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Evaluation of multi-orbital SAR and multi-sensor optical data for empirical estimation of rapeseed biophysical parameters

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***Abstract*— This paper aims to evaluate the potential of multi-temporal and multi-orbital remote sensing data acquired both in the microwave and optical domain to derive rapeseed biophysical parameters (crop height, dry mass, fresh mass and plant water content). Dense temporal series of 98 Landsat-8 and Sentinel-2 images were used to derive Normalized Difference Vegetation Index (NDVI), green fraction cover (fCover) and Green Area Index (GAI), while backscattering coefficients and radar vegetation index (RVI) were obtained from 231 mages acquired by Synthetic Aperture Radar (SAR) onboard Sentinel-1 platform. Temporal signatures of these Remote Sensing Indicators (RSI) were physically interpreted, compared each other and to ground measurements of biophysical parameters acquired over 14 winter rapeseed fields throughout the 2017-2018 crop season. We introduced new indicators based on the cumulative sum of each RSI that showed a significant improvement of their predictive power. Results particularly reveal the complementarity of SAR and optical data for rapeseed crop monitoring throughout its phenological cycle. They highlight the potential of the newly introduced indicator based on: the VH polarized backscatter coefficient to estimate height (R^2 = 0.87), plant water content (R^2 = 0.77, from flowering to harvest) and fresh mass (R^2 = 0.73) and RVI to estimate dry mass (R^2 = 0.82). Results also demonstrate that multi-orbital SAR data can be merged without significantly degrading the performance of SAR-based relationships, while strongly increasing the temporal sampling of the monitoring. These results are promising in view of assimilating optical and SAR data into crop models for finer rapeseed monitoring.**

***Index Terms*—Rapeseed, Sentinel-1, Sentinel-2, Landsat-8, crop monitoring, biomass, plant water content, crop height.**

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I. Introduction

In the context of the global change and an increasing world demography, one of the major issues for mankind is to develop agriculture practices allowing to ensure together food security, sustainability of natural resources and economic profitability for farmers [1], [2]. To address these challenges, precision agriculture became an essential scientific topic [3]. Precise crop monitoring systems generally rely on the high frequency acquisition and assessment of crop biophysical parameters such as Green/Leaf Area Index (GAI/LAI), dry (DM) and fresh masses (FM), crop height or plant water content (PWC). These parameters are key variables since they express the phenological and physiological plant response to meteorological events [4], [5], pest and diseases outbreaks [6], fertilizer applications [7] or water management practices [8]. They are in addition paramount for crop yields estimation from modeling approaches [9], [10]. However, for most crops, *in situ* ground measurements are lacking. Ground survey of such parameters is time-consuming and thus cannot be reproduced at fine spatio-temporal scale in real or near-real time. To overcome this limitation, satellite remote sensing has been recognized as an effective solution to monitor spatio-temporal evolutions of crops at scales compatible with decision makers of landscape management [11], [12].

Both optical and microwave domains have been intensively explored for crop parameters retrieval [13]–[15]. In the optical domain, a large panel of studies has demonstrated the interest of using reflectance or vegetation index to derive biophysical parameters, in particular LAI [16]–[18], biomass [19] or crop height [20]. However, the use of optical data has major drawbacks, first and foremost their sensitivity to weather and lightening conditions that can drastically limit their availability in terms of temporal frequency. To overcome these shortcomings, more and more studies have focused on the use of microwave data (acquired by SAR sensors) to estimate crop biophysical parameters [21]–[24] or on the use

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of combined optical and microwave signals [25]–[30]. However, SAR data are not without limitations. They remain complex to interpret since they are sensitive to both soil and vegetation properties (wetness, roughness, phytomass, vegetation structure, etc.).

Regarding the potential use of the main microwave bands (X-, C- and L-bands), many authors have highlighted the interest of the X- and L-bands for the monitoring of wheat [30], [31], corn [27], barley [21] or rice [32]. However, the lack of dense temporal satellite data series acquired at L-band and/or their high cost (acquired for example by Alos-2, Terrasar-X, Tandem-X or Cosmoskymed constellation) do not permit their use in fine temporal approaches for crop monitoring. The launch of European Space Agency's Sentinel satellites from 2015 resolves this limitation in the C-band domain. Indeed, they offer an unprecedented opportunity to monitor crops worldwide in both SAR (with Sentinel 1A and 1B) and optical (with Sentinel 2A and 2B) domains at high temporal frequency and high spatial resolution [33]. Moreover, the multiplicity of Sentinel-1's orbits which can cover the same field theoretically offers the opportunity to increase data frequency. In this sense, the feasibility of merging Sentinel-1 data from different orbits deserves to be studied. Regarding optical images, at field scale, data frequency can also potentially be increased by the combination of different sensors with different features. In particular, Sentinel-2 and Landsat-8 both seem to meet requirements, in terms of spatial resolution, of worldwide field-scale applications.

Nonetheless, most of the few studies that focused on the synergy of optical and SAR data for crop monitoring suffer from the unavailability of a sufficient dense dataset containing concomitant *in situ* and satellite data [27], [34]. Such shortcomings intrinsically weaken the statistical robustness of the relationships established between satellite indicators and *in situ* biophysical parameters. This is particularly true for rapeseed for which robust ground measurements are scarce, especially in Europe. However, rapeseed is one of the most important seasonal crops cultivated in the world for oil, proteins and biofuel production. In 2018, rapeseed was the seventh world crop in terms of cultivated area with almost 37.6 million hectares for a total production of 75 million tons (FAO statistics for 2018).

In this context, the objectives of this study consist in: (i) analyzing the temporal signatures of SAR data from Sentinel-1 and optical data from Sentinel-2 and Landsat-8 throughout the rapeseed crop cycle, (ii) analyzing the effect of multi-orbit acquisitions on SAR data and multi-sensor acquisitions on optical data for rapeseed fields, and (iii) evaluating the potential of both multi-orbital SAR data from Sentinel-1 and multi-sensor optical data from both Sentinel-2 and Landsat-8 to empirically derive rapeseed biophysical parameters (BP) i.e. DM, FM, height and PWC. This paper is structured as follows. Section II introduces the material and methods used including weather data and ground measurements of rapeseed BP (sections II.A and II.B), satellites data (section II.C) and the methodology employed to derive BP from Remote Sensing Indicators (RSI) and evaluate the predictive power of each RSI (section II.D). Section III is dedicated to the presentation of results. Firstly, the temporal signatures of optical and SAR RSI are analyzed regarding the temporal evolutions of measured BP all along the rapeseed phenological cycle (Section III.A). Secondly the feasibility of a fusion of Sentinel-1 data from different orbits is scrutinized through an analysis of angular effects on backscatter coefficients (section III.B.1). In parallel, the sensitivity of optical data to sensor (Sentinel-2 or Landsat-8) is analyzed (section III.B.2). Finally, relationships between RSI and rapeseed BP are studied and predictive power of each RSI is analyzed in Section III.C. Results are discussed in Section IV according to (i) the effect of multi-orbit and multi-sensor acquisitions on SAR and optical data, respectively, (ii) the impact of fields sampling on empirical relationships, (iii) the order of the empirical polynomials functions, and (iv) the impact of radiometric correction in SAR processing. Lastly, conclusions and perspectives of this work are given in Section V.

II. Material and Methods

A. Description of the Study Sites and Meteorological Conditions

Monitored rapeseed fields used in this study are located in two study sites, specialized in annual grain crops, in southwestern and central France with contrasted pedoclimatic conditions (Figure 1). We used meteorological data (i.e. rainfall, temperature, and global radiation) from Méteo-France (Issoudun, Le Subdray, Bourges, Farges-en-Septaine and Prémery stations) and Arvalis Institut du végétal (En Crambade station). These data have been daily acquired by six meteorological stations situated at less than 19 km far from the monitored rapeseed fields (Table I; Figure 1). Figure 2 provides an ombrothermic diagram for these six meteorological stations for the entire agricultural season of rapeseed (i.e. from August 2017 to July 2018). Compared to other stations, the southern-most station, i.e. En Crambade, is characterized by milder temperatures, a drier 2017 autumn and a strongly rainier end of season from May to July 2018. Prémery and Farges-en-Septaine are the coldest stations especially during winter. Bourges and Farges-en-Septaine show a rainier autumn. Le Subdray shows significantly higher rainfalls in December and June and winter temperatures comparable to En Crambade. Issoudun has an intermediary behavior.

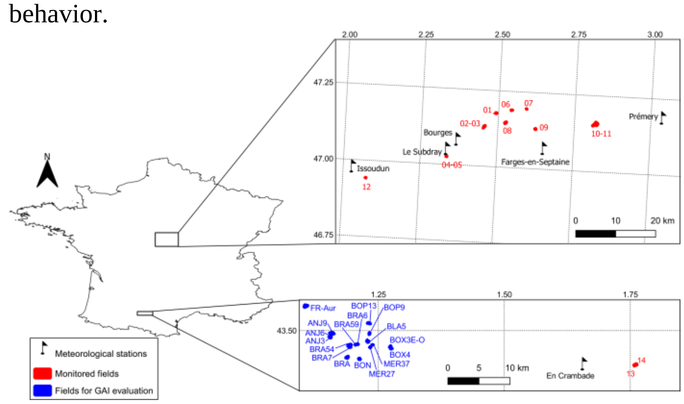

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Fig. 1. Map of monitored rapeseed fields (red dots) and those used for GAI measurements (blue dots). Meteorological stations are represented by black flags.

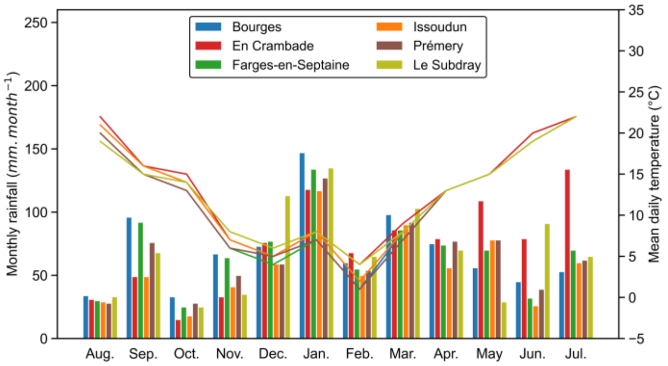

Fig. 2. Ombrothermic diagram of the six meteorological stations for the 2017-2018 agricultural season of rapeseed. Mean daily temperature and monthly rainfall are represented by lines and vertical colored bars, respectively (according to weather station).

TABLE I
IDENTIFIER, SOWING AND HARVEST DATES OF MONITORED RAPESEED FIELDS. FOR EACH FIELD, THE DISTANCE FROM THE NEAREST METEOROLOGICAL STATION, THE NUMBER OF GROUND MEASUREMENTS AND THE MEAN SLOPE ARE MENTIONED

Field identifier	Sowing date	Harvest date	Nearest meteorological station	Distance from meteorological station (km)	Number of sampling dates	Mean slope (°)
01	2017/08/16	2018/07/03	Bourges	15.57	13	1.9
02	2017/08/22	2018/07/08	Bourges	9.24	13	1.1
03	2017/08/22	2018/07/08	Bourges	9.24	13	1.1
04	No data	No data	Le Subdray	0.71	11	0.4
05	No data	No data	Le Subdray	0.56	11	0.4
06	2017/08/20	2018/06/29	Farges-en-Septaine	17.30	12	1.7
07	2017/08/23	2018/07/18	Farges-en-Septaine	18.57	12	1.6
08	2017/08/16	2018/06/28	Farges-en-Septaine	14.28	12	1.2
09	2017/08/16	2018/07/06	Farges-en-Septaine	9.05	12	1.6
10	2017/08/17	2018/06/29	Prémery	16.29	12	0.6
11	2017/08/19	2018/07/02	Prémery	16.38	12	0.9
12	2017/08/29	2018/07/07	Issoudun	4.15	12	0.7
13	2017/08/27	2018/06/28	En Crambade	8.39	9	2.4
14	2017/08/27	2018/06/28	En Crambade	8.83	9	2.2

B. Ground Measurements

In the framework of the R&D project named Colza digital, an intensive field campaign was carried out to collect ground data over 14 fields of winter varieties of rapeseed (*Brassica napus* L.) during the 2017-2018 growing season (Figure 1 and Table I).

