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## Understanding the temporal behavior of crops using Sentinel-1 and Sentinel-2-like data for agricultural applications

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1                   **Understanding the temporal behavior of crops**  
2                   **using Sentinel-1 and Sentinel-2-like data for agricultural**  
3                   **applications**

4  
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7  
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10  
11  
12  
13                   **Abstract:**

14                   Crop monitoring information is essential for food security and to improve our understanding of the  
15                   role of agriculture on climate change, among others. Remotely sensing optical and radar data can  
16                   help to map crop types and to estimate biophysical parameters, especially with the availability of an  
17                   unprecedented amount of free Sentinel data within the Copernicus programme. These datasets,  
18                   whose continuity is guaranteed up to decades, offer a unique opportunity to monitor crops  
19                   systematically every 5 to 10 days. Before developing operational monitoring methods, it is important  
20                   to understand the temporal variations of the remote sensing signal of different crop types in a given  
21                   region. In this study, we analyse the temporal trajectory of remote sensing data for a variety of  
22                   winter and summer crops that are widely cultivated in the world (wheat, rapeseed, maize, soybean  
23                   and sunflower). The test region is in southwest France, where Sentinel-1 data have been acquired  
24                   since 2014. Because Sentinel-2 data were not available for this study, optical satellites similar to  
25                   Sentinel-2 are used, mainly to derive NDVI, for a comparison between the temporal behaviors with  
26                   radar data. The SAR backscatter and NDVI temporal profiles of fields with varied management  
27                   practices and environmental conditions are interpreted physically. Key findings from this analysis,  
28                   leading to possible applications of Sentinel-1 data, with or without the conjunction of Sentinel-2, are  
29                   then described. This study points out the interest of SAR data and particularly the VH/VV ratio, which  
30                   is poorly documented in previous studies.

31  
32                   **Keywords:** Crops, Remote sensing, Multi-temporal Sentinel-1 data, optical data.

33

## 34 **1. Introduction**

35 There is a general demand for achieving optimal and sufficient crop productivity, while taking into  
36 account socio-economic conditions and the environmental impacts that the agricultural systems may  
37 cause. Crop management must be attentive to climate variability and adapt its practices according to  
38 given conditions. In this context, it is essential to achieve a full understanding of the processes driving  
39 the current patterns of crops production and also the cropland carbon, water and energy dynamics  
40 needed in implementation of climate change mitigation strategies.

41 Remotely sensing data can help to monitor crop growth by providing precise and timely information  
42 on the phenological status and development of vegetation. They constitute a valuable tool for  
43 tackling those issues at different scales, from local to global extents, especially when combined with  
44 agro-hydrological models for studies related to crop yield (Duchemin et al., 2015, Baup et. al, 2015),  
45 carbon (Veloso et al., 2014, Revill et al., 2013) and water budget (Le Page et al., 2014, Ferrant et al.,  
46 2014).

47 Optical data are used to explore the links between the photosynthetic and optical properties of the  
48 plant leaves, via vegetation indices. The most used is the Normalized Difference Vegetation Index  
49 (NDVI). Optical satellite images have significantly contributed to provide a range of crop added-value  
50 products, for instance crop area extent estimates, crop type maps (Inglada et al., 2015) and estimates  
51 of different biophysical parameters at various crop phenological stages (Quarmby et al., 1993,  
52 Doraiswamy et al., 2004, Baret et al., 2007, Bontemps et al., 2015). These applications have been  
53 widely developed based on data from various satellites, e.g. Landsat, MODIS and SPOT, although  
54 optical sensors are affected by the presence of clouds. Regarding synthetic aperture radar (SAR) data,  
55 studies have been carried out at various frequencies and incidence angles for interpreting crop  
56 temporal trajectories, based on electromagnetic modeling (Chiu et al., 2000, Cookmartin et al., 2000,  
57 Picard et al., 2002) and/or experimental data (Bush 1976, Engdahl et al., 2001, Hajnsek et al., 2007,  
58 Baghdadi et al., 2009, McNairn et al., 2014). Crop type maps using SAR have also been produced, for  
59 example by Dobson et al. (1996), Skriver et al. (2011) or Deschamps et al. (2012). However,  
60 compared to optical data, the use of SAR data in agricultural applications has not been well  
61 developed, partly due to the complexity, diversity and availability of SAR data, and partly due to the  
62 difficulty of data interpretation.

63 Up to now, monitoring crop dynamics was hampered by the lack of availability of high temporal and  
64 spatial resolutions satellite time series. A new era started with the launch of the first Sentinel  
65 satellite developed by the European Space Agency, providing a large and unprecedented amount of  
66 free data for the operational needs of the Copernicus program. Sentinel-1A, the first SAR satellite,

67 launched in April 2014, has started to provide multi-temporal series of SAR imagery (C-band) at an  
68 outstanding time interval of 12 days. With Sentinel-1B, launched in April 2016, the data provision is  
69 expected for every 6 days. Sentinel-2A, the optical satellite, launched in June 2015, provides data at a  
70 time interval of 10 days. With Sentinel-2B, the time interval will be 5 days. Those dense time series  
71 are not yet available worldwide, but for Europe Sentinel-1A and Sentinel-2A are already in operation.  
72 The dense time series of Sentinels offer a unique opportunity to systematically monitor crops at a  
73 weekly repeat cycle (from 5 to 12 days, depending of the data type and the region in the world). In  
74 addition, the continuity of Sentinel data is guaranteed up to 2030 and the next generation of Sentinel  
75 is planned beyond 2030, allowing long-term environmental monitoring.

76 So far, few studies have been using dense time series SAR data for crop monitoring. Only recently,  
77 Sentinel-1 data have been used (Navarro et al., 2016, Inglada et al., 2016). In order to derive  
78 methods using dense time series SAR and optical data, there is a need to study their temporal  
79 behavior for a variety of crop types that are widely cultivated. The objective of this paper is to  
80 analyse and interpret time series of Sentinel-1 data, and to compare the temporal variation with  
81 NDVI derived from optical data. The experimental dataset contain 28 Sentinel-1 data in 2014 and  
82 2015 over our study area in the South of France. A multi-image filter (Bruniquel and Lopes 1997,  
83 Quegan and Yu 2001) was applied to reduce the speckle effect while preserving the spatial resolution  
84 and the fine structure present in the image. This strategy takes advantage of the Sentinel-1 dense  
85 temporal series and is particularly suited for monitoring even small crops. Since Sentinel-2 data were  
86 not yet available, we use a set of 71 data from different optical satellites that we will refer to as  
87 Sentinel-2-like data. The paper focuses on the analysis of the temporal behavior of SAR backscatter  
88 coefficients and NDVI of the main crop types in the temperate world (wheat and barley, rapeseed,  
89 maize, soybean and sunflower) over fields with varied management practices (e.g. tillage, sowing)  
90 and environmental conditions (rainfall, temperature). The study is conducted over 256 crop fields in  
91 Southwest France, surrounding two Joint Experiments for Crop Assessment and Monitoring (JECAM)  
92 experimental sites (Auradé and Lamasquère) that belong to the Regional Observation System (OSR)  
93 in Southwestern France.

94 The paper is organized as follows. The following section provides information on the study area and  
95 the data and Section 3 presents the results. Finally, conclusions are given in Section 4.

96

97 **2. Study area and Data**

98 **2.1. Study area**

99 The study area shown in Figure 1 is located in southwest France next to Toulouse and covers an area  
 100 of approximately 70 x 40 km. The study region is mainly covered by arable lands (approximately  
 101 60%). The main cultivated crops are wheat (*Triticum aestivum* L.), barley (*Hordeum vulgare* L.),  
 102 rapeseed (*Brassica napus* L.), maize (*Zea mays* L.), soybean (*Glycine max* (L.) Merr.) and sunflower  
 103 (*Helianthus annuus* L.). The climate in the region is temperate and mild and is characterized by warm  
 104 and dry summers, sunny autumns, mild winters and rainy springs. The annual mean precipitation is  
 105 approximately 656 mm, and the annual mean temperature is 13°C. The Garonne River crosses the  
 106 study area, and the soil textures are mainly clay and loam. However, most of the maize and  
 107 sunflower crops in this study are cultivated over silty (boulbenes) and clayey limestone soils  
 108 respectively.

109 A set of 256 fields were surveyed on the ground at different dates for providing land-use data. The  
 110 crop type classes included in the dataset and the amount of surveyed fields per class are: wheat (64),  
 111 barley (1), sunflower (116), maize (57), rapeseed (10) and soybean (8). The surface area of the fields  
 112 varies between 1.75 and 45 ha. Table 1 presents the typical calendar of some of the main  
 113 phenological stages and management practices for the investigated crop type classes.

