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Exploiting the centimeter resolution of UAV multispectral imagery to improve remote-sensing estimates of canopy structure and biochemistry in sugar beet crops

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Abstract

The recent emergence of unmanned aerial vehicles (UAV) has opened a new horizon in vegetation remote sensing, especially for agricultural applications. However, the benefits of UAV centimeter-scale imagery are still unclear compared to coarser resolution data acquired from satellites or aircrafts. This study aims (i) to propose novel methods for retrieving canopy variables from UAV multispectral observations, and (ii) to investigate to what extent the use of such centimeter-scale imagery makes it possible to improve the estimation of leaf and canopy variables in sugar beet crops (*Beta Vulgaris* L.). Five important structural and biochemical plant traits are considered: green fraction (GF), green area index (GAI), leaf chlorophyll content (C_{ab}), as well as canopy chlorophyll (CCC) and nitrogen (CNC) contents.

Based on a comprehensive data set encompassing a large variability in canopy structure and biochemistry, the results obtained for every targeted trait demonstrate the superiority of centimeter-resolution methods over two standard remote-sensing approaches (i.e., vegetation indices and PROSAIL inversion) applied to average canopy reflectances. Two variables (denoted $GF_{GREENPIX}$ and VI_{CAB}) extracted from the images are shown to play a major role in these performances. $GF_{GREENPIX}$ is the GF estimate obtained by thresholding the Visible Atmospherically Resistant Index (*VARI*) image, and is shown to be an accurate and robust (e.g., against variable illumination conditions) proxy of the structure of sugar beet canopies, i.e., GF and GAI. VI_{CAB} is the mND_{blue} index value averaged over the darkest green pixels, and provides critical information on C_{ab} . When exploited within uni- or multivariate empirical models, these two variables improve the GF, GAI, C_{ab} , CCC and CNC estimates obtained with standard approaches, with gains in estimation accuracy of 24, 8, 26, 37 and 8 %, respectively.

28 respectively. For example, the best CCC estimates ($R^2 = 0.90$) are obtained by multiplying C_{ab} and GAI
29 estimates respectively derived from VI_{CAB} and a log-transformed version of $GF_{GREENPIX}$, $\log(1-GF_{GREENPIX})$.

30 The $GF_{GREENPIX}$ and VI_{CAB} variables, which are only accessible from centimeter-scale imagery, contributes to a
31 better identification of the effects of canopy structure and leaf biochemistry, whose influences may be
32 confounded when considering coarser resolution observations. Such results emphasize the strong benefits of
33 centimeter-scale UAV imagery over satellite or airborne remote sensing, and demonstrate the relevance of
34 low-cost multispectral cameras to retrieve a number of plant traits, e.g., for agricultural applications.

35 Keywords: Chlorophyll content, Field phenotyping, Green fraction, Green area index, Nitrogen content,
36 Remote sensing, Sugar beet, UAV.

37 1. Introduction

38 Non-destructive and timely monitoring of crop structural and biochemical traits is of major importance to
39 assess the physiological and phenological status of the plants and to further understand their functioning over
40 time. A number of applications benefit from such an accurate monitoring, including (i) precision agriculture,
41 which aims to adapt cultural practices to the actual state of the canopy over space and time (McBratney et al.,
42 2005; Zhang and Kovacs, 2012), and (ii) plant phenotyping, which aims to identify the genetic basis of
43 important traits controlling yield and quality (Furbank and Tester, 2011; Sankaran et al., 2015; Zaman-Allah et
44 al., 2015).

45 Some of the most relevant crop structural and biochemical traits to be monitored characterize the efficiency
46 with which light, water and nutrients are captured and used for biomass production and yield (Araus and
47 Cairns, 2014). Since the green area index (GAI) and the green fraction (GF) closely relate to the capability of
48 the crop to intercept the incoming photosynthetically-active radiation (PAR), they are both key variables for
49 photosynthesis, respiration and evapotranspiration (Verger et al., 2014). GAI and GF are also good proxies of
50 biomass as well as good indicators of developmental stages and various abiotic and biotic stresses (Yang et al.,
51 2017). For all these reasons, GAI is considered as an essential state variable for crop modeling (Baret et al.,

52 2007; Clevers, 1997; Dong et al., 2017; Dorigo et al., 2007; Launay and Guerif, 2005). In addition to these
53 structural variables, knowledge of leaf chlorophyll content (C_{ab}) provides critical information on the capability
54 of the crop to absorb the intercepted PAR and to produce biomass (Gitelson et al., 2005; Houborg et al., 2015).
55 C_{ab} is also a proxy of nitrogen content (Schlemmer et al., 2013) and maximum rate of carboxylation (Croft et
56 al., 2017; Houborg et al., 2015). Changes in C_{ab} can also be related to nutrient stresses and developmental
57 stages (Gitelson et al., 2005). By upscaling C_{ab} to the canopy level, thus considering the canopy chlorophyll
58 content (CCC), it is possible to assess the total canopy-scale productivity of the crop (Gitelson et al., 2006b;
59 Inoue et al., 2016). As CCC is also an accurate proxy of canopy nitrogen content (CNC) (Baret et al., 2007; Jay
60 et al., 2017b; Schlemmer et al., 2013), it is therefore a critical variable for many agricultural applications.