For each field, *in situ* measurements of crop height, aboveground dry mass (DM), aboveground fresh mass (FM) and plant water content (PWC) were regularly carried out (20 days timestep on average) from sowing to harvest. For each ground measurement date, 3 samples of rapeseed plants were collected on a 1 m^2 ESU (Elementary Sampling Unit). All ESUs were located inside a 20 by 30 m^2 area, the center of which was located on average 60 m far from the edge of the field. Aboveground FM was obtained by directly weighing plants on field. Aboveground DM was obtained after drying plants in an oven (80°C during 36 hours). PWC was obtained from DM and FM. For each biophysical parameter, the final value is given by averaging measurements performed on the 3 samples. Phenological stages according the BBCH scale [35] have also been recorded (see Appendix A). All ground measurements, including BBCH stages, have later been linearly interpolated at daily time step. Sowing dates vary from August 16, 2017, to August 29, 2017, whereas harvest dates vary from June 28, 2018, to July 18, 2018 (Table I).

In addition to the 14 monitored fields, 18 other independent winter rapeseed fields have been used to evaluate the GAI derived from Sentinel-2 and Landsat-8 images (see blue fields in Figure 1) and sensor effect on optical data. GAI measurements were carried out on one ESU of 30 by 30 m^2 for each field using the SunScan Canopy Analysis System (Delta-T Devices Ltd, UK) for the FR-Aur field and from hemispherical photography acquired according to the protocol described by [36] and treated with the CAN-EYE software [37] for the other fields (see Appendix B for more details on the features of these fields).

C. Satellite Acquisitions

Figure 3 shows a chronogram of satellite acquisitions performed in both optical (Sentinel-2, Landsat-8) and microwave (Sentinel-1) domains during the 2017-2018 rapeseed crop season.

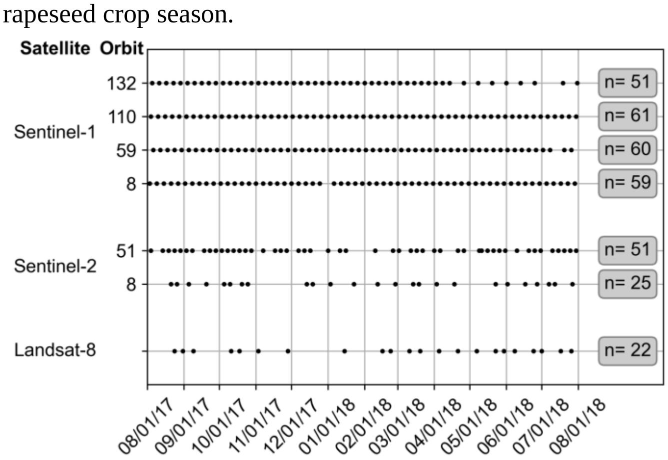

Fig. 3. Chronogram of satellite acquisitions performed in the optical (Sentinel-2, Landsat-8) and microwave (Sentinel-1) domains during the rapeseed crop cycle, according to orbit number: 8, 59, 110 and 132 for Sentinel-1, and 51 and 8 for Sentinel-2 acquisitions. n is the number of respective acquisitions.

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1) SAR Data

The backscatter coefficients at C-band (5.405 GHz) were provided by SAR sensor onboard Sentinel-1 satellite (Table II). They were derived from the Interferometric Wide (IW) mode and Ground Range Detected (GRD) processing from four different orbits (i.e. 132, 110, 59 and 8; Figure 3). Mean incidence angles at field scale are θ_{132} = 43.5°, θ_{110} = 38.3°, θ_{59} = 36.6° and θ_{8} = 30.3° for the four orbits allowing a repetitiveness of 2.6 days on average for all combined orbits (231 images). Backscatters coefficients for the four orbits and the two polarizations (VH and VV) were extracted for each field (noted σ^0_{VH} and σ^0_{VV} in the following) from pre-processed GRD data using the Google Earth Engine (GEE) website [38]. The GEE preprocessing includes the following steps: orbit file application, GRD border noise removal, thermal noise removal, radiometric calibration (sigma naught), Range Doppler terrain correction and resampling at 10 m spacing. Two indexes were derived from σ^0_{VH} and σ^0_{VV}: the co-cross-polarization ratio (σ^0_{VH-VV}) and the Radar Vegetation Index (RVI). Originally introduced by [39], RVI is generally calculated using quad-polarized SAR data. Since Sentinel-1 only provides VH and VV polarizations, RVI was computed according to [40] who adapted the concept of RVI for dual-polarization Sentinel-1 data as follows:

$$RVI = \frac{4\sigma^0_{VH}}{\sigma^0_{VV} + \sigma^0_{VH}} \quad (1)$$

where σ^0_{VH} and σ^0_{VV} are the backscatter coefficients in VH and VV polarization, respectively. They are expressed in $m^2.m^{-2}$, and RVI has no unit.

TABLE II
MAIN FEATURES OF SENTINEL-1 A OR B IMAGES USED IN THIS STUDY

Frequency	5.405 GHz (C-band)
Mode	Interferometric Wide Swath
Product type	Ground Range Detected
Ground range resolution	5 m
Azimuth resolution	20 m
Temporal resolution	12 days
Orbits	Ascending (59, 132) & Descending (8, 110)
Polarization	Dual (VV & VH)
Swath	250 km
Incidence angle	30,3 - 43,5°

2) Optical Data

NDVI, fCover and GAI were calculated from both ESA Sentinel-2 level-1C and USGS Landsat-8 level-1 products (Table III). fCover and GAI were obtained by inverting the PROSAIL canopy reflectance model [41] with the Overland processor developed by Airbus DS GEO (https://www.intelligence-airbusds.com/verde-processing/). Overland processing principle is based on the coupling of combined PROSPECT leaf optical properties model [42] and SAIL canopy bidirectional reflectance model [43], [44] with the LOWTRAN 7 atmospheric model [45] completed with an ad-hoc cloud model. Overland uses top of atmosphere radiances as inputs to perform inversion of above described coupled model through minimization techniques. Thanks to its built-in atmospheric model, Overland performs autonomous atmospheric corrections of reflectance as well as an automatic masking of thin clouds and dark shadows. The Overland processor also includes a co-registration algorithm to deal with differences in native resolutions and geometric performances of Sentinel-2 and Landsat-8. A detailed description of the Overland algorithms can be found in [46]. Only fCover, NDVI and GAI estimations derived from images with more than 80 % of cloud free pixels over considered rapeseed fields were conserved. fCover, NDVI and GAI were finally derived from 76 Sentinel-2 images and 22 Landsat-8 images for the 14 monitored rapeseed fields throughout the entire rapeseed growth-cycle (Figure 3). Field-scale fCover, NDVI and GAI were obtained using the mean value of pixels included in the field.

TABLE III
MAIN FEATURES OF OPTICAL IMAGES USED IN THIS STUDY

Sensors	Sentinel-2	Landsat-8
Bands	B1 (443 nm) B2 (452 - 512 nm), B3(636 - 673 nm), B4 (636 - 673 nm), B5 (851 - 879 nm), B6 (1566 - 1651 nm), B7 (2107 - 2294 nm), B8 (842 nm), B8a (865 nm) B9 (940 nm), B10 (1375), B11 (1610 nm), B12 (2190 nm)	B1 (435 - 451 nm), B2 (452 - 512 nm), B3(636 - 673 nm), B4 (636 - 673 nm), B5 (851 - 879 nm), B6 (1566 - 1651 nm), B7 (2107 - 2294 nm), B9 (1363 - 1384 nm)
Product type	Level-1C Top-Of-Atmosphere reflectance	Level-1 Top-Of-Atmosphere reflectance
Spatial resolution	10 m (B2, B3, B8), 20 m (B5, B6, B7, B8a, B11, B12), 60 m (B1, B9, B10)	30 m
Temporal resolution	5 days	16 days
Orbits	51 & 8	-
Swath	290 km	185 km

D. *Methodology*

Firstly, the temporal signatures of SAR and optical signals were analyzed in light of the temporal evolution of *in situ* biophysical parameters (section III.A). In this study, four orbits from Sentinel-1 have been simultaneously exploited to increase SAR data acquisitions for each studied rapeseed field. Acquisitions from different orbits necessarily induce different angular configurations which can affect backscatter coefficients values. Consequently, orbital effects on SAR data have been scrutinized (section III.B.1). Optical data have also been acquired from two different sensors, i.e. Sentinel-2 and Landsat-8, whose impact on the accuracy of GAI estimates was assessed (section III.B.2).

We then analyzed and evaluated the relationship between both SAR and optical Remote Sensing Indicators (RSI), respectively derived from Sentinel-1 and Sentinel-2 and Landsat-8, and the ground measurements of DM, FM, height and PWC acquired on the 14 monitored rapeseed fields during the entire 2017-2018 crop cycle (section III.C). In a first step regarding SAR RSI aside, evaluation was performed for the

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complete SAR dataset (section III.C.1). In a second step, for a fair statistical comparison between optical and SAR RSI, this evaluation was performed for concurrent acquisitions of optical and SAR data (section III.C.2). We also scrutinized the effect of phenological stages on the suitability of empirical relationship by analyzing distribution of residuals (i.e. differences between measured and estimated BP) of the best RSI-based relationship by BBCH main stages (Section III.D).

1) Definition of Remote Sensing Indicators (RSI)

Four SAR RSI, i.e. σ^0_{VH}, σ^0_{VV}, $\sigma^0_{VH\text{-}VV}$ and RVI, and three optical RSI, i.e NDVI, fCover and GAI, have been considered. As an alternative of raw RSI, we proposed new indicators (noted η_{RSI}) based on the cumulative sum of each RSI, and already successfully applied to the estimation of wheat parameters [47]:

$$\eta_{RSI}(d_i) = \sum_{0}^{n} |RSI(d_i)|\,(d_i - d_{i-1}) \tag{2}$$

where RSI (d_i) is the value of the given remote sensing indicator at day d_i, n is the total number of remote sensing acquisitions, and ($d_i - d_{i-1}$) is the number of days between day d_i and the previous acquisition date d_{i-1}. This term allows taking into account the differences of acquisition frequency between monitored fields for both SAR (mainly due to orbits configurations) and optical (mainly due to cloud cover conditions) images. For all RSI, a common starting date d_0 is set for all fields for which η_{RSI} is initialized to 0. In this study d_0 was set to the 4th of August 2017 for both SAR and optical data, matching the dates of the first pre-sowing available Sentinel-1 image and/or the first pre-sowing available Sentinel-2 or Landsat-8 image. A complete list of RSI analyzed in this paper is given in Table IV.