114

115 **Table 1: Average periods of the main phenological stages for different crop types in the study area**

		<b>Sowing</b>	<b>Emergence</b>	<b>Heading/Flowering</b>	<b>Harvest</b>
<b>Winter crops</b>	<b>Wheat &amp; Barley</b>	Mid-October – late November	Sowing + 15 days	Late April – early May	Late June – mid-July
	<b>Rapeseed</b>	Late August – September	Sowing + 15-30 days	April	Late June – early-July
<b>Summer crops</b>	<b>Maize &amp; Soybean</b>	Mid-April – late May	Mid-May – mid-June	July	1-15 September (silage) October (grain)
	<b>Sunflower</b>	Early April – mid-May	Sowing + 10 days	1-20 July	September

116

117 In the study area, two agricultural sites have been intensively monitored since 2005, the so-called  
 118 Auradé (shown in Figure 2) and Lamasquère sites (Béziat et al., 2009). The two sites are part of the  
 119 FLUXNET global network [<http://fluxnet.ornl.gov>] and the Joint Experiment for Crop Assessment and

120 Monitoring [JECAM: <http://www.jecam.org/project-overview/france-osr>] networks. They are also  
121 Integrated Carbon Observation System (ICOS) sites and therefore, meteorological and flux  
122 measurements are standardized according to the ICOS protocols. In addition, fresh biomass and  
123 **green area index** (GAI) have been measured in both sites in 2015. ***The concept of GAI (Baret et al.,***  
124 ***2010, Duveiller et al., 2011) corresponds to the photosynthetically active plant area without organ***  
125 ***distinctions. We preferred to use the GAI instead of LAI because it is better correlated with remote***  
126 ***sensing observations.***

127 The two sites have similar climatic conditions but different soil properties, topography and  
128 management practices. It is noted that Auradé and Lamasquère crop rotations are representative of  
129 the main regional crop rotations.

130 The Auradé plot (23.5 ha) is located on a hillside area near the Garonne river terraces and is  
131 characterized by a rapeseed - winter wheat - sunflower - winter wheat four-year rotation that only  
132 receives mineral fertilizers and does not receive irrigation. Only the grain is exported whereas all  
133 other parts of the plants are left. Superficial tillage (5–10 cm depth) is usually done after harvest to  
134 plough residues, spontaneous regrowth and weeds into the soil. The Lamasquère plot (23.8 ha) is  
135 part of an experimental farm owned by the Purpan Engineering School EIP (Ecole d'Ingénieurs de  
136 Purpan) and is characterized by a maize - winter wheat two-year rotation that is used to feed  
137 livestock and provide litter. Therefore, nearly all aboveground biomass is exported as grain and straw  
138 for winter wheat, and maize is harvested when it is still green for silage. Both organic and mineral  
139 fertilizers are applied and the maize is irrigated. **In the 2015 season, a hose-reel irrigator was used.**  
140 **This field was irrigated 5 times between May and August.** Superficial tillage after harvest may be  
141 performed, depending on the cultivated crops. Deep tillage (30 cm depth) is usually performed in  
142 November before sowing of summer crops (essentially maize).

143 For the 2014-2015 agricultural season considered in this study, barley was cultivated (instead of  
144 wheat) at Auradé and maize at Lamasquère. Their crop growth and development will be investigated  
145 in detail in section 3.

146

## 147 **2.2. Field data**

### 148 **2.2.1. Vegetation data**

149 For the Auradé and Lamasquère plots, destructive measurements of **green area index (GAI)** and  
150 fresh and dry aboveground biomass were performed regularly to characterize crop development  
151 during the vegetative cycle (five times each site). **Measured GAI is defined as the half-surface of all**  
152 **green organs. It was measured by means of a LiCor planimeter (LICOR 3100, Lincoln Inc.,**  
153 **Nebraska).** For maize in Lamasquère, twenty plants were collected at each date along a transect

154 crossing the plot. For barley in Auradé, ten 0.25 m long rows were collected at each sampling date.  
155 Plant height was also measured. Yield data were provided by the farmers who cultivate the two sites.

156

### 157 **2.2.2. Meteorological data**

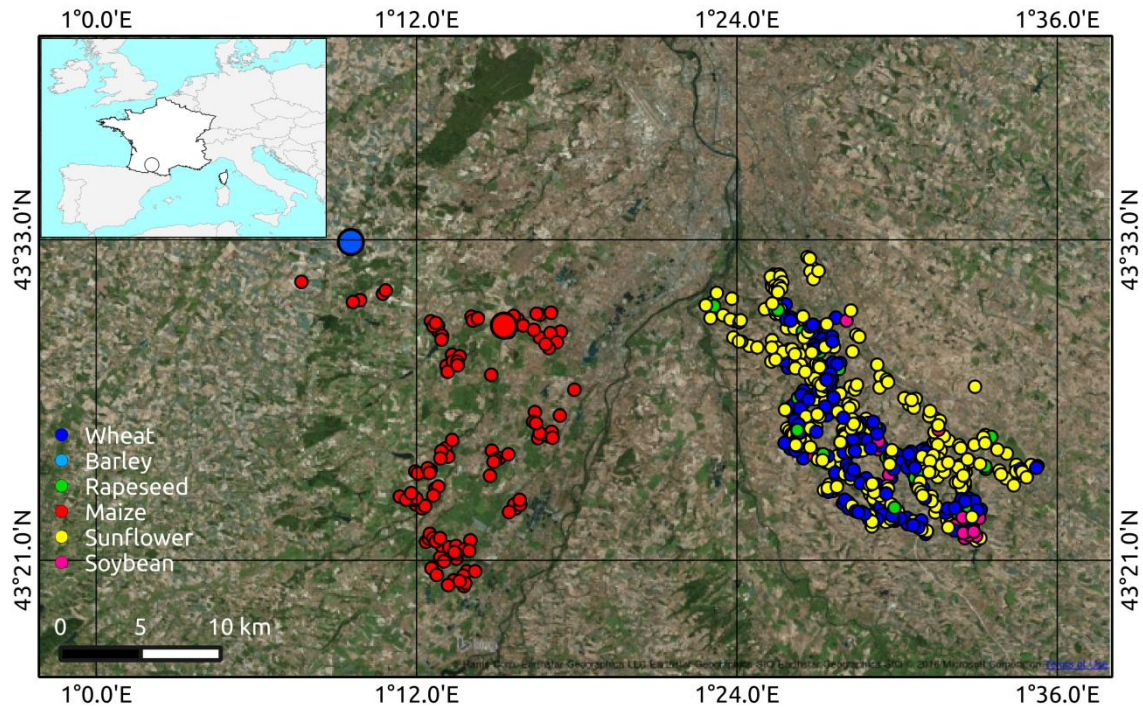
158 Air temperature and precipitation measurements were continually recorded over the Auradé and  
159 Lamasquère sites (Béziat et al., 2009). Data were originally pre-processed and delivered at a time  
160 scale of 30 min. For this study, air temperature recorded at 6 a.m. was selected, which corresponds  
161 to the approximate time of the Sentinel-1 data acquisition. The precipitation measurements were  
162 integrated to obtain daily values. The Lamasquère site temperature values were used qualitatively in  
163 the analysis of the results for all the 256 other fields under study, assuming that temperatures do not  
164 change drastically within the study area. However, precipitation data over the 256 other fields were  
165 derived from the Global Satellite Mapping of Precipitations (GSMaP) project (Aonashi et al., 2009).  
166 The GSMaP project provides precipitation data based on the combined microwave-infrared algorithm  
167 using GPM-Core GMI, TRMM TMI, GCOM-W1 AMSR2, DMSP series SSMIS, NOAA series AMSU,  
168 MetOp series AMSU, and Geostationary infrared developed by the GSMaP project. The newly  
169 developed algorithm for the Global Precipitation Measurement (GPM) mission (GPM-GSMaP Ver.6) is  
170 used to retrieve rainfall at 0.1 degree latitude/longitude resolution every hour. We assigned for each  
171 crop the corresponding daily rainfall value.

172

### 173 **2.2.3. Soil water content data**

174 At Auradé and Lamasquère sites, theta probes ML2X (DeltaT devices) measuring volumetric soil  
175 water content (SWC) were settled in 3 independent pits, at 0.5 cm and 5 cm depth. A site-specific  
176 calibration function, determined with gravimetric measurement, was applied to convert the mV  
177 signal into volumetric SWC. **The root mean square error (RMSE) and the square of the Pearson's  
178 linear correlation coefficient ( $r^2$ ) related to the linear regression between the mV signal and the  
179 SWC were 5.6% and 0.57 respectively over the Auradé site and 3.2% and 0.87 respectively at the  
180 Lamasquère site.** Then, volumetric SWC was estimated by averaging the 3 measurements. Data were  
181 delivered at a time scale of 30 min, and averaged at daily time step.

