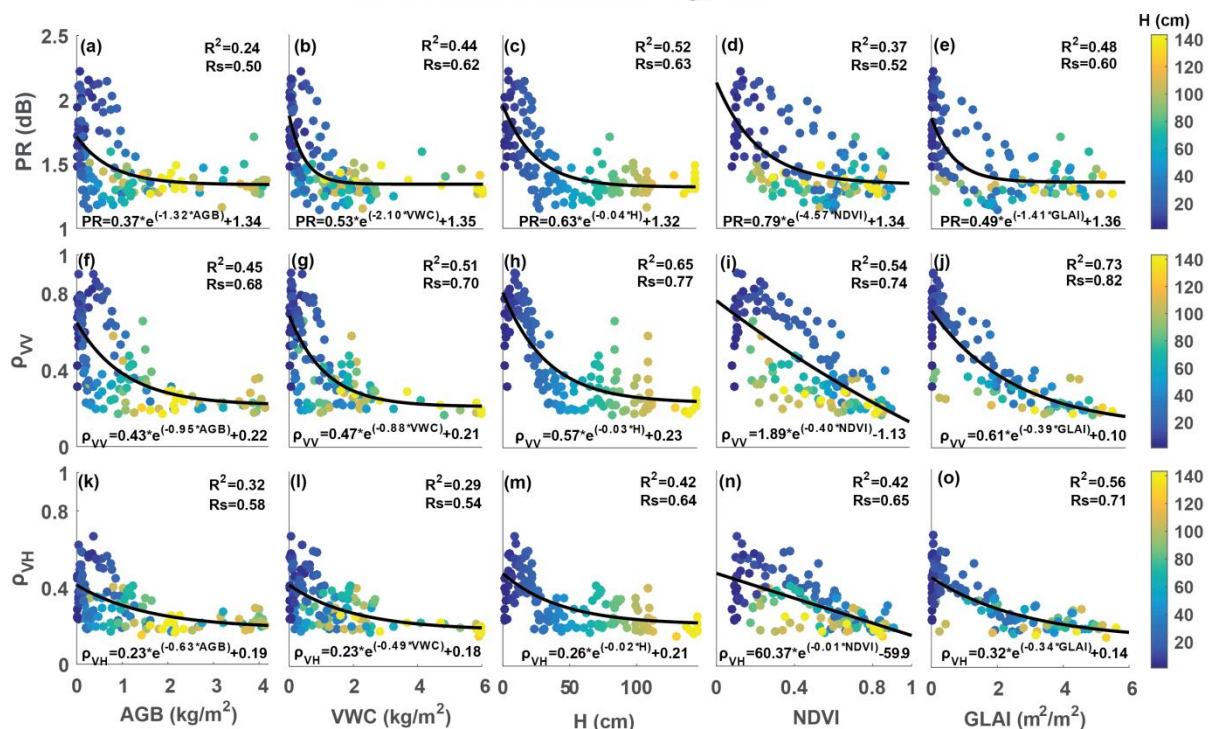



Figure A9. Scatterplots of the relationships between PR, ρ_{VV} and ρ_{VH} and AGB, VWC, H, NDVI and GLAI at 45.6° angle of incidence. The entire database is used from the three fields (F1, F2 and F3). H is used to monitor the evolution during the growing season. All the determination coefficient R^2 and the Spearman rank correlation Rs are significant at 99%.

579 Tableau A1: Details of the field campaigns during the 2016-2017, 2017-2018 and 2018-2019
580 agricultural seasons.

2016-2017 saison

Date	h_{rms} & L	H	Fc	LAI	AGB	FAGB	VWC
29/11/2016	x						
30/11/2016	x						
09/12/2016	x						
20/12/2016	x	x	x	x			
03/01/2017	x		x	x			
09/01/2017	x	x	x	x			
31/01/2017	x	x	x	x			
07/02/2017					x	x	x
14/02/2017	x	x	x	x	x	x	x
17/02/2017		x			x	x	x
24/02/2017		x	x	x	x	x	x
02/03/2017		x	x	x	x	x	x
08/03/2017		x			x	x	x
17/03/2017			x	x			
28/03/2017		x	x	x	x	x	x
31/03/2017		x			x	x	x
07/04/2017		x	x	x	x	x	x
12/04/2017		x			x	x	x
13/04/2017					x	x	x
19/04/2017		x	x	x	x	x	x
27/04/2017		x			x	x	x
29/04/2017			x	x			
03/05/2017		x			x	x	x
09/05/2017					x	x	x
12/05/2017					x	x	x
15/05/2017					x	x	x

2017-2018 saison

Date	h_{rms} & L	H	Fc	LAI	AGB	FAGB	VWC
21/12/2017	x						
28/12/2017	x		x	x			
04/01/2018	x		x	x			
16/01/2018	x	x	x	x			
25/01/2018	x	x	x	x	x	x	x
31/01/2018	x	x	x	x			
12/02/2018		x	x	x	x	x	x
19/02/2018	x						
08/03/2018	x				x	x	x
14/03/2018		x	x	x	x	x	x
22/03/2018	x				x	x	x
28/03/2018		x	x	x			
03/04/2018		x	x	x	x	x	x
20/04/2018		x	x	x	x	x	x
27/04/2018		x					
02/05/2018					x	x	x
14/05/2018					x	x	x
06/06/2018					x	x	x

2018-2019 saison

Date	h_{rms} & L	H	Fc	LAI	AGB	FAGB	VWC
29/11/2018	x		x	x			
07/12/2018			x	x			
12/12/2018	x						
18/12/2018			x	x			
04/01/2019	x		x	x			
15/01/2019	x	x	x	x	x	x	x
01/02/2019		x	x	x	x	x	x
13/02/2019		x	x	x	x	x	x
04/03/2019		x	x	x	x	x	x
13/03/2019		x	x	x	x	x	x
26/03/2019		x	x	x			
03/04/2019	x						
09/04/2019	x				x	x	x
16/04/2019	x						
20/04/2019	x				x	x	x
27/04/2019	x				x	x	x

581

582 **Author contribution.** NO, LJ, JE and SK designed the experiments. NO, MK, JE, AC and AB carried the experiements out.

583 NO processed the Sentinel-1 products. NO, LJ, JE and SK analyzed the data. NO wrote the original draft and all the co-

584 authors contribute in the review and editing of the manuscript.

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