TABLE IV
REMOTE SENING INDICATORS (RSI) USED IN THIS STUDY

RSI	Domain	Unit
NDVI	Optical	-
fCover	Optical	%
GAI	Optical	$m^2.m^{-2}$
η_{NDVI}	Optical	days
η_{fCover}	Optical	%.days
η_{GAI}	Optical	$m^2.m^{-2}$.days
σ^0_{VH}	SAR	dB
σ^0_{VV}	SAR	dB
$\sigma^0_{VH\text{-}VV}$	SAR	dB
RVI	SAR	-
$\eta_{\sigma VH}$	SAR	dB.days
$\eta_{\sigma VV}$	SAR	dB.days
$\eta_{\sigma VH\text{-}VV}$	SAR	dB.days
η_{RVI}	SAR	days

2) Analysis of orbital effects on SAR data

To consider the feasibility of the fusion of Sentinel-1 data from different orbits, we scrutinized angular effects on backscattering coefficients. To do so, we analyzed the temporal evolution of the Γ variable (in dB.°$^{-1}$) defined as follows:

$$\Gamma = \frac{\Delta\sigma^0}{\Delta\theta} \tag{3}$$

where $\Delta\sigma^0$ (dB) and $\Delta\Theta$ (°) are the differences between either σ^0_{VH}, σ^0_{VV} or $\sigma^0_{VH\text{-}VV}$ and the incidence angles from two successive acquisitions in different orbits. Considering sensitivity of SAR data to soil moisture, in this analysis, we also computed cumulated rainfall values from the nearest meteorological station between two consecutive acquisitions. In this way, we investigated if the difference between σ^0 values can rather be explained by a rainfall event than by a difference in incidence angle.

3) Evaluation of optical GAI and analysis of sensors effects on optical data

To explore the effect of sensors on optical data, two kind of analysis have been carried out. In a first one, the accuracy of GAI estimations derived from Sentinel-2 and Landsat-8 have been assessed by comparing them with *in situ* measurements acquired on the 18 fields with available ground GAI (see blue fields in Figure 1). For this comparison, the results were analyzed according to the sensor and according to the time difference between ground measurements and acquisition dates of satellite images.

In a second analysis, GAI, fCover and NDVI derived from Sentinel-2 and Landsat-8 have been compared each other for all monitored fields (i.e. blue and red fields in Figure 1) by considering a maximal difference of one day between acquisition dates of Sentinel-2 and Landsat-8 images.

4) From satellite to crop parameters

Linear (Eq.4) and 2nd-order polynomial (Eq.5) regressions were established between either SAR or optical indicators and measured biophysical parameters:

$$BP = aRSI + b \tag{4}$$
$$BP = aRSI^2 + bRSI + c \tag{5}$$

where BP is a rapeseed Biophysical Parameter (DM, FM, PWC, height), RSI is a Remote Sensing Indicator from either SAR or optical domain and a, b, c are parameters of the regression. Performance of each relationship was evaluated using coefficient of determination (R^2), Root Mean Square Error (RMSE) and relative Root Mean Square Error ($RMSE_r$).

III. RESULTS

A. SAR and optical temporal signatures

Figure 4 shows the temporal evolution of fCover, NDVI (Fig. 4.c), GAI (Fig. 4.d), σ^0_{VH}, σ^0_{VV} (Fig. 4.e), $\sigma^0_{VH\text{-}VV}$ and RVI (Fig. 4.f), $\eta_{\sigma VH}$, $\eta_{\sigma VV}$, $\eta_{\sigma VH\text{-}VV}$, η_{RVI} (Fig. 4.g), η_{fCover}, η_{NDVI}, η_{GAI} (Fig. 4.h), as well as *in situ* measurements of height and PWC (Fig. 4.a), DM and FM (Fig. 4.b) as the mean and standard deviation of all studied fields. In this figure, for display reasons, ground measurements, optical and radar indicators have been linearly interpolated beforehand at a daily timescale.

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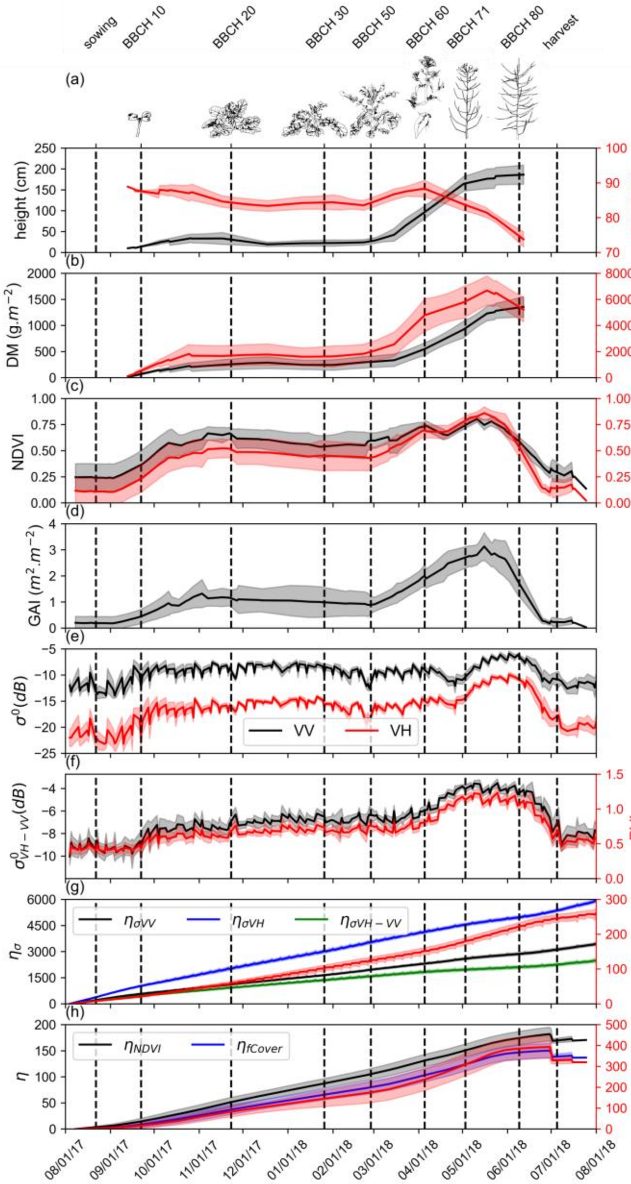

Fig. 4. Temporal evolution of *in situ* height and PWC (a), DM and FM (b), optical NDVI and fCover (c), GAI (d), SAR backscattering coefficients (e) and backscattering coefficients ratio and RVI (f) as well as η_{RVI} and η_σ for VH and VV polarization and VH-VV ratio (g) and η_{NDVI}, η_{fCover} and η_{GAI} (h). Lines and shadow areas represent the mean and standard deviation of considered variable, respectively. Mean of *in situ* observed date of the main rapeseed phenological stages are given by vertical dashed lines with corresponding stages name and plant illustration in the top of the panel (a).

1) Optical signatures

NDVI and fCover showed similar behavior, both rapidly increasing from cotyledon emergence (BBCH 09) to the development of first leaves (BBCH ~ 13). This increase was steeper than the one showed by *in situ* height, DM and FM. On the contrary, PWC showed a slight decrease from sowing to the first leaves development. Similarly to all BP, NDVI and fCover then stagnated until the end of stem elongation (BBCH 39). However, measured height showed a particular behavior with a winter decrease, during the beginning of December where inter-field variability is high before decreasing until BBCH 50. Such a winter decrease was clearly attenuated for DM and FM that rather exhibited stagnation. Both NDVI and fCover later increased from BBCH 50 to reach a peak during siliques development (around BBCH 73). This peak was reached earlier than the peak of measured FM. NDVI and fCover finally rapidly decreased until harvest like *in situ* FM and PWC whereas height and DM stagnated. Note that during early April, when rapeseed is flowering, NDVI showed a slight decrease whereas fCover stagnated. Note also that NDVI showed higher saturation effect than fCover during non-growing periods (before sowing and after harvest), during which vegetation cover was particularly sparse, even absent.

GAI showed a similar time curve but with a higher intra-annual variability. More precisely, the increase during the leaves development (BBCH 10 to 29) was smoother whereas the increase from inflorescence emergence (BBCH 50) to fruit development (BBCH ~ 73) and the decrease during fruit maturation were steeper. During the peak phase, inter-field variability was higher for GAI (coefficient of variation CV = 17.1 %) than for NDVI (CV = 6.6 %) and fCover (CV = 7.1 %). Regarding optical η_{RSI}, they all showed a quasi-linear increase with a slight higher slope from sowing to the first leaves development and from stem elongation to fruits development, corresponding to an increase in NDVI, fCover and GAI values.

2) SAR signatures

Regarding SAR indicators, σ^0_{VH} and σ^0_{VV} were particularly noisy (CV = 9.0 and 13.7 %, respectively) during the beginning of the agricultural season when vegetation cover was less developed. This is probably due to their sensibility to soil moisture and surface roughness at this stage. The use of σ^0_{VH-VV} allowed reducing this noise (CV = 5.9 %). σ^0_{VH-VV} and RVI showed very similar behavior. Similarly to optical RSI, $\sigma^0_{VH,}$ σ^0_{VV}, σ^0_{VH-VV} and RVI started from low values (around - 22 dB, - 12 dB, - 10 dB and 0.36, respectively) and increased during the development of the first leaves and rapidly reached a quasi-plateau until the inflorescence emergence. Note that the increase for σ^0_{VH-VV} and RVI was smoother than for $\sigma^0_{VH,}$ σ^0_{VV}. Then, both σ^0_{VH-VV} and RVI increased and reached a new plateau around - 4 dB (respectively 1.2) during fruits development before rapidly decreased during fruits maturation following the desiccation of rapeseed organs, as illustrated by the PWC decrease. Standard deviation increases during this decline due to the variability in the harvest dates. Unlike σ^0_{VH-VV} and RVI, σ^0_{VH} and σ^0_{VV} showed a slight decrease during flowering. Note also that the decrease during fruits maturation is stronger for σ^0_{VH} than for σ^0_{VV}. Inter-fields variability was globally smaller for SAR RSI (CV of 8.7 % on average) than for optical RSI (CV of 24.1 % on average).

Similarly to optical η_{RSI}, SAR η_{RSI} showed a quasi-linear increase with a slightly higher slope from sowing to the first leaves development, corresponding to an increase in backscatter coefficients values, and a slightly lower slope (respectively higher) from BBCH 80 to harvest for η_σ (respectively η_{RVI}), corresponding to a decrease in backscatter coefficients values.

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B. Analysis of orbital and sensors effects

1) Feasibility of Sentinel-1 orbits fusion: analysis of angular effects on backscatter coefficients

Figure 5 shows the temporal evolution of Γ for all the studied fields for σ^0_{VV} (Figure 5.a), σ^0_{VH} (Figure 5.b) and σ^0_{VH-VV} (Figure 5.c). Only data with a difference of acquisition date of one day and a difference of incidence angle superior to 5° have been considered. For informational purpose, cumulated rainfall between two acquisitions is also given in the color bar. Both σ^0_{VV} and σ^0_{VH} data showed significant Γ dispersion (standard deviation of 0.13 dB.°$^{-1}$ for both polarization) with values ranging from 0 to 0.74, and 0 to 0.87 dB.°$^{-1}$ respectively and a mean value superior to 0.15 dB.°$^{-1}$ (0.18 and 0.16 dB.°$^{-1}$ respectively). Particularly high Γ values (> 0.40 dB.°$^{-1}$) were observed during the first months of the rapeseed crop cycle (from August to November) for which surface heterogeneity was the highest since soil was not fully covered by the vegetation. For σ^0_{VH-VV}, Γ values were less dispersed (standard deviation of 0.06 dB.°$^{-1}$) whatever the considered crop cycle period and mean value was significantly lower (i.e. 0.07 dB.°$^{-1}$). Note that whatever the considered SAR indicator, cumulated rainfall between two acquisitions had not significant impact on Γ values. These results suggest that Sentinel-1 data fusion from multi-orbits is practicable for σ^0_{VH-VV}, but is subject to higher angular effects for both σ^0_{VH} and σ^0_{VV} as demonstrated with Radarsat data in [30].