182

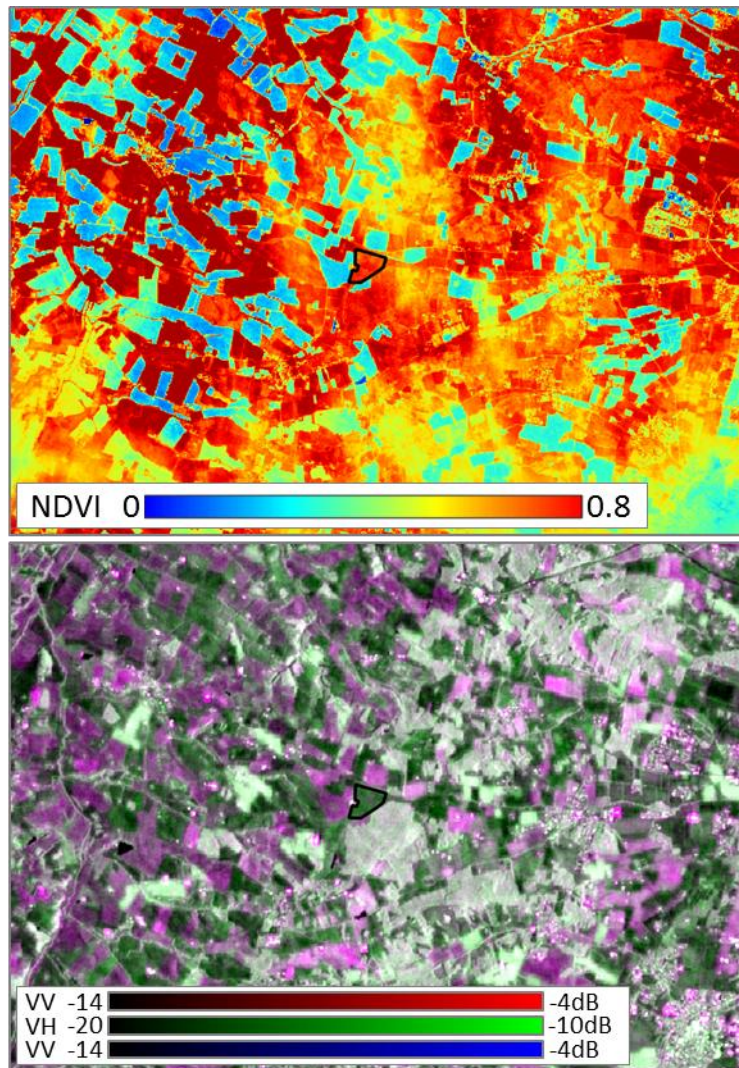


183

184 **Figure 1: Field data over a 70x40 km area in South-West France, superposed to very high resolution optical data from**  
 185 **Bing Map. Large circles represent the two Joint Experiment for Crop Assessment and Monitoring (JECAM) experimental**  
 186 **sites (Auradé and Lamasquère). Small circles represent the other crop fields studied in this paper. In this area, in average**  
 187 **between 2006 and 2013, 43% of cultivated crops were cereals, 25% were sunflower, 5% were maize and 5% rapeseed,**  
 188 **(from detailed French national land use database, the RPG (in French, *Registre Parcellaire Graphique*)).**

189





190  
 191 **Figure 2:** The experimental site of Auradé (surrounded in black) and its surroundings. Auradé is located 28 km south-west  
 192 of Toulouse, in France. At the top, the NDVI map derived from a SPOT5-Take5 image (10 m resolution) acquired on 29  
 193 April 2015; at the bottom, an RGB image of VV and VH backscatters from a Sentinel-1 image (20 m resolution) acquired  
 194 on 5 May 2015. Vegetated areas appear in green. The 17.5 x 12.5 km area is centered on 43.549°N, 1.106°E.

195  
 196 **2.3. Remote Sensing data**  
 197 **2.3.1. SAR data**

198 Twenty-eight Sentinel-1A images have been acquired between 6 November 2014 and 7 December  
 199 2015. The ESA Sentinel-1 observation strategy defines the Interferometric Wideswath (IW) mode as  
 200 the pre-defined mode over land. This mode provides dual-polarisation (VV and VH) imagery, at a  
 201 resolution of 10 meters, with a swath of 250km. The incidence angle over the surveyed fields shown  
 202 in Figure 1 ranges approximately from 38 to 41°.

203

204 All the Sentinel-1 imagery is made available free of charge by ESA. In this study, we used Level-1  
205 Ground Range Detected (GRD) products that consist of focused SAR that has been detected, multi-  
206 looked and projected to ground-range using an Earth ellipsoid model. The data have been first  
207 calibrated to obtain the  $\gamma^0$  backscatter coefficient, **using the “Calibration” module in the Sentinel**  
208 **Application Platform SNAP (ESA, 2017).**

209 We additionally multi-looked the data with a window size of 2x2 (**“Multilooking” module in the**  
210 **SNAP**) to reduce the speckle noise effect, reaching a spatial resolution of 20m. Then, terrain  
211 correction was applied (**“Range-Doppler Terrain Correction” module in the SNAP**) to geocode  
212 **accurately** the images by correcting SAR geometric distortions (foreshortening, layover and shadow)  
213 using the digital elevation model from the Shuttle Radar Topography Mission (**that allows to take**  
214 **into account the local elevation variations**). The images are therefore overlaid, without additional  
215 coregistration. A speckle filter (Bruniquel and Lopes 1997, Quegan and Yu 2001) was then applied to  
216 further reduce the speckle effect while preserving the 20m spatial resolution and the fine structure  
217 present in the image. As evidenced for example in Mermoz et al. (2014, 2016), this filter produces  
218 images with reduced speckle effects from multi-temporal (28 dates) and multi-polarised (VH and VV)  
219 images, and is expressed as follows:

220

$$J_k(u) = \frac{\langle I_k(u) \rangle}{N} \sum_{i=1}^N \frac{I_i(u)}{\langle I_i(u) \rangle} \quad \text{with } k=1, \dots, N \quad (1)$$

221

222 where  $J_k(u)$  is the radar intensity of the output image  $k$  at pixel position  $u$ ,  $I_i(u)$  is the radar intensity  
223 of the input image  $i$ ,  $\langle I_i(u) \rangle$  is the local average intensity of the input image  $i$  (window size of 7x7) and  
224  $N$  is the number of images. **We implemented this filter using the Matlab software (R2011 version).**  
225 **The resulting theoretical equivalent number of looks (ENL) was estimated using the following**  
226 **equation (Quegan and Yu 2001):**

$$ENL = L \frac{M \cdot N}{M + N - 1} \quad (2)$$

227

228 **where L is the initial number of looks, M the number of images (28 dates x 2 polarisations) using a**  
229 **fixed window size of N pixels (7x7 pixels). L is found to be 17,6 that is the product of approximately**  
230 **4.4 initial looks for GRD data at 10m (ESA report, 2016) multiplied by 4 (multi-look of 2x2).**  
231 **According to equation 2, the final theoretical ENL per pixel is 464. In the following, the ENL per**  
232 **crop is even much higher as tens to hundreds of pixels were grouped to derive average values by**  
233 **crops.**

234 Radar backscatter is affected by factors related to crop biomass, structure and ground conditions.  
235 Past studies agreed that the observed backscatter at C-band is a combination of the ground  
236 backscatter attenuated by the canopy layer and the backscatter from the canopy, which includes  
237 simple and multiple scattering, and the vegetation-ground interaction (Attema and Ulaby, 1978;  
238 Ulaby et al., 1986; Bouman and Hoekman, 1993). The backscatter from vegetation canopy is  
239 affected by vegetation 3D structure and water content (related to biomass) (Karam et al., 1992). The  
240 ground backscatter at C-band is affected by soil moisture, surface roughness and terrain topography  
241 (Schmugge, 1983). Note that the moderate topography of the plots used in this study (mean slope of  
242 4.3°), together with the Sentinel-1 processing that reduced radiometric and geometric distortions,  
243 ensure low topographic effects. The vegetation-ground interaction depends on both vegetation and  
244 ground characteristics (Brown et al., 2003). The relative importance of these 3 scattering  
245 components depends on the radar frequency, polarisation, incidence angle, the crop type and  
246 growth stage, and the ground conditions. In general, the ground scattering is dominant at the early  
247 and late crop growth stage, and in-between vegetation scattering dominates (Mattia et al., 2003).  
248 However, during the period when the vegetation scattering is more important, the relationship  
249 between the radar backscatter and the vegetation biophysical parameters is considerably influenced  
250 by the dynamics of the canopy structure, including orientation, size and density of the stems and the  
251 dielectric constant of the crop elements, which depend on the phenological stage. For example, a  
252 drastic difference in the sensitivity of backscatter to wheat biophysical parameters has been found  
253 before and after the heading stage by Mattia et al. (2003). In terms of incidence angle, the shallow  
254 incidence angles (>35-40°) increase the path length through vegetation and maximize the vegetation  
255 scattering contribution (Blaes et al., 2006), whereas steep incidence angles (<30°) reduces the  
256 vegetation attenuation and maximize the ground scattering contribution in the return, which is more  
257 useful for soil moisture measurement (Mattia et al., 2006). In our datasets, the incidence angles are  
258 approximately 40° (38° to 41°), the data are therefore suitable to the crop parameters retrieval.  
259 Regarding the polarisation effect, it is well known that HH is more sensitive to surface scattering and  
260 HV to volume scattering, and VV a combination of the two. HV backscatter is therefore often used for  
261 the retrieval of crop parameters, and HH, ground parameters. However, theoretical modeling and  
262 ground-based SAR measurements have indicated that VH and VV can contain vegetation ground  
263 interaction (double-bounce term) (Picard et al., 2003). **In fact, soil returns at VH polarisation is  
264 probably caused by double scattering (stem-ground) (Brown et al., 2003). This hypothesis is  
265 supported by simulation results based on a second-order radiative transfer model (Brown et al.,  
266 2000), showing that double-bounce scattering exceeds the direct backscatter from the soil.** In this  
267 case, the ratio VH/VV can reduce the double-bounce effect. **In addition, the ratio VH/VV probably  
268 reduce errors associated to the acquisition system (e.g. due to the radiometric stability) or**

269 **environmental factors (e.g. due to variations of soil moisture) and might appear as a more stable**  
270 **indicator in time than VH or VV backscatter.** Nevertheless, the scattering mechanisms are in general  
271 much more complex and experimental observations are needed to provide insights into the  
272 scattering behavior of each crop type.