61 Optical sensors embedded on ground-based platforms, aircrafts and satellites have long been used for
62 vegetation monitoring. Indeed, because the canopy structure and biochemistry strongly affect the reflected
63 solar radiation in the optical domain (Jacquemoud and Baret, 1990; Verhoef, 1984), they can potentially be
64 retrieved from the canopy reflectance measured from remote sensing. However, satellite or aerial remote-
65 sensing imagery generally lacks spatial resolution to observe single microplots of a few dozen square meters
66 in the context of field phenotyping (Gago et al., 2015; Sankaran et al., 2015; Yang et al., 2017; Zaman-Allah et
67 al., 2015). Further, the revisit frequency combined with possible cloud occurrence limit the use of satellites
68 for agricultural applications, when observations need to be completed over short critical periods (Inoue et al.,
69 2012; Launay and Guerif, 2005). Possible alternatives to satellites and aircrafts include a variety of ground-
70 based platforms, such as towers (Hilker et al., 2011) or “phenomobiles” (Araus and Cairns, 2014; Busemeyer
71 et al., 2013; Comar et al., 2012; Deery et al., 2014). However, these platforms are limited by their spatial
72 coverage and the difficulty in transporting them from one location to another (Gago et al., 2015; Sankaran et
73 al., 2015; Yang et al., 2017).

74 Unmanned Aerial Vehicles (UAVs) offer a very attractive alternative : they can be operated conveniently and
75 offer high spatial and temporal resolutions as well as a reasonable spatial coverage (Gago et al., 2015;
76 Sankaran et al., 2015; Van Der Meij et al., 2017; Verger et al., 2014; Zaman-Allah et al., 2015; Zarco-Tejada et

77 al., 2013). Interestingly, the high spatial resolution of UAV data makes it possible to document the within-
78 microplot variability in field phenotyping experiments (Araus and Cairns, 2014; Zaman-Allah et al., 2015). For
79 all of these reasons, UAVs are currently becoming appealing tools for crop monitoring (e.g., Aasen et al., 2015;
80 Domingues Franceschini et al., 2017; Duan et al., 2014; Jin et al., 2017; Van Der Meij et al., 2017; Verger et al.,
81 2014; Zarco-Tejada et al., 2013; Zhou et al., 2017).

82 Despite this success, the benefits of using the fine spatial resolution accessible from UAV imagery for retrieving
83 the above-mentioned structural and biochemical crop traits have not been clearly quantified yet. The
84 possibility to remove soil and shadow pixels is likely to improve the estimation of leaf biochemistry (Jay et al.,
85 2017a; Moorthy et al., 2008; Zarco-Tejada et al., 2004, 2013, 2001). However, there still lacks methods that
86 take full advantage of the centimeter resolution to improve estimates of canopy variables.

87 Therefore, the objectives of this study are (i) to propose novel methods for retrieving canopy variables in sugar
88 beet (*Beta Vulgaris* L.) crops using centimeter-scale multispectral imagery, and (ii) to investigate to what
89 extent the use of centimeter-scale imagery makes it possible to improve the estimation of GF, GAI, C_{ab} , CCC
90 and CNC in sugar beet crops at the microplot level. Using an extensive two-year multi-site field experiment,
91 several variables are extracted from UAV multispectral images of microplots, including VI values computed
92 over various subsets of pixels, or GF estimates obtained by thresholding pixel-level VI values. These variables
93 are directly related to the targeted traits, or combined, e.g., within Multiple Linear Regression (MLR) models.
94 These methods are compared to two standard remote-sensing approaches used with coarser resolution data,
95 i.e., Vegetation Indices (VIs) and PROSAIL inversion (Baret et al., 1992; Jacquemoud et al., 2009) applied to the
96 averaged reflectances of microplots. Note that this study follows our previous studies based on ground
97 measurements (Jay et al., 2017b, 2017a), upscaling the results to UAV observations in the perspective of high-
98 throughput field phenotyping and precision agriculture.

99 2. Materials and methods

100 2.1. Field experiments

101 Field experiments were conducted in France during the 2016 and 2017 growing seasons. Four sites with
 102 different soil properties (sandy loam for Barenton, calcareous loam for St-Memmie, chalk for Charmont and
 103 clay loam for Nizy) were considered (Table 1 and Fig. 1). For each site, one to three trial(s) were monitored.
 104 Each trial was organized as a randomized complete block design using a factorial arrangement of various
 105 nitrogen fertilizations and/or cultivars and/or plant densities. The microplots were 7 to 10 m long and
 106 encompassed four to twelve rows, with 45 cm row spacing and 16 to 18 cm plant spacing. In total, fourteen
 107 cultivars, eight nitrogen fertilization and seven plant densities were considered over the two years and under
 108 various soil and weather conditions, resulting in 274 microplots available.