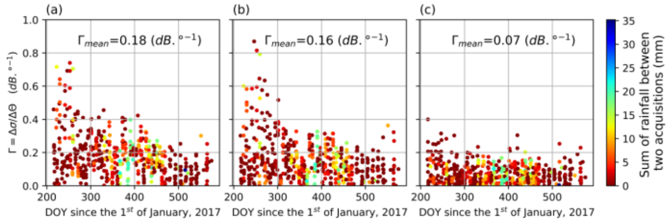

Fig. 5. Temporal evolution of Γ for σ^0_{VV} (a) σ^0_{VH} (b) σ^0_{VH-VV} (c). The color of each dot represents the sum of rainfall between two acquisitions in millimeters.

2) Sensitivity of optical signal to sensors

Figure 6 provides an evaluation of satellite GAI estimates compared to *in situ* measurements for both Landsat-8 (Figure 6.a) and Sentinel-2 (Figure 6.b) images. Results are displayed by field (color of points) and according to the number of days between satellites overpasses and ground measurements (size of points) as both acquisitions are not systematically concomitant. Sentinel-2 -derived GAI estimates were in good agreement with *in situ* measurements showing R^2 of 0.78 and RMSE of 0.36 $m^2.m^{-2}$ with differences between satellite and ground acquisitions varying from 0 to 8 days. Landsat-8 estimates showed lower accuracy with R^2 of 0.78 and RMSE of 0.41 $m^2.m^{-2}$.

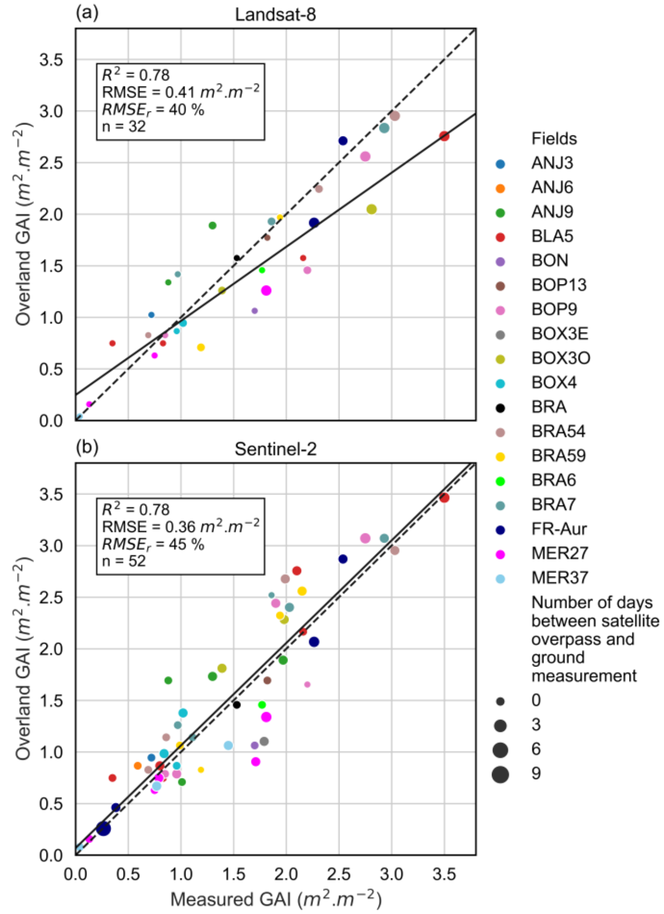

Fig. 6. Comparison between Overland GAI and *in situ* GAI for Landsat-8 (a) and Sentinel-2 (b) images. Dashed line is a 1:1 line and solid line is the linear regression between satellite-derived and measured GAI. The color of points corresponds to the fields' identifiers whereas their size corresponds to the number of days between satellites overpass and ground measurement. Coefficient of determination (R^2) and Root Mean Square Error (RMSE) and relative RMSE ($RMSE_r$) are given in the top left of each panel.

For further evaluation of sensor impacts on optical RSI, Figure 7 provides a comparison between Landsat-8 and Sentinel-2 -derived GAI (Figure 7.a), fCover (Figure 7.b) and NDVI (Figure 7.c) with a maximal difference in acquisition date of one day. Globally, Landsat-8 and Sentinel-2 -derived RSI are in good agreement with R^2 values higher than 0.93 and $RMSE_r$ values below 25 %. Landsat-8 estimates showed a slight underestimation for high GAI (> 2 $m^2.m^{-2}$) and fCover (> 0.5) values. For NDVI, Landsat-8 showed higher values for low NDVI values (< 0.6) and lower values for high NDVI values (> 0.6). The combined use of Landsat-8 and Sentinel-2 data allowed an average revisit interval of 12.1 days against 14.2 days for Sentinel-2 acquisitions alone. Moreover, evaluation of Overland GAI from both sensors showed consistent results that permit GAI computation from combined sources.

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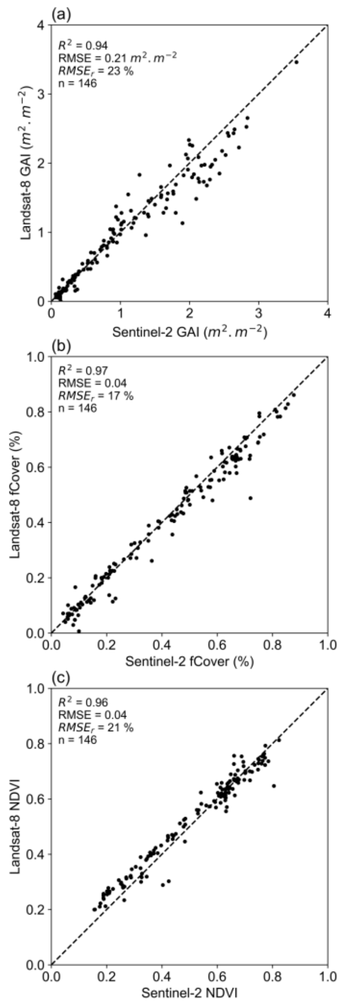

Fig. 7. Comparison between Landsat-8 and Sentinel-2 -derived GAI (a), fCover (b) and NDVI (c). Dashed line is a 1:1 line. Coefficient of determination (R^2), Root Mean Square Error (RMSE) and relative RMSE ($RMSE_r$) are given in the top left of each panel.

C. Relationships between SAR or optical RSI and crop biophysical parameters

1) Comparison between SAR RSI for multi-orbital Sentinel-1 acquisitions

Figure 8 shows performance of empirical relationships between SAR RSI and rapeseed biophysical parameters (n = 1436). Figure 9 shows the best relationships obtained between rapeseed biophysical parameters and SAR RSI. For further information, values of $RMSE_r$ and R^2 for each SAR RSI and each empirical relationship are provided in Appendix C.

Globally, the use of η_{RSI} tended to improve the performance of relationships whatever the RSI considered, except $\sigma^0_{VH\text{-}VV}$. Moreover, 2^{nd}-order-polynomial relationship always outperformed simple linear regression. σ^0_{VV} showed particularly low predictive power whatever the relationship and the BP considered with maximal R^2 values ranging from 0.01 to 0.25 and $RMSE_r$ values ranging from 86.66 % to 99.45 %.

Regarding height, the best results were obtained with $\eta_{\sigma VH}$ using 2^{nd}-order-polynomial relationship (R^2 = 0.87, RMSE = 21.19 cm and $RMSE_r$ = 35.73 %; Figures 8a and 9.a). $\eta_{\sigma VV}$ using 2^{nd}-order-polynomial relationship showed only a slightly lower performance (R^2 = 0.85, RMSE = 22.84 cm and $RMSE_r$ = 38.51 %). For PWC, σ^0_{VH} was the best predictor (R^2 = 0.60, RMSE = 2.37 % and $RMSE_r$ = 63.04 % using 2^{nd}-order-polynomial relationship; Figures 8.b and 9.b). Globally all SAR RSI provided low performance for PWC retrieval.

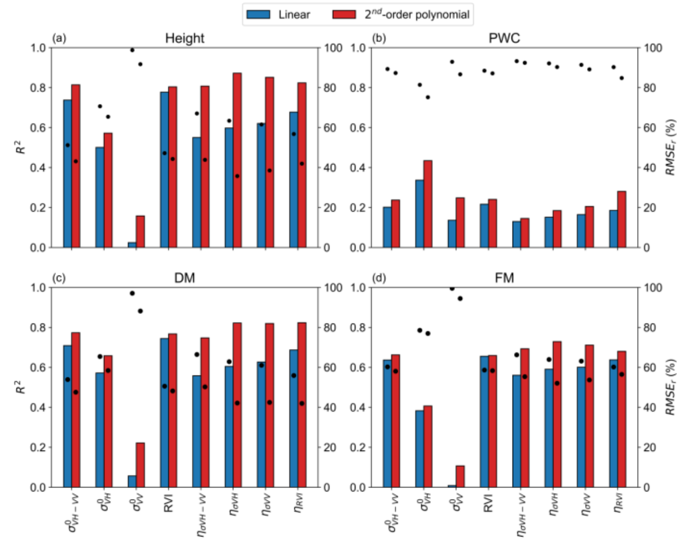

Fig. 8. Coefficient of determination (R^2; bars) and relative Root Mean Square Error ($RMSE_r$; dots) of empirical relationships between SAR indicators and *in situ* measured height (a), plant water content (b), dry mass (c) and fresh mass (d).

Regarding DM, η_{RVI} was the best predictor (R^2 = 0.82, RMSE = 155.71 g.m^{-2} and $RMSE_r$ = 41.97 % using 2^{nd}-order polynomial relationship; Figure 8.c and 9 .c). Using 2^{nd}-order polynomial regression, $\eta\sigma_{VH}$ and $\eta_{\sigma VV}$ showed similar performance (R^2 = 0.82, RMSE = 156.37 g.m^{-2}, $RMSE_r$ = 42.15 % and R^2 = 0.82, RMSE = 157.54 g.m^{-2}, $RMSE_r$ = 41.97 %, respectively). Using 2^{nd}-order polynomial regression, $\eta_{\sigma VH}$ was the best predictor for FM (R^2 = 0.73, RMSE = 1035.46 g.m^{-2}, and $RMSE_r$ = 52.04 %; Figures 8.d and 9.d) followed by $\eta_{\sigma VV}$ (R^2 = 0.71, RMSE = 1068.62 g.m^{-2}, and $RMSE_r$ = 53.71 %).