273 **For additional information on interactions between electromagnetic waves and crops, in particular**  
274 **using multipolarisation or polarimetric data at C-band, you may refer to the thorough review of**  
275 **McNairn et al. (2004). For a recent and complete review on the use of SAR data (including PolSAR,**  
276 **PolInSAR or TomoSAR techniques at various frequencies) or even scatterometers and radiometers**  
277 **for applications in agriculture, please read Steele-Dune et al. (2017).**

278

### 279 **2.3.2. Optical data**

280 Seventy-one Sentinel-2-like optical images have been acquired by four satellites, SPOT5-Take5 (39  
281 acquisitions), Landsat-8 (27 acquisitions), Deimos-1 (3 acquisitions) and Formosat-2 (2 acquisitions),  
282 between 2 November 2014 and 25 December 2015.

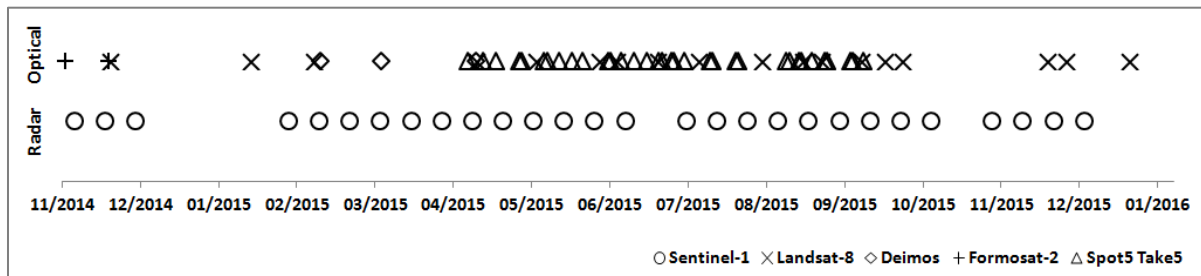
283 Formosat-2 is a Taiwanese satellite that provides images with spatial resolution of 8 m in four visible  
284 and near-infrared reflective bands. Images are taken at nearly constant viewing angles. Deimos-1  
285 provides 22 m resolution images in three spectral bands (red, green and near-infrared) that have  
286 been designed to be compatible with the same channels of the Landsat series, allowing full  
287 compatibility. The Landsat 8 is an American satellite, launched in 2013, that provides multispectral  
288 images (at nine spectral bands) along the entire Earth at 30 m resolution with a repeat cycle of 16  
289 days.

290 In the frame of the SPOT Take 5 experiments, the Centre National d'Etudes Spatiales (CNES) lowered  
291 the orbit altitude of SPOT, to place it on a five-day repeat cycle orbit for a given duration. Images  
292 were acquired at 10 m resolution every 5 days under constant angles, at four spectral bands (green,  
293 red, near infrared and short wave infrared). Data were processed by THEIA [www.theia-land.fr] Land  
294 Data Center and were distributed with a free and open policy for scientific purposes.

295 The four optical remote sensing datasets were pre-processed using the Multi-sensor Atmospheric  
296 Correction and Cloud Screening prototype (MACCS, Hagolle et al., 2008, 2015) spectro-temporal  
297 processor. One particularity of MACCS is that it uses multi-temporal criteria to build cloud, cloud  
298 shadow, water and snow masks and to detect the aerosols before the atmospheric correction. All  
299 datasets were processed to level 2A within the THEIA Land Data Center.

300 Next, NDVI was computed. Note that the NDVI time series were not smoothed despite the  
 301 different spatial and spectral resolutions of the four optical sensors. However, we consider that  
 302 these differences do not have a significant effect on the NDVI estimates as they were averaged  
 303 over each field within surface areas ranging from 1.75 to 45 ha.

304



305

306 Figure 3: Calendar of the remote sensing data acquisitions, expressed in month/year. At the top, the 71 optical data  
 307 acquisitions from: Landsat-8 (cross), Deimos (diamond), Formosat-2 (plus) and SPOT5-Take5 (triangles). At the bottom:  
 308 28 radar acquisitions from Sentinel-1 (circle).

309

### 310 3. Results and Discussion

311 The time series of optical NDVI and radar backscatter (VH, VV and VH/VV) are analysed and physically  
 312 interpreted with the support of rainfall and temperature data, as well as the destructive in situ  
 313 measurements (GAI and fresh biomass, when available). The analysis is performed for each crop type  
 314 separately, grouped in winter and summer crops. The square of the Pearson's linear correlation  
 315 coefficient  $r^2$  indicated in this section represents correlation between temporal interpolated NDVI  
 316 and SAR backscatter (VV, VH and VH/VV). The number of available SAR observations during the  
 317 growth cycle determines the number N of samples used for computing these correlations. The  
 318 NDVI profiles were interpolated (using a third degree polynomial) to have corresponding NDVI  
 319 values at the SAR acquisition dates.

320

#### 321 3.1. Winter crops

##### 322 3.1.1. Cereals (Barley and Wheat)

323 Barley and wheat are two cereals that are grown as winter crops in the study area, with a very similar  
 324 plant structure and phenology. They are therefore treated in the same subsection, first by analysing  
 325 in detail one barley field with associated *in situ* data, and then a set of 64 wheat fields. Note that the  
 326 results and analysis below for barley, based on one single field, might be not fully representative of  
 327 the barley crop behavior.

328 Barley in the Auradé site was sown on 22 October 2014, emergence occurred approximately on 5  
329 November 2014, and the field was harvested on 27 June 2015. The corresponding remote sensing  
330 time series are shown in Figure 4. The most striking feature is the sensitivity of the VH/VV ratio to the  
331 barley growth cycle. While NDVI starts increasing immediately after the emergence of barley plants  
332 and appears therefore correlated to the greenness of small vegetation, VH/VV remains relatively  
333 stable during winter and starts increasing significantly at the tillering stage, around beginning of  
334 March. In fact, VH/VV is always more correlated to the fresh biomass than to the photosynthetic  
335 activity.