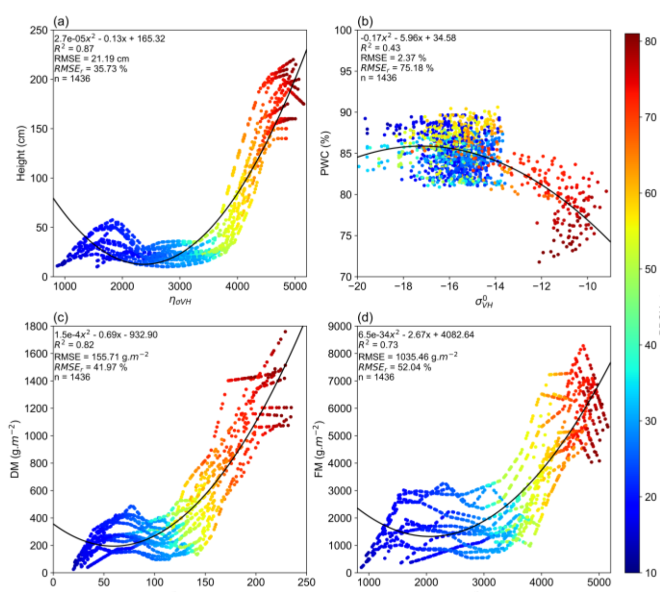

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Fig. 9. Best relationships between *in situ* measured height (a), plant water content (b), dry mass (c) and fresh mass (d) and SAR indicators. Equation of the regression as well as values of coefficient of determination (R^2), Root Mean Square Error (RMSE) and relative RMSE ($RMSE_r$) and number of observations (n) are given in the top left corner of each panel.

2) *Evaluation of SAR and optical RSI performances for concurrent acquisitions*

Figure 10 shows overall performances of empirical relationships between RSI and rapeseed biophysical parameters for SAR and optical concurrent acquisitions (n = 86), whereas Figure 11 focuses on the best relationships. For further information, values of $RMSE_r$ and R^2 for each RSI and each empirical relationship are provided in Appendix D.

Again, the use of η_{RSI} improved the performance of relationships whatever the considered RSI, except $\sigma^0_{VH\text{-}VV}$ and GAI. NDVI provided poor results whatever considered BP. For every BP and every RSI, 2nd-order polynomial regression outperformed linear regression.

Concerning height, the best results were obtained with $\eta_{\sigma VH}$ using polynomial regression (R^2 = 0.88, RMSE = 21.98 cm and $RMSE_r$ = 33.76 %; Figures 10.a and 11.a). η_{NDVI} using 2nd-order polynomial relationship showed only a slightly lower performance (R^2 = 0.88, RMSE = 22.37 cm and $RMSE_r$ = 34.35 %). σ_{VV} and NDVI showed particularly low predictive power whatever the considered relationship with R^2 values below 0.43 and $RMSE_r$ values above 74 % (RMSE > 48 cm).

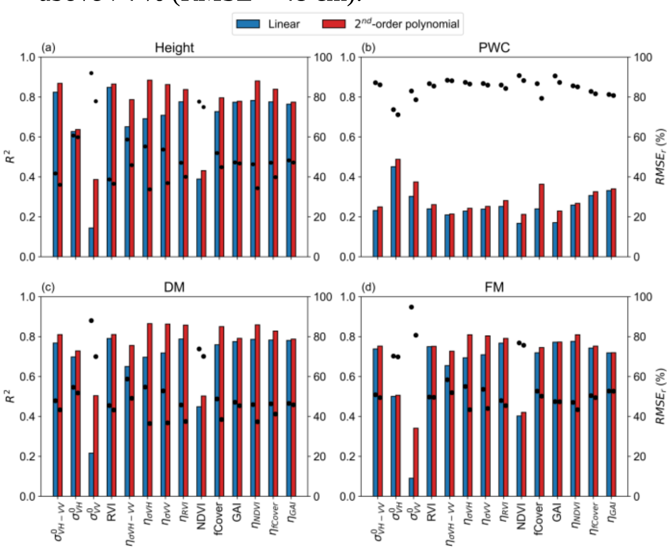

Fig. 10. Coefficient of determination (R^2; bars), relative Root Mean Square Error ($RMSE_r$; dots) of empirical relationships estimated between satellite indicators and *in situ* measured height (a), plant water content (b), dry mass (c) and fresh mass (d).

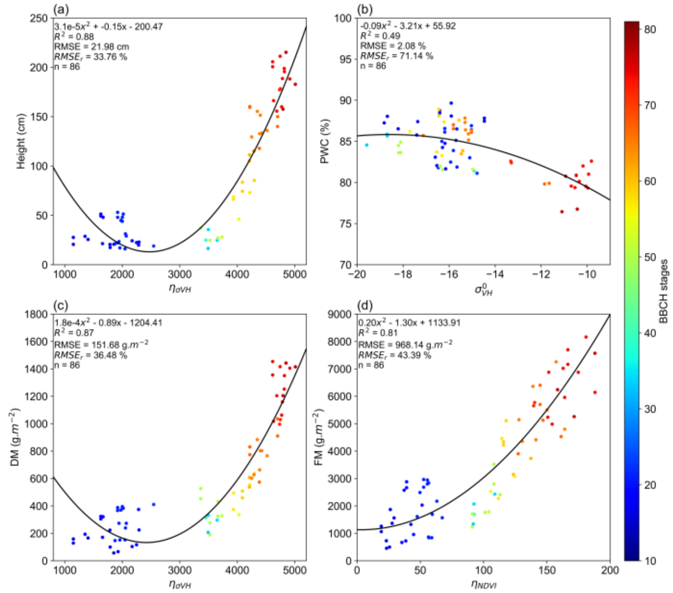

Fig. 11. Best relationships between *in situ* measured height (a), plant water content (b), dry mass (c) and fresh mass (d) and optical remote sensing indicators. Equation of the regression as well as values of coefficient of determination (R^2), Root Mean Square Error (RMSE) and relative RMSE ($RMSE_r$) and number of observations (n) are given in the top left corner of each panel.

For PWC, no RSI provided satisfactory results (R^2 = 0.17 – 0.49 and $RMSE_r$ = 71.14 – 90.71 %; Figure 10.b) throughout the entire crop cycle. The best performance were obtained with σ^0_{VH} using 2nd-order polynomial regression (R^2 = 0.49, RMSE = 2.08 % and $RMSE_r$ = 71.14 %; Figure 11.b). Regarding DM, $\eta_{\sigma VH}$ was the best predictor using 2nd-order polynomial regression (R^2 = 0.87, RMSE = 151.68 $g.m^{-2}$ and $RMSE_r$ = 36.48 %; Figure 11.c). $\eta_{\sigma VV}$ (R^2 = 0.86, RMSE = 153.06 $g.m^{-2}$ and $RMSE_r$ = 36.81 %), η_{RVI} (R^2 = 0.86, RMSE = 155.83 $g.m^{-2}$ and $RMSE_r$ = 37.48 %) and η_{NDVI} (R^2 = 0.86, RMSE = 155.27 $g.m^{-2}$ and $RMSE_r$ = 37.34 %) showed similar performance (Figure 10.c). Using 2nd-order polynomial regression, η_{NDVI} was the best predictor for FM (R^2 = 0.81, RMSE = 968.14 $g.m^{-2}$ and $RMSE_r$ = 43.39 %), closely followed by $\eta_{\sigma VH}$ (R^2 = 0.81, RMSE = 968.23 $g.m^{-2}$ and $RMSE_r$ = 43.40 %) (Figures 10.d and 11.d).

D. *Inter-phenological stages variability*

Figure 12 shows standard deviation in observations (between fields) and boxplots of residuals (i.e. the differences between measured and simulated BP) of the best multi-orbit SAR-based relationship for each BP (see section III.C.1). These values are calculated for the main phenological stages and for all stages. Due to the lack of observations for BBCH above 80, fruits development and fruits ripening stages have been clustered.

Regarding height, interquartile range of residuals was enlarged for inflorescence emergence, flowering and fruits development and ripening compared to the previous stages (Figure 12.a). More precisely, residuals were significantly negatively skewed during inflorescence emergence (median of -20.2 and average of -16.7 cm) and positively skewed during flowering (median of 5.9 and average of 12.9 cm) and fruits

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development and ripening (median of 15.7 and average of 16.0 cm) indicating an overestimation (respectively an underestimation) of rapeseed height. Note that these stages were those associated with the largest standard deviation in observed height.

Regarding PWC, the fruits development and ripening stages showed a particular behavior with a large number of negative outliers resulting in a large overestimation of derived PWC. Note that whatever considered BP it was the only case for which standard deviation was higher for one phenological stage than for all stages combined. The leaves development stage showed a higher interquartile range and a slightly positively skewed distribution of residuals (median of 1.4 and average of 0.7 %).

For DM, inter-fields variability (i.e. standard deviation in observations) globally increased with the growth of rapeseed (Figure 12.c). Compared to other stages, residuals distribution was strongly enlarged for fruits development and ripening and showed a negative skewness (median of 125.7 and average of 91.9 g.m^{-2}). Other stages showed a similar interquartile range and a slighter skewness of residuals distribution.

The distribution of residuals for FM was not significantly skewed whatever the considered phenological stage except for stem elongation (Figure 12.d). A larger distribution was observed for the development of side shoots and inflorescence emergence. The latter was associated with the highest standard deviation in observed FM. The flowering and fruits development and ripening stages also showed a higher interquartile range compared to previous stages.

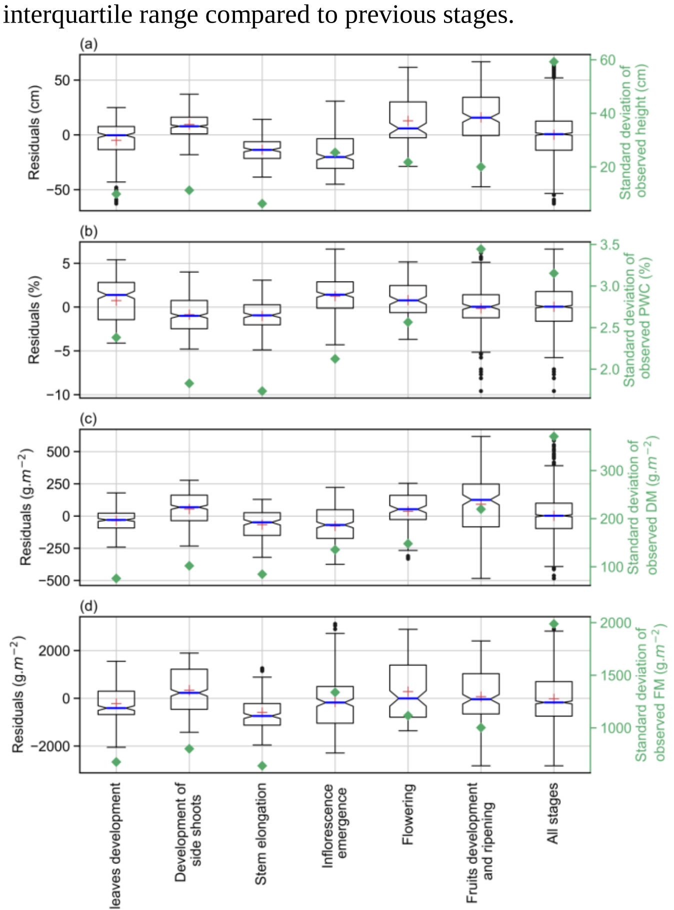

Fig. 12. Boxplots of residuals of the best SAR-based relationship for height (a), Plant Water Content (b), Dry Mass (c) and Fresh Mass (d) by main phenological stages. Blue lines and red crosses represent the median and the mean of each distribution, respectively. Green diamonds represent the standard deviation of *in situ* measurements of each biophysical parameter for the considered main phenological stage.

IV. Discussion

A. Impact of multi-orbit acquisitions on SAR RSI predictive power

Similarly to Section III.C.1, we performed SAR RSI-based regressions to retrieve rapeseed BP but for mono-orbital (orbit 110) Sentinel-1 acquisitions. We then computed the difference in terms of R^2 and $RMSE_r$ values between mono-orbit and multi-orbit best relationships for each RSI and each BP. Results of this procedure are shown in Figure 13. Globally, except for σ^0_{VV}, the mono-orbit approach induced a slight improvement of R^2 and $RMSE_r$ values. However differences of performance between mono-orbit and multi-orbit approaches remained relatively low. The best improvement was achieved for PWC and FM. Note that for the mono-orbit approach, the best predictors using a 2nd-order polynomial regression are $\eta_{\sigma VH}$ for height (R^2 = 0.95, RMSE = 21.48 cm and $RMSE_r$ = 28.25 %), σ^0_{VH} for PWC (R^2 = 0.53, RMSE = 2.39 % and $RMSE_r$ = 66.74%), η_{RVI} for DM (R^2 = 0.87, RMSE = 148.60 g.m^{-2} and $RMSE_r$ = 34.81 %) and $\eta_{\sigma VV}$ for FM (R^2 = 0.84, RMSE = 1107.85 g.m^{-2} and $RMSE_r$ = 38.60 %).

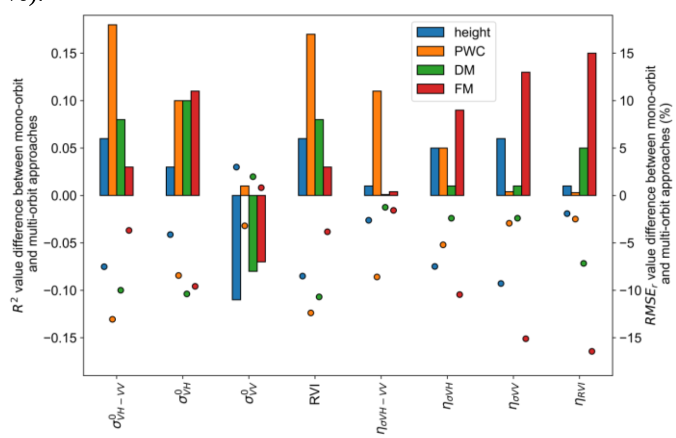

Fig. 13. Differences in coefficient of determination (R^2; bars) and relative Root Mean Square Error ($RMSE_r$; dots) between mono-orbit and multi-orbit SAR-based best relationship for rapeseed biophysical parameter retrieval.

Furthermore, for three of the biophysical monitored parameters (i.e. height, PWC and FM), RSI based on the polarized backscattering coefficients (VV or VH) stood out as being the most efficient although they showed greater sensitivity to angular effects from orbits fusion than the polarization ratio (see section III.B.1). On the one hand, if the multi-orbital approach offered satisfactory results, a slight degradation of statistical performance was observed compared to the mono-orbital approach whatever BP considered. On the other hand, the multi-orbital approach allows to materially increase the number of acquisitions with an average revisit interval of 2.6 days against 6 days for mono-orbital acquisitions (combining Sentinel-1A and B). Hence, the

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choice between mono-orbital and multi-orbital approach will depend on the objective sought between the statistical accuracy of the empirical relationship and the desired frequency of considered BP estimations.

B. Impact of fields sampling on empirical relationships

Figure 14 shows boxplots by fields of residuals of the best multi-orbit SAR-based relationship for each BP (see section III.C.1). Important discrepancies could be observed in field-specific residuals distribution. Whatever considered BP, field 01 always showed a negatively skewed distribution of residuals whereas plots 02, 03 and 11 were associated with a positively skewed distribution. The field showing an average behavior, i.e. the field showing the less skewed distribution and a small interquartile range, varies according to the considered BP. Regarding height, field 07 showed the less skewed distribution of residuals (median of -0.17 cm and mean of -2.22 cm) and the smallest interquartile range. For PWC, field 04 showed the least skewed distribution of residuals (median of - 0.25 % and mean of - 0.05 %) whereas it was field 10 for DM (median of 31.3 cm and mean of 122.5 $g.m^{-2}$) and field 06 for FM (median of -27.2 cm and mean of -32.2 $g.m^{-2}$). Other plots tended to show either positively or negatively skewed distributions of residuals.

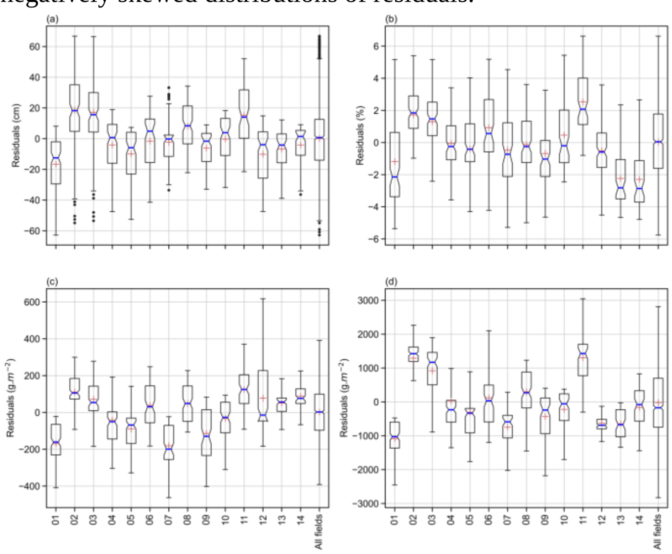

Fig. 14. Boxplots of residuals of the best SAR-based relationship for height (a), Pant Water Content (b), Dry mass (c) and Fresh mass (d) by field. Blue lines and red crosses represent the median and the mean of each distribution, respectively.

These results highlight the importance of the fields sampling strategy adopted to establish relationships between RSI and measured BP. The sample size and variability of *in situ* observations affect the statistical robustness of these relationships. It is thus necessary to consider a sufficient range of fields with different situations in terms of climatic conditions and agricultural practices. To illustrate this point, we calculated the best relationship for each field separately and we showed the variability of obtained relationships in Figure 15. One can observe that this variability is significant and varies according to the considered BP and phenological stages. In particular, for DM, it increased throughout the rapeseed phenological cycle (Figure 15.c), while it was relatively constant for height and FM (Figures 15.a and d) and strongly enlarged for PWC during the beginning and the end of the agricultural season (Figure 15.b).

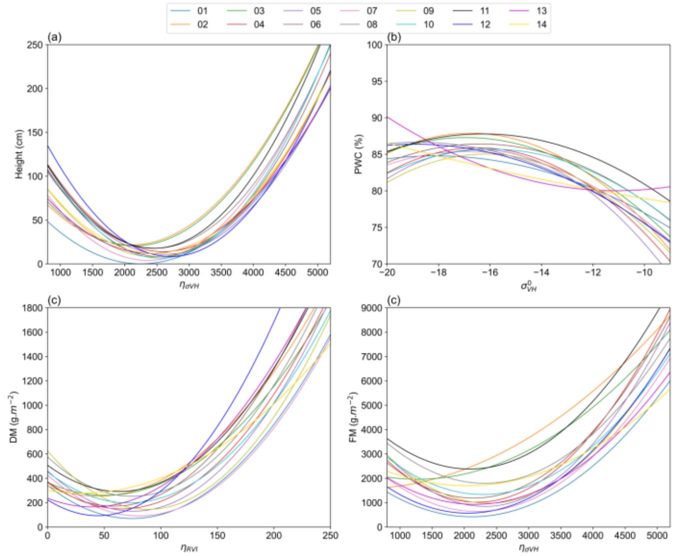

Fig. 15. Best relationships between in situ measured height (a), plant water content (b), dry mass (c) and fresh mass (d) and SAR indicators for each field taken separately (color code by field identifier)

C. Complementarity and potential of combined SAR/optical-derived BP for monitoring and modeling fields of rapeseed

Most of the time, during the core of the rapeseed growth cycle, SAR and optical signals are out of phase (see section III.B). More precisely, the increase in optical GAI occurred at the beginning of inflorescence emergence (BBCH 50) whereas backscatter coefficients and RVI remained quite stable until BBCH 60 from which volume scattering increases resulting in an increase of $\sigma^0_{VH\text{-}VV}$ and RVI. Finally the GAI peak was raised during the first half of May whereas backscatter coefficients showed a peak at the end of May around BBCH 80. After flowering, the rapeseed canopy becomes randomly oriented with the fall of leaves and the inset of siliques. [28] demonstrated that this steep architecture change induces a strong increase in the canopy contribution in volume scattering. This can explain the delayed peak of backscatter coefficients compared to GAI. Indeed, leaves fall induces a decrease of GAI but the development of fruits, less covering than leaves, contributes to volume scattering. Furthermore, during winter, most of the fields located in Central France showed a slight decrease of GAI (not shown). This decrease is explained by the loss of the first well developed leaves due to winter frosts [48]. Such a phenomenon was not captured in SAR indicators that remained stable during this period.

For purpose of the assimilation of these remote sensed data in crop models, this complementarity of SAR RSI and optical GAI and the good predictive power of η_{RVI} for DM retrieval are promising. Indeed, in agrometeorological models, GAI and DM are state variable often linked in models formalism (see e.g. [49]). Consequently, the possibility to drive these two dependent variables by means of independent time series (SAR-derived DM and optically-derived GAI) should provide the right conditions for optimizing rapeseed monitoring and yields modeling. Benefits of combined assimilation of optically-derived GAI and SAR-derived DM in agrometeorological models have been already proved for maize [25], [26], soybean [50], [51] or sunflower [52] but remained to be demonstrated for rapeseed. Besides, the analysis of residuals distribution by phenological stages carried out in section III.D offered the opportunity to develop an assimilation strategy by periods through a weighing scheme according to the confidence in SAR and/or optical -based relationship for each phenological stage.

D. Performance of RSI-based relationship for biophysical parameters retrieval in light of relevant previous studies

Newly introduced SAR η_{RSI} provided very satisfactory results for DM (with η_{RVI}) and height (with $\eta_{\sigma VH}$) with R^2 above 0.82 and $RMSE_r$ below 42 %. For FM, results are more lukewarm with higher inter-fields variability resulting in higher $RMSE_r$ (52.04 %). Globally no clear relationship can be inferred from the comparison of RSI with PWC measurements. However, results for PWC retrieval can be drastically improved (R^2 = 0.76, RMSE = 2.02 % and $RMSE_r$ = 49.51 %) by using $\eta_{\sigma VH}$ and considering ground measurements from inflorescence emergence (BBCH 60) only, when vegetation starts drying out (Figure 16).

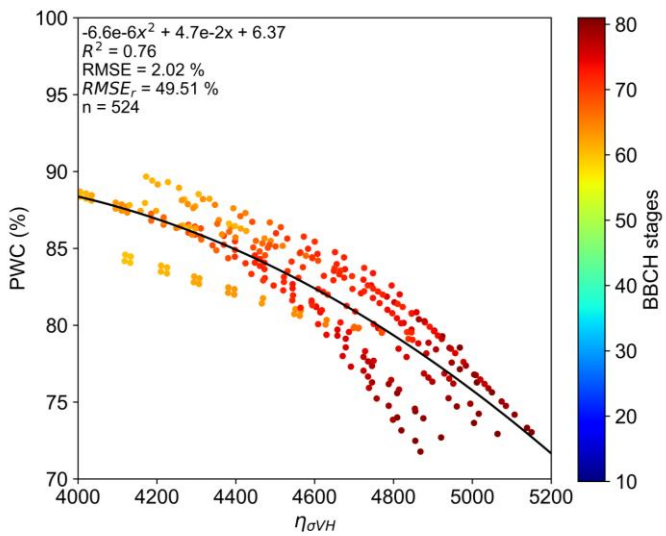

Fig. 16. Best relationship between *in situ* measured PWC and $\eta_{\sigma VH}$ for BBCH stages beyond 60. Equation of the regression as well as values of coefficient of determination (R^2), Root Mean Square Error (RMSE) and relative RMSE ($RMSE_r$) and number of observations (n) are given in the top left corner of the panel.