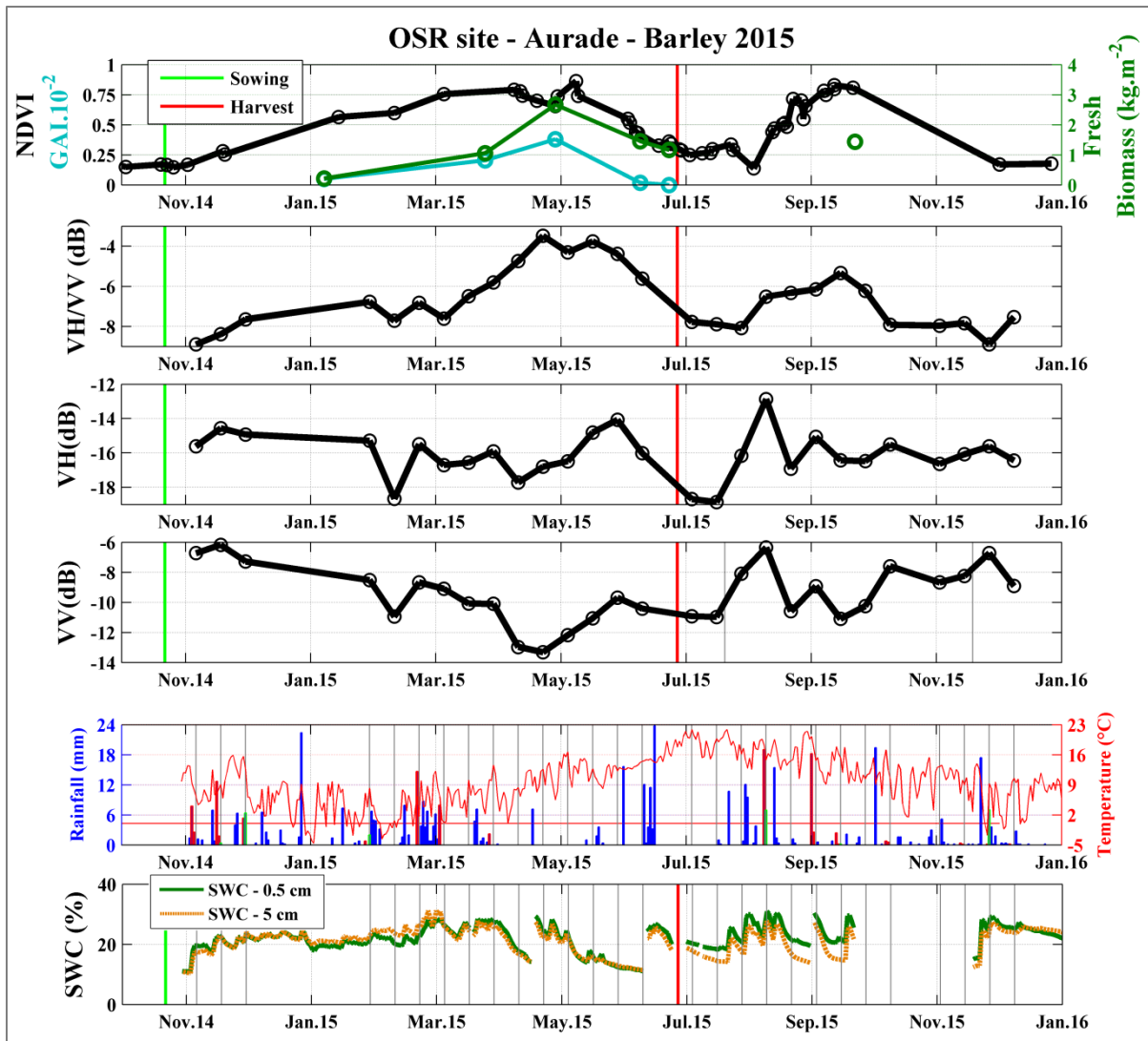
336 VH/VV appears more stable in time than VH or VV backscatter as anticipated and detailed in section  
337 2.3.1., and more sensitive to the barley growth cycle. But although the VH and VV profiles appear  
338 complex, most of their variations can be physically explained. During winter, the vegetation remains  
339 short and VV and VH are affected mostly by variations in the soil backscatter driven by SWC and  
340 surface roughness. For example, rainfall events just before the two first Sentinel-1 acquisitions may  
341 explain the slight increase of the backscatter. Then, a slight decrease of VV and VH backscatters is  
342 observed until beginning of March, which can be explained by the soil backscatter attenuated by the  
343 growing vegetation, plus probably by the progressive smoothing of the soil until early April 2015.  
344 Note that the strong and abrupt decrease of VV and VH backscatters on 10 February 2015 (observed  
345 in all the fields regardless the crop type) is caused by the frost (Khaldoune et al., 2009) as confirmed  
346 by the temperature records. At the tillering stage in March and during the stem elongation phase in  
347 April, the volume fraction of the vegetation increases as a result of the increase in the number of  
348 stems per plant and in the length of these stems. The VH backscatter, which is dominated by the  
349 attenuated double-bounce and volume scattering mechanisms, increases **as reported in Lopez-**  
350 **Sanchez et al. (2013) and Wiseman et al. (2014)**, while the VV backscatter, which is dominated by  
351 the direct contribution from the ground and the canopy, decreases due to the rising attenuation  
352 from the predominantly vertical structure of the barley stems (Brown et al., 2003), especially in April,  
353 during the stem elongation (Jia et al., 2013). Note that under drier meteorological conditions at the  
354 same period, the contribution of ground vegetation interaction in the VH backscatter may decrease  
355 compared with the volume contribution, leading to a more increasing VH backscatter.

356

357 The resulting VH/VV therefore increases until end of April, whereas NDVI remains stable from  
358 beginning of March. At the beginning of May, the observed increase in VH and VV is related to the  
359 heading (that causes an increase in the fresh biomass), as previous experimental (Mattia et al., 2003)  
360 and theoretical (Picard et al., 2003) studies have found for similar frequencies and incidence angles.  
361 This illustrates the potential of Sentinel-1 time series to capture very short phenological events.  
362 During the senescence, which starts at the beginning of June, both the NDVI and the VH/VV ratio are

363 characterized by a steady decrease until harvest, as a consequence of the decreasing chlorophyll and  
364 water content.

365 Another important finding is the capacity of VH/VV to detect post-harvest spontaneous regrowth  
366 (refer to the photographs in Figure S1), which is visible in the form of a second cycle (Figure 4) from  
367 end of July to beginning of October at the Auradé site. The regrowth is due to a combination of soil  
368 work on 20<sup>th</sup> July, which together with the rainfall events, allowed the grain fallen on the soil at  
369 harvest to emerge in the beginning of August (stale seedbed). This is a promising result for future  
370 applications such as the monitoring of post-harvest events, like regrowth and cover crops, which  
371 store carbon in agricultural soils (Poeplau and Don, 2015, Ceschia et al., 2010) and therefore  
372 represent interesting levers for climate change mitigation.



373  
 374 Figure 4: Observations over the barley field: temporal behavior of optical NDVI, radar VH/VV, VH, and VV, rainfalls,  
 375 temperatures and soil water content (SWC) over the Auradé site, where barley was cultivated in 2015. The blue and  
 376 green profiles superposed to NDVI are fresh biomass and GAI, respectively. In the second to last plot, temperatures in  
 377 red were measured at the Sentinel-1 acquisition time 6 a.m. The horizontal red line is the 0°C line. Precipitation is  
 378 represented by the blue bars. They are displayed in green when occurring in the same days than Sentinel-1 acquisitions  
 379 and in red if rainfall events take place in the two days before Sentinel-1 acquisitions (assuming that wet soil due to  
 380 rainfalls may still affect Sentinel-1 backscatter two days later). Vertical grey bars represent Sentinel-1 acquisition events.  
 381 In the last plot, soil water content (SWC) has been measured at 0.5 cm (green) and 5 cm (brown) depth.

382  
 383 Figure 5 shows the mean values (blue circles) and standard deviations (represented by the filled blue  
 384 color domains surrounding the mean profile), calculated over the 64 winter wheat fields, as well as  
 385 the 10 rapeseed fields that will be analysed in the next section. The global behaviors of NDVI, VH/VV,  
 386 VH and VV over the wheat fields are similar to those of the Auradé barley field from sowing to  
 387 harvest (as found by Lopez-Sanchez et al., (2013) at HV polarisation). This finding was expected  
 388 because the two crops present similar plant structure and functioning, as well as management



389 **practices.** VH/VV and VV are correlated to NDVI ( $r^2$  is 0.74 and 0.58 respectively,  $N=16$ ) contrary to  
390 VH ( $r^2$  is approximately 0.01). The decrease of VV at the tillering stage, as explained before, explains  
391 this correlation. One interesting feature is that, during this period, the standard deviations of VH and  
392 VV between different fields are relatively high (probably revealing the different agricultural practices,  
393 but the polarisation ratio VH/VV has a low standard deviation, indicating that the contribution of the  
394 ground is reduced in a homogeneous way across all fields.

395 **As demonstrated by the analysis of our available plots, VH/VV is therefore a reliable growth**  
396 **indicator of winter cereals that can be used to separate cereals from other crops such as rapeseed,**  
397 **for example in the frame of a crop type classification,** instead of the HH/VV ratio that was found to  
398 be reliable as well (Ulaby et al., 1986, Moran et al., 2012, Fieuzal et al., 2013) but not available in the  
399 Sentinel-1 IW acquisition mode. Reversely, after harvest, the standard deviations of VH and VV are  
400 relatively low, but VH/VV has a high standard deviation, indicating a variety of scattering mechanisms  
401 across fields. This is justified by the diversity of post-harvest management practices across the 64  
402 fields, which also explains the lack of a clear second growth cycle (regrowth, cover crop) in the mean  
403 optical and radar profiles.

404

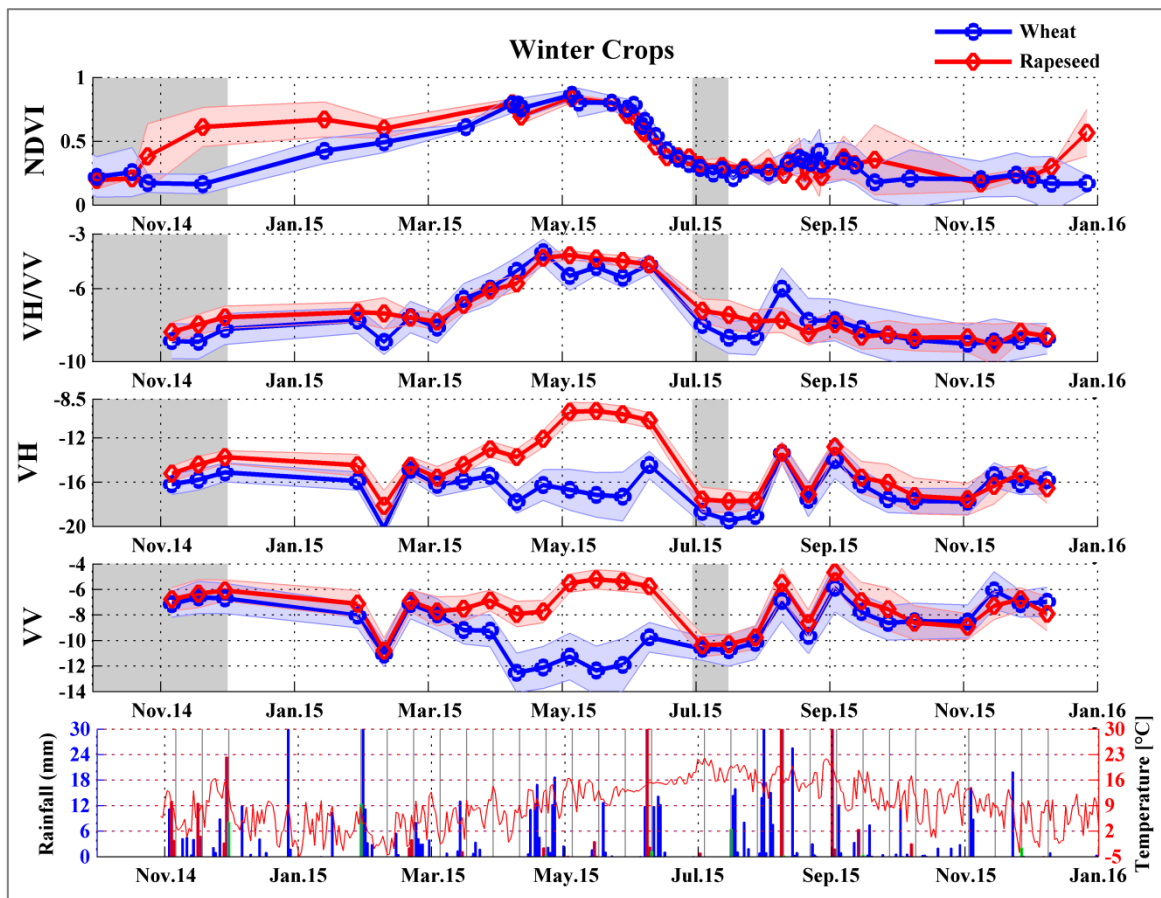
### 405 **3.1.2. Rapeseed**

406 Compared to the cereal winter crops, rapeseed has earlier sowing/harvest dates and a very different  
407 plant structure. At full development, the plants are twice taller (reaching approximately 1.5m),  
408 randomly organized with no strong vertical structure.

409 NDVI and VH/VV ( $r^2$  is 0.30,  $N=16$ ) both follow the vegetation cycle (red profiles in Figure 5), with an  
410 earlier start of the NDVI, compared to the cereal winter crops. Also, NDVI reaches high values (above  
411 0.5) shortly after plant emergence, which occurs around October, and remains high until the  
412 beginning of senescence in June. On the opposite, VH/VV clearly starts increasing in March,  
413 corresponding to the spring growth restart (stem elongation, inflorescence emergence). At the end  
414 of flowering and during ripening (end of April-beginning of June), VH/VV remains stable at high  
415 values, until it starts decreasing at the beginning of the senescence.

416 Contrary to the cereal winter crops (displayed in blue in Figure 5), VH and VV follow the VH/VV trend  
417 during the growth period, in a similar way although correlation between NDVI and VH ( $r^2$  is 0.38) is  
418 greater than with VV ( $r^2$  is 0.25). In fact, taller rapeseed plants compared to cereals, in addition to  
419 randomly oriented branches, causes high volume scattering mechanism and lower attenuation of the  
420 signal from the ground. **Note that the increasing behavior of VH backscatter for rapeseed during its**  
421 **growth cycle has been previously reported (Yang et al., 2014; Wisemann et al., 2014; Lopez-**  
422 **Sanchez et al., 2013). In particular, in conformity with the results of Wisemann et al. (2014) based**

423 on RADARSAT-2 data, we observe a small decrease of backscatter at the onset of flowering  
 424 (beginning of April) and a 5dB increase when the pods reach maturation (May).  
 425



426  
 427 **Figure 5: Observations over winter wheat and rapeseed fields: temporal behavior of optical NDVI, radar VH/VV, VH, and**  
 428 **VV, rainfalls and temperatures over winter crops, i.e. 64 wheat crops (in blue) and 10 rapeseed crops (in red). Mean**  
 429 **values are represented by dots and standard deviations are represented by the filled color domains surrounding the**  
 430 **curves. In the last plot (bottom), temperatures in red were measured at the Sentinel-1 acquisition time 6 a.m. Vertical**  
 431 **precipitation bars in blue are drawn in green the same days than Sentinel-1 acquisitions and in red the two days before**  
 432 **Sentinel-1 acquisitions, assuming that wet soil due to rainfalls may still affect Sentinel-1 backscatter two days later.**  
 433 **Vertical grey bars represent Sentinel-1 acquisition events. The typical periods of sowing and harvest are indicated by the**  
 434 **grey shaded areas.**

435  
 436 **3.2. Summer crops**

437 **3.2.1. Maize**

438 Maize time series are first analysed in detail for the Lamasquère site (one maize field) with associated  
 439 *in situ* data in Figure 6 (photographs are shown in Figure S2) and then for a set of summer crop fields  
 440 (maize, soybean and sunflower) in Figure 7.

441 In Figure 6, the NDVI and VH/VV ratio are similarly sensitive to the maize phenology. Between the  
442 soil work on 26<sup>th</sup> November and the soil preparation for sowing on 16<sup>th</sup> April, VH and VV (and VH/VV)  
443 steadily decreases due to gradual smoothing of the soil with time (intensified by rainfalls). Just after  
444 sowing in the beginning of May, a short decrease of VV and VH (and VH/VV) is observed due to soil  
445 work (harrowing) that breaks up, smoothes out and dries the soil surface. Then, the NDVI and VH/VV  
446 ratio increase in the same way until the beginning of the harvest on the 8<sup>th</sup> September. During this  
447 period, VH increases because vegetation provides the main volume scattering contribution to the  
448 backscattered signal (in fact maize reaches approximately 2.5 m height), and the soil influence  
449 becomes marginal (SWC variations shown in Figure 6 do not influence the backscatter).

450 We can observe that both NDVI and VH/VV profiles are in good agreement with the destructive GAI  
451 and fresh biomass measurements. This finding highlights the potential of Sentinel-1 (and Sentinel-2)  
452 data for maize biomass retrieval. In the Lamasquère site, there is no senescence stage because maize  
453 is harvested when it is still green for silage, which is reflected by an abrupt decrease in NDVI.  
454 However, VH/VV decreases gradually from harvest until mid-October. This may be explained by  
455 standing green residues (or weed) remaining on the field, which dry out progressively. On 14<sup>th</sup>  
456 October, soil tillage is performed. Soil tillage allows for preparing the soil for the next crop sowing  
457 (wheat). This results in the smoothing of the soil surface leading to a decrease in VV, and therefore  
458 an increase of VH/VV.

459 Note that the Lamasquère site was irrigated 5 times between May and August. However, the impact  
460 of these irrigation events onto the radar backscatter could not be observed because no Sentinel-1  
461 images were acquired just after irrigation events. In addition, the soil influence becomes very small  
462 when maize is well developed. This is the reason why the signal is stable whatever the SWC  
463 variations (see Figure 6) as observed in Bériaux et al. (2015) and Fieuzal (2013).