The performance of the fitting between SAR RSI and measured BP can also be improved using n-order polynomial regression (3rd and 4th -order polynomial regressions have been tested; Figure 17). Table V provides the values of the Akaike Information Criterion (AIC; [53]) for each rapeseed biophysical parameter and each tested regression for the best RSI. Note that the best RSI changed when n-order polynomial regressions are considered. The best improvement is achieved for DM, $\eta_{\sigma VH}$ being the best RSI (R^2 = 0.88, RMSE = 126.07 $g.m^{-2}$ and $RMSE_r$ = 33.98; Figure 17.b) using 3rd-order polynomial regression (a decrease of skill scores is observed for 4th-order polynomial regression; Table V). For height (R^2 = 0.90, RMSE = 18.29 cm, and $RMSE_r$ = 30.85 % with $\eta_{\sigma VV}$; Figure 17.b) and FM (R^2 = 0.78, RMSE = 942.19 $g.m^{-2}$ and $RMSE_r$ = 47.35 % with η_{RVI}; Figure 17.c), the improvement is lower and required a 4th-order polynomial regression. The use of these n-order relationships reduces the skill scores difference between mono-orbital and multi-orbital approaches (not shown).

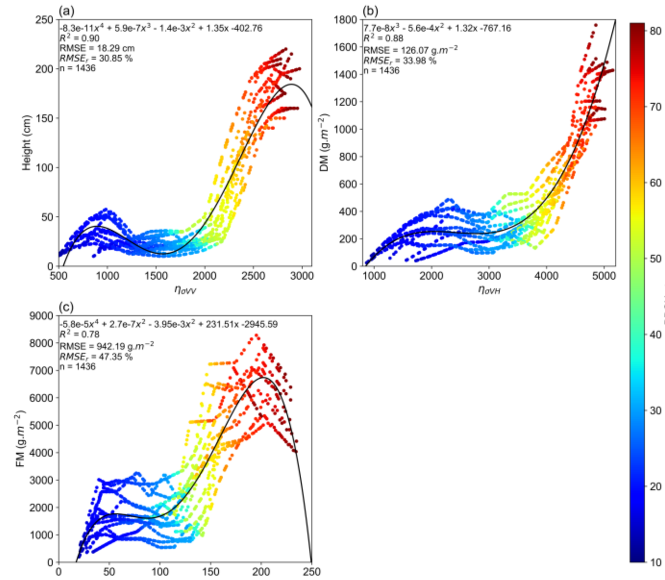

Fig. 17. Best relationships between *in situ* measured height (a), dry mass (b) and fresh mass (c) and SAR indicators for polynomial regression of order 3 or 4. Equation of the regression as well as values of coefficient of determination (R^2), Root Mean Square Error (RMSE) and relative RMSE ($RMSE_r$) and number of observations (n) are given in the top left corner of each panel.

TABLE V
VALUES OF AKAIKE INFORMATION CRITERION (AIC) OF THE RELATIONSHIPS (ORDER 1 TO 4) BETWEEN THE BEST INDICATOR AND EACH RAPESEED BIOPHYSICAL PARAMETER. THE BEST INDICATOR IS GIVEN AFTER EACH AIC VALUE AND THE LOWER AIC VALUE FOR EACH PARAMETER IS GIVEN IN BOLD.

	Height	PWC	DM	FM
Linear	13649/RVI	6787/σ^0_{VH}	19112/RVI	24362/RVI
2nd-order polynomial	12851/$\eta_{\sigma VH}$	6561/σ^0_{VH}	18579/η_{RVI}	24020/$\eta_{\sigma VH}$
3rd-order polynomial	12647/$\eta_{\sigma VH}$	6057/η_{RVI}	**17974**/$\eta_{\sigma VH}$	24007/$\eta_{\sigma VH}$
4th-order polynomial	**12433**/$\eta_{\sigma VV}$	**6051**/η_{RVI}	18023/$\eta_{\sigma VH}$	**23753**/η_{RVI}

Unlike other crops, in particular winter wheat, studies focusing on the potential of SAR and/or optical data to derive biophysical parameters of rapeseed are scarce, limiting comparison with relevant studies. Direct comparison between studies is particularly tricky due to differences in remote sensed indicators set compared, sensors used and phenological stages range available from ground measurements.

Using Radarsat-2 quad-polarization data acquired over 4 rapeseed fields in Southwest France, [30] showed that $\sigma^0_{HV\text{-}HH}$ was the best predictor for crop height using linear regression (R^2 = 0.76 $RMSE_r$ = 43%, n = 36), notably outperforming σ^0_{VV} (R^2 = 0.58, $RMSE_r$ = 71%, n = 32) and σ^0_{VH} (R^2 = 0.44, $RMSE_r$ = 80%, n = 40). However, they obtained better

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statistical performance with NDVI derived from SPOT-4/5 and Formosat-2 images (R^2 = 0.82 $RMSE_r$ = 25 %, n = 26). For the same fields, [28] studied the predictive power of polarimetric parameters derived from 14 quad-polarization Radarsat-2 images and NDVI derived from 16 optical images from Formosat-2 and Spot 4/5 sensors. Using an exponential regression, authors obtained the best results with RVI for DM monitoring (R^2 = 0.8, $RMSE_r$ = 7 %, n = 9) and the degree of polarization for height monitoring (R^2 = 0.67, $RMSE_r$ = 15 % n = 40) both largely outperforming optically-derived NDVI. Using Radarsat-2 quad-polarization wide mode SAR data from 8 images acquired over 7 rapeseed fields in southern Manitoba (Canada), [24] obtained the best correlation with entropy using logarithmic regression for DM (R^2 = 0.65, n = 64). Authors also showed a saturation of the C-band signal for dry mass beyond 800 $g.m^{-2}$. Using compact polarimetric data from five Radarsat-2 images acquired over 11-14 rapeseed fields (according to the date), [54] showed the potential of Stokes parameters to derive DM (R^2 = 0.77) and stem height (R^2 = 0.92) using 2nd-order polynomial regressions. Authors showed a non-negligible improvement of predicted DM (R^2 = 0.93, n = 30) and height (R^2 = 0.95, n =22) using a Random Forest model and 27 compact polarimetric parameters. For the same dataset, and using fully polarimetric data, [55]obtained the best results with the ratio between volume scattering and the sum of odd and double-bounce scattering for both DM (R^2 = 0.85, n = 24) and FM (R^2 = 0.76, n = 36). Note that these studies concerned summer varieties with low biomass production and a shorter life-cycle without wintering stage compared to our winter rapeseed fields. Such differences jeopardize the direct comparison of the results.

From Sentinel-1 images acquired over 3 fields in Austria (n = 25), [23] showed that σ^0_{VH-VV} was the best predictor for PWC (R^2 = 0.34), FM (R^2 = 0.34) and crop height (R^2 = 0.51). More recently, using Gaussian processes regression (GPR) with Sentinel-1 and Sentinel-2 images for a drastically smaller dataset (3 rapeseed fields, 5 dates), [34] demonstrated that σ^0_{VH-VV} was the best SAR indicator to derive DM (R^2 = 0.80) and FM (R^2 = 0.75) whereas σ^0_{VH} was the best indicator for PWC (R^2 = 0.60). However, authors obtained better results using band 11 of Sentinel-2 for DM (R^2 = 0.85) and FM (R^2 = 0.77).

Globally, the results of this paper are in line with these previous studies demonstrating the high potential of C-band SAR data for rapeseed BP monitoring, in particular for height and DM. Compared to these studies, we introduced new indicators based on the cumulated sum of backscatter coefficients, polarization ratio or RVI that proved to significantly improve performances of rapeseed BP retrieval (see Figures 8 and 10). These indicators allow for the integration of backscattering phenomena over time and are thus intrinsically less sensitive to sudden changes (crop architecture, soil moisture due to rainfall or irrigation, dew, etc.) between two acquisitions. Moreover, the present work offered an increased robustness of the developed statistical relationship (14 fields, n = 1436) and a potential ranking by phenological stages. For instance, we pointed out that the best relationship for DM based on η_{RVI} showed significantly larger residuals distribution for post-flowering stages suggesting that confidence in the developed relationship is impaired for these stages. Such seasonal information should be exploited by providing a dynamic uncertainty or confidence interval of BP estimations according to the considered phenological stage.

E. Impacts of Radiometric Terrain Flattening (RTF) in SAR data processing

The backscatters generated by GEE pre-processing are not fully corrected from the terrain deformation as they do not undergo a radiometric terrain flattening process. This can introduce bias in radiometric values due to the topographical properties of each field combined to the tilt of the SAR antenna onboard Sentinel-1. The impact of the RTF processing has been evaluated by comparing the sigma backscatters (σ^0) derived from GEE and pre-processed gamma backscatters (γ^0 being the ratio between σ^0 and the cosine of the incidence angle) using the SNAP software (ESA Sentinel Application Platform v8; http://step.esa.int) in VV and VH polarizations as well as for derived polarization ratios and RVI from acquisitions in orbit 110 (Figure 18).

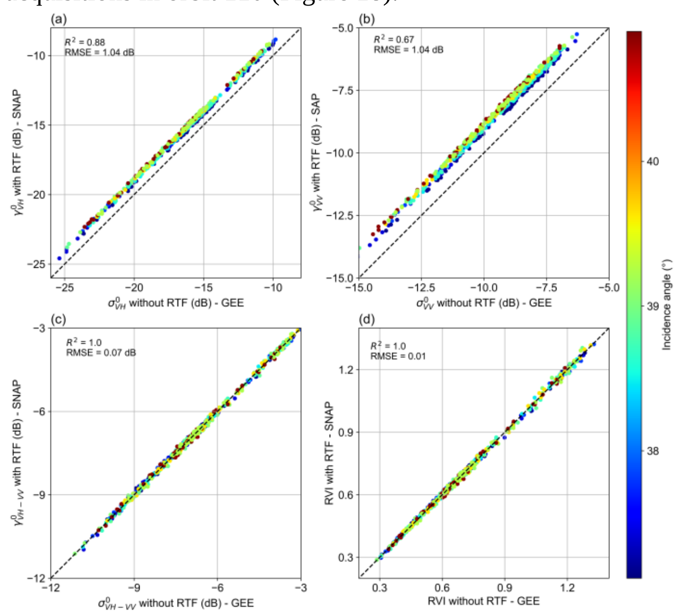

Fig. 18. Comparison between γ^0 with Radiometric Terrain Flattening (RTF) from SNAP and σ^0 without RTF from GEE for VH (a) and VV (b) polarization, the polarization ratio (c) and the RVI (d) The color of points corresponds to the local incidence angle derived from SNAP processing. Coefficient of determination (R^2) and Root Mean Square Error (RMSE) are given in the top left corner of each panel.

Results show that the use of γ^0 with RTF instead of σ^0 without RTF has a significant impact on values derived in VH and VV polarization (R^2 = 0.88 and 0.67, respectively with RMSE = 1.04 dB for both polarizations). These differences become negligible for RVI and the polarization ratio (R^2 = 1 and RMSE = 0.01 and 0.07 dB, respectively). The effect of local incidence angle (derived from the SNAP processing) is more visible for the VV polarization than for the VH polarization (the differences in backscatter values increasing with the local incidence angle). Note that the comparison

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between γ^0 with and without RTF (all other processing being identical) shows negligible impact of the RTF processing (R^2 = 1, RMSE = 0.12 dB for VV and VH polarization, RMSE = 0.001 dB for the polarization ratio and 0.005 for RVI).

The impact of the use of γ^0 with RTF processing rather than σ^0 on the here established relationships between SAR RSI and biophysical parameters has been assessed. This impact is significant on the relationships based on non-cumulated VH and VV backscatters, but slighter for the polarization ratio and RVI (the use of γ^0 inducing a systematic improvement of skill scores; not shown). Finally, when cumulative sums (η_{RSI}) are used, these impacts become totally negligible and the skill scores remain similar whatever the order of the considered polynomial relationship (Table VI).

TABLE VI
VALUES OF ROOT MEAN SQUARE ERROR (RMSE) AND CORRELATION COEFFICIENT (R^2) OF THE BEST RELATIONSHIP BETWEEN SAR η_{RSI} DERIVED FROM σ^0 OR γ^0 ACQUIRED IN ORBIT 110 AND RAPESEED BIOPHYSICAL PARAMETERS. THE BEST SKILL SCORES WERE OBTAINED FROM 4TH-ORDER POLYNOMIAL REGRESSIONS USING η_{RVI} FOR HEIGHT, PWC AND DM AND USING $\eta_{\sigma VH-VV}$ ($\eta_{\gamma VH-VV}$ RESPECTIVELY) FOR FM

	Best relationship with σ^0		Best relationship with γ^0	
	RMSE	R^2	RMSE	R^2
Height (cm)	16.3	0.93	16.3	0.93
PWC (%)	1.7	0.74	1.7	0.74
DM ($g.m^{-2}$)	126.1	0.90	125.7	0.90
FM ($g.m^{-2}$)	951.6	0.79	952.2	0.79

V. CONCLUSION

This paper aimed to evaluate the potential of multi-orbital SAR and multi-sensor optical remote sensed data for rapeseed monitoring and the retrieval of its key biophysical parameters. We introduced new indicators based on the cumulative sum of each RSI (noted η_{RSI}). We showed that the use of η_{RSI} allowed to significantly improve the predictive power of each indicator whatever BP considered. The best results were obtained with $\eta_{\sigma VH}$ for height (R^2 = 0.87, RMSE = 21.19 cm, $RMSE_r$ = 35.73 %), FM (R^2 = 0.73, RMSE = 1035.46 $g.m^{-2}$, $RMSE_r$ = 52.04 %) and PWC (R^2 = 0.76, RMSE = 2.37 %, $RMSE_r$ = 49.51 % for post-inflorescence emergence stages only) and η_{RVI} for DM (R^2 = 0.82, RMSE = 155.71 $g.m^{-2}$, $RMSE_r$ = 41.97 %). We also demonstrated that multi-orbital Sentinel-1 SAR data could be used with low impact on the performance of SAR-based relationships allowing to divide by more than two the mean revisit interval. Finally, the asynchronous behaviors of GAI and backscattering coefficients from inflorescence emergence to fruits ripening suggest complementarity between both optical and SAR domains. To further evaluate their robustness, here developed relationships will be tested for other rapeseed fields for which ground dataset have been acquired during the 2018-2019 and 2019-2020 crop seasons in the framework of the Colza Digital project. The use of polarimetric indicators based on fully and compact SAR images should also be investigated on summer rapeseed as illustrated in [54] and [55]. An assimilation scheme in an agrometeorological model will be later developed for combined SAR and optical remote sensing data-driven rapeseed yields modeling. In a near-real time simulations perspective, such an approach could be extremely useful to develop insurance products allowing to strengthen financial protection of farmers.

APPENDIX

Appendix A: BBCH scale of main phenological stages of rapeseed

BBCH	Main stages
00	Germination
10	Leaves development
20	Development of side shoots
30	Stem elongation
50	Inflorescence emergence
60	Flowering
70	Fruits development
80	Fruits ripening
90	Senescence

Appendix B: Features of rapeseed fields used for GAI evaluation

Field identifier	Measurements method	Number of sampling	Sampling dates
FR-Aur	SunScan	5	2018/01/09, 2018/02/27, 2018/03/26, 2018/04/18, 2018/05/09
ANJ9	Hemispherical photography	5	2017/11/29, 2018/03/01, 2018/04/05, 2018/05/02, 2018/05/28
ANJ6	Hemispherical photography	2	2017/11/28, 2018/03/01
ANJ3	Hemispherical photography	1	2017/11/28
BRA54	Hemispherical photography	5	2017/11/28, 2018/03/01, 2018/04/06, 2018/05/04, 2018/05/28
BRA7	Hemispherical photography	5	2017/11/28, 2018/03/01, 2018/04/06, 2018/05/04, 2018/05/28
BRA	Hemispherical photography	1	2017/11/28
BON	Hemispherical photography	1	2017/11/28
MER27	Hemispherical photography	5	2017/11/28, 2018/02/27, 2018/04/05, 2018/05/04, 2018/05/28
MER37	Hemispherical photography	3	2017/11/28, 2018/02/27, 2018/05/28
BOX4	Hemispherical photography	3	2017/11/28, 2018/02/27, 2018/04/04
BOX3E	Hemispherical photography	1	2018/02/27
BOX3O	Hemispherical photography	4	2017/11/28, 2018/04/04, 2018/05/04, 2018/05/28,
BLA5	Hemispherical photography	6	2017/11/28, 2018/02/27,

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			2018/04/05, 2018/05/28
BOP9	Hemispherical photography	5	2017/11/28, 2018/02/27, 2018/04/06, 2018/05/04, 2018/05/28
BOP13	Hemispherical photography	1	2017/11/28
BRA6	Hemispherical photography	1	2017/11/28
BRA59	Hemispherical photography	5	2017/11/27, 2018/03/01, 2018/04/05, 2018/05/04, 2018/05/28

Appendix C: $RMSE_r$ (%) / R^2 values of regressions between rapeseed biophysical parameters and SAR RSI for multi-orbital Sentinel-1 acquisitions (n = 1436)

	σ_{VH-VV}	σ_{VH}	σ_{VV}	RVI	$\eta_{\sigma VH-VV}$	$\eta_{\sigma VH}$	$\eta_{\sigma VV}$	η_{RVI}
Height (cm)								
Linear	51.22 / 0.74	70.65 / 0.50	98.74 / 0.02	47.20 / 0.78	67.04 / 0.55	63.41 / 0.60	61.56 / 0.62	56.76 / 0.68
2^{nd}-order polynomial	43.11 / 0.81	65.39 / 0.57	91.72 / 0.16	44.30 / 0.80	43.85 / 0.81	35.73 / 0.87	38.51 / 0.85	41.97 / 0.82
PWC (%)								
Linear	89.32 / 0.20	73.66 / 0.45	92.91 / 0.14	88.48 / 0.22	93.25 / 0.13	92.09 / 0.15	91.37 / 0.16	90.24 / 0.19
2^{nd}-order polynomial	87.29 / 0.24	75.18 / 0.43	86.66 / 0.25	87.12 / 0.24	92.41 / 0.15	90.27 / 0.18	89.11 / 0.21	84.77 / 0.28
DM ($g.m^{-2}$)								
Linear	53.93 / 0.71	65.41 / 0.57	97.08 / 0.06	50.57 / 0.74	66.44 / 0.56	62.86 / 0.60	61.07 / 0.63	55.92 / 0.69
2^{nd}-order polynomial	47.57 / 0.77	58.43 / 0.66	88.18 / 0.22	48.20 / 0.77	50.24 / 0.75	42.15 / 0.82	42.46 /0.82	41.97 /0.82
FM ($g.m^{-2}$)								
Linear	60.24 / 0.64	78.52 / 0.38	99.54 / 0.01	58.65 / 0.66	66.26 / 0.56	63.95 / 0.59	63.15 / 0.60	60.20 / 0.64
2^{nd}-order polynomial	58.07 / 0.66	76.98 / 0.41	94.45 / 0.11	58.36 / 0.66	55.35 / 0.69	52.04 / 0.73	53.71 / 0.71	56.50 / 0.68

Appendix D: $RMSE_r$ (%) / R^2 values of regressions between rapeseed biophysical parameters and RSI for SAR and optical concurrent acquisitions (n = 86)

	σ_{VH-VV}	σ_{VH}	σ_{VV}	RVI	$\eta_{\sigma VH-VV}$	$\eta_{\sigma VH}$	$\eta_{\sigma VV}$	η_{RVI}	NDVI	fCover	GAI	η_{NDVI}	η_{fCover}	η_{GAI}
Height (cm)														
Linear	41.68 / 0.82	60.71 / 0.63	91.98 / 0.14	38.73 / 0.85	58.71 / 0.65	55.20 / 0.69	53.69 / 0.71	47.04 / 0.78	77.69 / 0.39	51.95 / 0.73	47.25 / 0.77	46.32 / 0.78	47.08 / 0.78	48.25 / 0.76
2^{nd}-order polynomial	36.03 / 0.87	59.87 / 0.64	77.86 / 0.39	36.53 / 0.87	45.89 / 0.79	33.76 / 0.88	36.87 / 0.86	40.04 / 0.84	74.96 / 0.43	44.88 / 0.80	46.73 / 0.78	34.35 / 0.88	39.86 / 0.84	47.20 / 0.77
PWC (%)														
Linear	87.14 / 0.23	73.66 / 0.45	83.02 / 0.30	86.66 / 0.24	88.38 / 0.21	87.32 / 0.23	86.77 / 0.24	85.98 / 0.25	90.71 0.17	86.68 / 0.24	90.53 / 0.17	85.58 / 0.26	82.79 / 0.31	81.27 / 0.33
2^{nd}-order polynomial	86.11 / 0.25	71.14 / 0.49	78.61 / 0.37	85.46 / 0.26	88.14 / 0.21	86.50 / 0.24	85.97 / 0.25	84.28 / 0.28	88.23 / 0.21	79.31 / 0.36	87.29 / 0.23	85.09 / 0.27	81.63 / 0.33	80.76 / 0.34
DM ($g.m^{-2}$)														
Linear	47.88 / 0.77	54.60 / 0.70	88.01 / 0.22	45.47 / 0.79	58.77 / 0.65	54.73 / 0.70	52.81 / 0.72	45.76 / 0.79	73.80 / 0.45	48.80 / 0.76	47.12 / 0.78	45.94 / 0.79	46.33 / 0.78	46.52 / 0.78
2^{nd}-order polynomial	43.30 / 0.81	51.78 / 0.73	70.00 / 0.50	43.25 / 0.81	49.11 / 0.76	36.48 / 0.87	36.81 / 0.86	37.48 / 0.86	70.11 / 0.50	38.47 / 0.85	45.38 / 0.79	37.34 / 0.86	41.22 / 0.83	45.83 / 0.79
FM ($g.m^{-2}$)														
Linear	50.85 / 0.74	70.23 / 0.50	94.79 / 0.09	49.74 / 0.75	58.39 / 0.66	55.00 / 0.69	53.61 / 0.71	47.94 / 0.77	76.84 / 0.40	52.70 / 0.72	47.44 / 0.77	47.02 / 0.78	41.22 / 0.83	52.73 / 0.72
2^{nd}-order polynomial	49.43 / 0.75	69.84 / 0.51	80.67 / 0.34	49.57 / 0.75	51.92 / 0.73	43.40 / 0.81	44.00 / 0.80	45.44 / 0.79	75.66 / 0.42	50.15 / 0.75	47.38 / 0.77	43.39 / 0.81	49.45 / 0.75	52.65 / 0.72

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