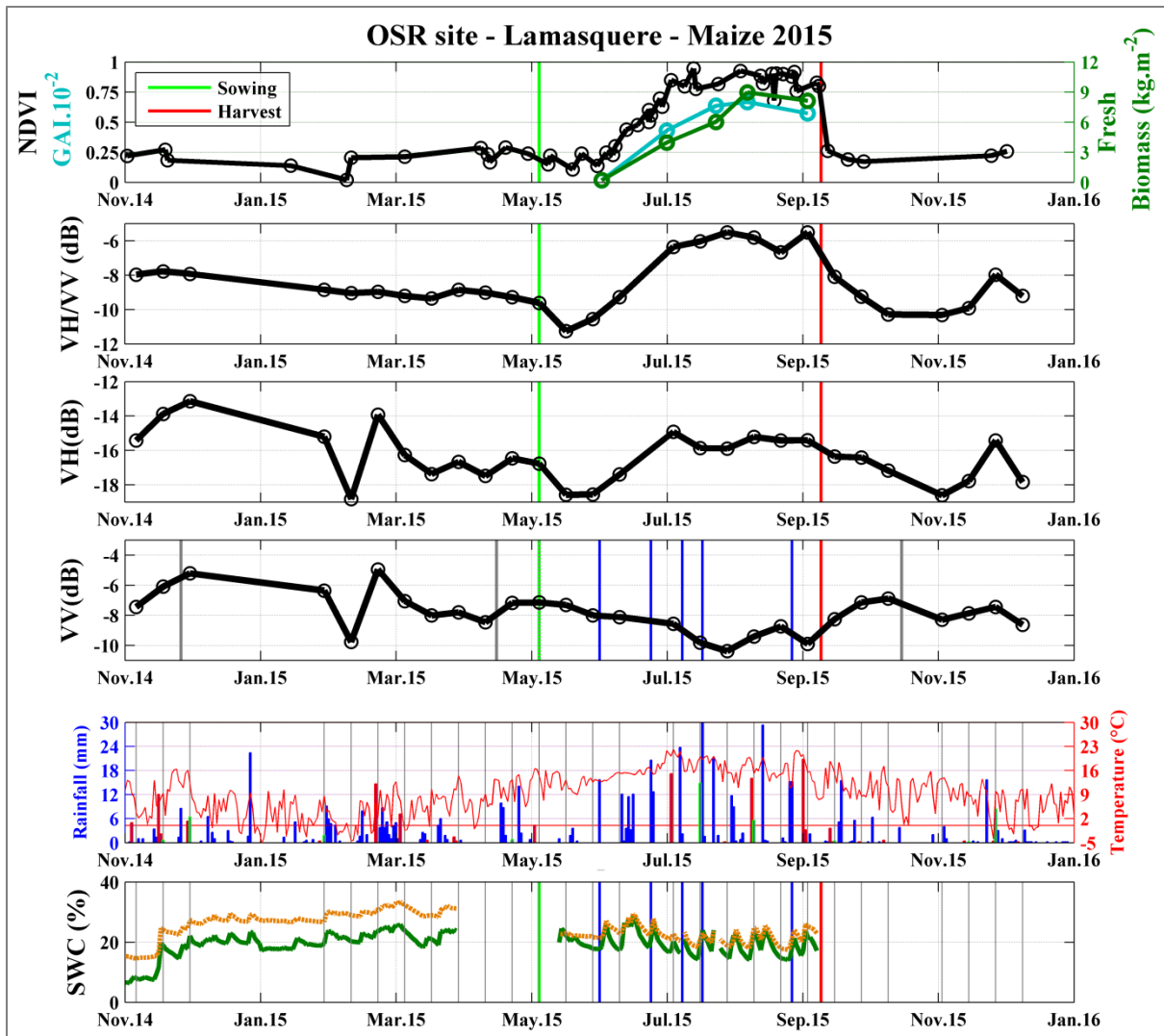
464 **We underline that the results and analysis presented above are based on one single maize field**  
465 **and might be not fully representative of the maize crop behavior, although in line with the results**  
466 **below based on a number of maize fields.**

467 The temporal profiles of the 57 maize fields (in blue), shown together with soybean and sunflower in  
468 Figure 7, are similar to the Lamasquère one during the growing period, with correlations  $r^2$  of 0.91  
469 between NDVI and VH/VV and 0.89 between NDVI and VH ( $N=13$ ). However, trends are not similar  
470 during the senescence. Indeed, many fields that are not harvested green for silage show a gradual  
471 decrease of NDVI and radar backscatter.

472 During winter, the soil is bare or the vegetation (such as weeds or re-growth of previous crops)  
473 remains short and VV and VH behaviors are mostly due to variations in the soil backscatter.

474

475



476  
 477 Figure 6: Observations on maize field: temporal behavior of optical NDVI, radar VH/VV, VH, and VV, rainfalls,  
 478 temperatures and soil water content (SWC) over the Lamasquère site, where maize was cultivated in 2015. The blue and  
 479 green profiles superposed to NDVI are fresh biomass and GAI, respectively. In the second to last plot, temperatures in  
 480 red were measured at the Sentinel-1 acquisition time 6 a.m. The horizontal red line is the 0°C line. Precipitation is  
 481 represented by the blue bars. They are displayed in green when occurring in the same days than Sentinel-1 acquisitions  
 482 and in red if rainfall events take place in the two days before Sentinel-1 acquisitions (assuming that wet soil due to  
 483 rainfalls may still affect Sentinel-1 backscatter two days later). Vertical grey bars represent Sentinel-1 acquisition events.  
 484 In the last plot, SWC has been measured at 0.5 cm (green) and 5 cm (brown) depth. Irrigation events are indicated by the  
 485 blue bars in the fourth (with VV profile) and in the last plot.

486

### 487 3.2.2. Soybean

488 The mean and standard deviation time series of 8 soybean crop fields are drawn in green in Figure 7.  
 489 One can observe very similar NDVI and VH/VV trends ( $r^2$  is 0.82,  $N=13$ ) and both parameters behave  
 490 almost similarly to maize despite some differences. For example, VV backscatter is lower for soybean  
 491 than for maize during the growth period. Then, NDVI starts to decrease earlier than VH/VV, despite

492 VH and VV backscatters start decreasing at the same time as NDVI. Even if the standard deviation at  
493 VV polarisation is, as expected, logically higher than for VH when the soil is bare, VH and VV  
494 backscatters show similar temporal behaviors, especially during the growing and senescence periods.  
495 This may be explained by the fact that the height of soybean only reaches approximately 0.7 m (up to  
496 3 times less than maize) and the number of soybean stems per surface unit is low, which leads to a  
497 significant surface scattering from the soil and a poor attenuation of the backscattered signal. In July  
498 and August, VV decreases slightly as compared to VH, which explain the lower correlation between  
499 NDVI and VV ( $r^2$  is 0.39) than between NDVI and VH ( $r^2$  is 0.69).

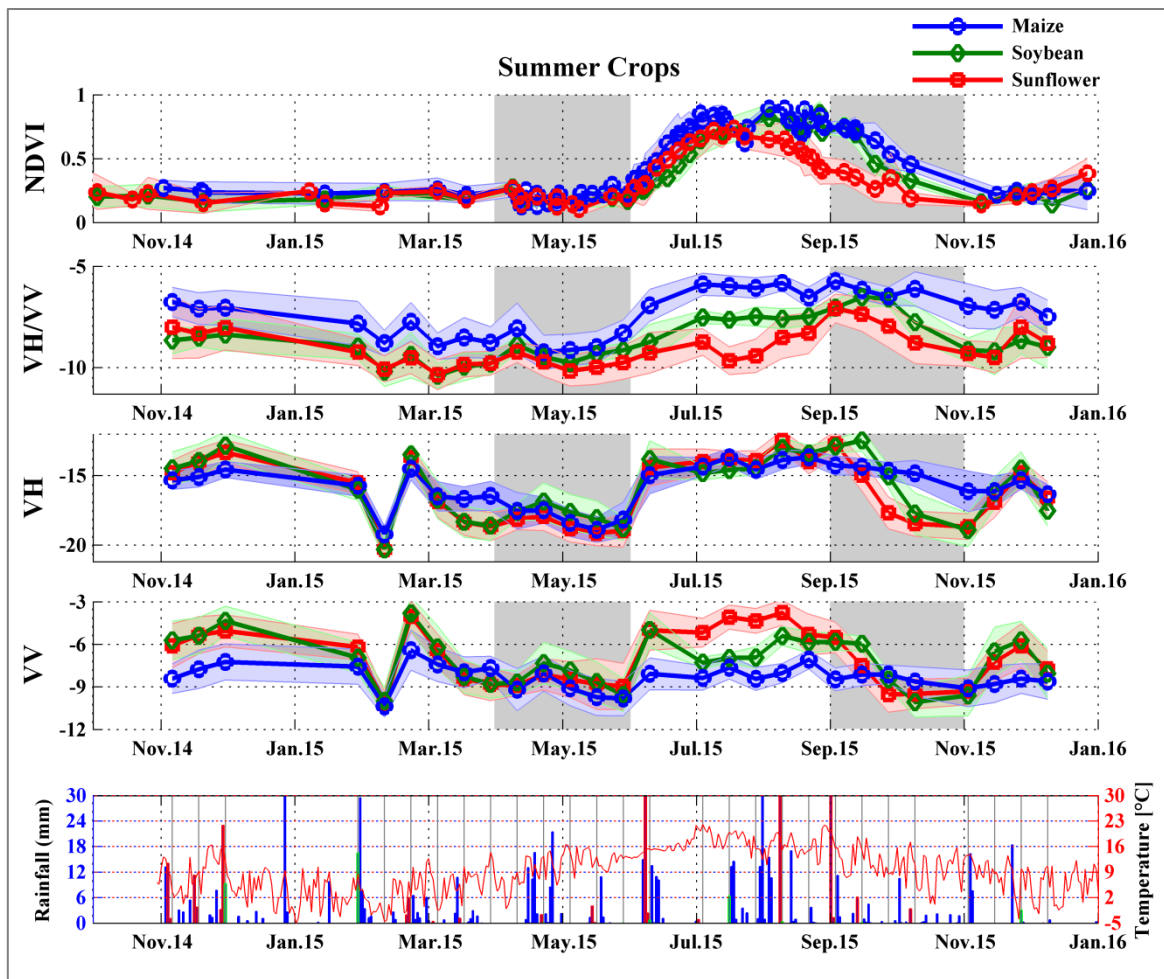
500

### 501 **3.2.3. Sunflower**

502 Figure 7 shows in red color the temporal behavior of the 116 sunflower fields. The NDVI temporal  
503 profile depicts well the growing and senescence period (with a high number of images acquired at  
504 that time). Note that NDVI is lower for sunflower than for maize and soybean during the senescence.  
505 Likewise, lower GAI were observed for sunflower than for maize (Claverie et al., 2012) and maize and  
506 soybean (Claverie, 2012).

507 VH/VV backscatter is poorly correlated to NDVI ( $r^2$  is 0.08,  $N=15$ ). Sunflower is therefore the only  
508 crop studied in this paper for which temporal monitoring using VH/VV is not recommended. VH  
509 backscatter, as for maize and soybean, follows well the NDVI trends ( $r^2$  is 0.71) despite the complex  
510 structure of sunflower plants. In addition, sunflower is the only crop for which VV is positively well  
511 correlated to NDVI ( $r^2$  is 0.77). In fact, VV is not affected by ground return because of large leaves and  
512 both VH and VV are dominated by volume scattering. Therefore, VH/VV does not reduce the surface  
513 and double-bounce effect and has smaller sensitivity to volume scattering than for maize and  
514 soybean.

515 At the beginning of July, the flowering stage causes a strong increase of VV that result in a VH/VV  
516 decrease, leading to the poor correlation between NDVI and VH/VV.



517  
 518 **Figure 7: Observations on maize, soybean and sunflower fields: temporal behavior of optical NDVI, radar VH/VV, VH, and**  
 519 **VV, rainfalls and temperatures over summer crops, i.e. 57 maize crops (in blue), 8 soybean crops (in green) and 116**  
 520 **sunflower crops (in red). Mean values are represented by dots and standard deviations are represented by the filled**  
 521 **color domains surrounding the curves. In the last plot (Bottom), temperatures in red were measured at the Sentinel-1**  
 522 **acquisition time 6 a.m. Vertical precipitation bars in blue are drawn in green the same days than Sentinel-1 acquisitions**  
 523 **and in red the two days before Sentinel-1 acquisitions, assuming that wet soil due to rainfalls may still affect Sentinel-1**  
 524 **backscatter two days later. Vertical grey bars represent Sentinel-1 acquisition events. The typical periods of sowing and**  
 525 **harvest are indicated by the grey shaded areas.**

526

### 527 3.3. Key findings for potential applications

528 In this section, we summarise some of the main findings of this paper and their potential impact on  
 529 crop mapping (e.g. crop types, irrigated crops and early crop identification) and biophysical  
 530 parameters estimation using Sentinel-1 and -2 data.

531 The analysis and interpretation of Sentinel-1 and Sentinel-2-like time series data led to  
 532 recommendations for feature selection in the frame of crop mapping. Feature selection is a process  
 533 by which we look for the best subset of attributes in a dataset. Performing feature selection allows  
 534 reducing the use of redundant and misleading data to reach highest accuracy, while reducing

535 computation time. As observed in Figure 5, VH and/or VV SAR backscatters are able to clearly  
536 separate winter wheat and rapeseed between the tillering and senescence stages (roughly between  
537 March and July). **Satalino et al. (2014) found the same results using the VH backscatter.** In addition,  
538 NDVI and VH backscatter may be used to distinguish wheat and rapeseed earlier, i.e. between  
539 November and December. Note that VH/VV ratio is less sensitive to cereal development than NDVI  
540 before March, suggesting that the use of the VH/VV ratio for winter crop detection may be  
541 recommended from March, as found in Inglada et al. (2016). Regarding the classification of summer  
542 crops, VH/VV could be used to distinguish maize, soybean and sunflower during the  
543 heading/flowering phase (between June and the end of August) as shown in Figure 7, allowing early  
544 crop type identification. VV backscatter as well could be used to separate summer crops in July and  
545 August. However, using VH is not recommended, except in October for detecting maize crops that  
546 are not harvested green for silage. NDVI is not recommended either for distinguishing summer crops,  
547 except sunflower during the senescence period, between August and September. This result brings  
548 to light the valuable contribution of SAR measurements for distinguishing crop types having similar  
549 NDVI profiles.

550 The analysis and interpretation of Sentinel-1 and Sentinel-2-like time series data also allows  
551 enhancing the estimation of the croplands production (biomass and yield) and soil moisture using  
552 agro-meteorological models (Revill et al., 2013, Ferrant et al., 2016). **Bernardis et al. (2016) have**  
553 **illustrated this complementarity by using together NDVI (from Landsat), the HH/VV ratio (from**  
554 **TerraSAR-X) air temperatures from a ground-based station for improving rice crop phenological**  
555 **estimation.** In addition, the sensitivity of SAR data to soil moisture may be useful for detecting  
556 irrigated crops. This may be useful for crop modeling by providing information on irrigation practices,  
557 and also for a better water management strategy.

558 Our results showed that, for barley and maize crops, the Sentinel-1 and Sentinel-2-like data are  
559 correlated to GAI and fresh biomass. Despite the lack of GAI and biomass *in situ* data for rapeseed  
560 and soybean, SAR data are likely to be reliable for biomass or GAI estimation given the good  
561 agreements between VH/VV and NDVI. GAI time series estimation can be useful for driving crop  
562 models, allowing to better set some crop parameters and thus improve the estimation of the model  
563 output variables, such as biomass and yield production. Alternatively, SAR data could be used to  
564 directly estimate crop biomass, which could be then assimilated by the models, allowing a more  
565 accurate estimation of other crop related features, such as the components of carbon fluxes.  
566 Besides, during periods of strong cover development, NDVI sensitivity to GAI and biomass is more  
567 likely to saturate. Therefore, SAR data could represent a solution for describing crop development  
568 under these conditions.

569 Finally, the joint use of SAR and optical data may allow the development of tillage change maps that  
570 are useful in the context of conservative agriculture.

571

## 572 **4. Conclusions**

573 In this study, we used a large number of temporal Sentinel-1 together with Sentinel-2-like data to  
574 assess the potential of the Sentinel satellites for winter and summer crops monitoring. We applied an  
575 adapted multi-image filter to the Sentinel-1 images, taking advantage of the Sentinel-1 dense  
576 temporal series to reduce the speckle effect, while preserving the fine structure present in the  
577 image, like the crop fields boundaries. The time series of optical NDVI and radar backscatter (VH, VV  
578 and VH/VV) were analysed and physically interpreted with the support of rainfall and temperature  
579 data, as well as the destructive *in situ* measurements (GAI and fresh biomass, when available). We  
580 showed that dense time series allow to capture short phenological stages and thus to precisely  
581 describe various crop development.

582 A better understanding of SAR backscatter and NDVI temporal behaviors under contrasting  
583 agricultural practices and environmental conditions will help many upcoming studies related to crop  
584 monitoring based on Sentinel-1 and -2, such as dynamic crop mapping and biophysical parameters  
585 estimation. Regarding crop mapping, we found that wheat and rapeseed could be better  
586 distinguished using VH and VV backscatters between March and July and using NDVI between  
587 November and December. Regarding summer crops, we recommend using VH/VV and VV to separate  
588 maize, soybean and sunflower during the heading/flowering phase. Results also showed that for  
589 barley and maize, both NDVI and VH/VV profiles are in good agreement with the destructive GAI and  
590 fresh biomass measurements. Thus, VH/VV ratio could be successfully used for biophysical  
591 parameters retrieval and direct biomass assimilation in crop models. VH/VV is also able to detect  
592 post-harvest spontaneous regrowth.

593 In general, SAR and optical data both accurately reproduce crop growth cycles and may be combined  
594 for having full gap-free time series, used as inputs for agro-meteorological models. This study points  
595 out the interest of SAR data and particularly the VH/VV ratio, which is poorly documented in previous  
596 studies (for notable exceptions see McNairn et al., 2009 and Inglada et al., 2016 for crop type  
597 classification, Fieuzal et al., 2013 for rapeseed and Blaes et al., 2006 for maize monitoring). Radar  
598 data could also be used to fill eventual gaps in the optical data series, namely during cloudy periods.  
599 The unprecedented amount of free Sentinel data, guaranteed up to and even beyond 2030 with the  
600 next generation of Sentinel, offers a unique opportunity to monitor crops in near real time as  
601 highlighted in this study.

602



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616

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618

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