109 Table 1 : Summary of field experiments.

Year	Trial	Soil	Plant density (plants/m ²)	Nitrogen rate (kgN/ha)	Cultivar Id.	Number of microplots	Number of replicates	Date	Number of reference measurements				
									GF	GAI	C _{ab}	CCC	CNC
2016	Barenton 1	Sandy loam	11.5	0; 100; 150	1-4	36	6	05/24	36	18	18	6	18
								06/06	36	12	18	6	18
								06/23	36	18	18	6	18
								07/04	36	N/A	18	N/A	18
								07/21	N/A	18	18	6	18
	Barenton 2	Sandy loam	7; 10; 14	0; 100; 150	5-13	11	1	06/06	11	11	11	11	N/A
06/22	11	11	10	10	N/A								
StMemmie 1	Calcareous loam	11	40; 80; 120	1-4	12	2	06/07	12	12	12	12	N/A	
StMemmie 2	Calcareous loam	7; 10; 14	40; 80; 120	5-13	11	1	06/07	11	11	11	11	N/A	
2017	StMemmie 3	Calcareous loam	10	0; 40; 80	14	6	2	07/04	6	6	6	6	N/A
								07/17	6	5	6	5	N/A
	Charmont	Chalk	10.5	0; 70; 110; 150	14	4	1	07/04	4	4	4	4	N/A
								07/21	4	4	4	4	N/A
	Nizy	Clay loam	9.5	0; 40; 80	1-4	29	5	07/19	29	5	23	5	24

110

111 2.2. GF, GAI, C_{ab}, CCC and CNC reference measurements

112 For each microplot, the proportion of green pixels as observed from nadir, GF (unitless), was estimated from
 113 millimeter-scale RGB imagery using Support Vector Machine (SVM) classification (Vapnik and Vapnik, 1998) to
 114 identify green pixels (see section 2.4.1).

115 GAI (unitless) was estimated based on five hemispherical photographs acquired with a digital camera
116 positioned above a representative part of the canopy. The CAN-EYE freeware ([http://www6.paca.inra.fr/can-](http://www6.paca.inra.fr/can-eye/)
117 [eye/](http://www6.paca.inra.fr/can-eye/)) was then used to retrieve the effective GAI (Weiss et al., 2004) from these photographs. Comparison
118 with destructive GAI measurements (see Jay et al. (2017b) for more details about the measurement
119 procedure) over twenty samples with GAI values ranging from 0.15 to 3.00, showed an error of 0.12, thus
120 confirming the strong accuracy of this indirect method (Demarez et al., 2008).

121 The mean C_{ab} (in $\mu\text{g}/\text{cm}^2$) value of each microplot was estimated using a Dualex scientific+TM leafclip (Force-A,
122 Orsay, France). After selecting six plants representative of the microplot in terms of color and plant structure,
123 five measurements per plant were performed at different shoot levels to account for the within-plant
124 variability. The thirty Dualex readings obtained for each microplot were converted into actual C_{ab} values using
125 the relationship provided by Cerovic et al. (2012) for dicotyledons to account for saturation occurring for high
126 C_{ab} values (Jay et al., 2016). Finally, the thirty C_{ab} values were averaged to obtain a single C_{ab} value for each
127 microplot.

128 For each microplot, CCC (in g/m^2) was computed as the product of GAI and C_{ab} (Baret et al., 2007; Jacquemoud
129 et al., 1995).

130 CNC was measured destructively after image acquisition. For this purpose, ten plants representative of each
131 microplot and corresponding to a 1 m^2 area, were harvested. Leaves were placed in an oven at 75°C until their
132 weight stabilized, and their dry mass was measured. The average leaf nitrogen concentration (in % of dry mass)
133 was measured using the Dumas method (Dumas, 1831). CNC (in g/m^2) was then determined by multiplying
134 leaf nitrogen concentration by dry mass per unit soil area.

135 The ground-based measurements of GAI, C_{ab} and CNC were performed within two days of the corresponding
136 UAV flight, during which variations of these variables were assumed to be negligible.

137 Unfortunately, not all the ground variables were measured for each of the 274 sampled microplots (Table 1).

138 In the case of Barenton 1 trial, GAI was only measured for three replicates out of six, while C_{ab} and CNC were

139 measured for the other three replicates. The three C_{ab} and GAI values available were thus averaged to provide
140 a proxy of the average CCC value over the six replicates. Note that GAI was measured for only two replicates
141 on June 6, 2016. Further, GAI was not measured on July 4, 2016, resulting in no CCC values for this date. Finally,
142 GF was not measured for the last date due to full canopy cover. In the case of Nizy trial, C_{ab} and CNC were
143 measured for four replicates out of five, while GAI was measured for the remaining one. The four C_{ab} values
144 available over the four replicates were thus averaged to provide proxies of C_{ab} values and therefore proxies of
145 CCC values for the last replicate with measured GAI. This was justified by the low variability in C_{ab} observed
146 over the four replicates (i.e., standard deviations were lower than $2 \mu\text{g}/\text{cm}^2$). Note that Barenton 1 and Nizy
147 were the only trials where CNC was measured.

148 2.3. UAV data acquisition

149 The two cameras used in this study were embedded on a hexacopter (based on Mikrokopter components),
150 and fixed on a two-axis gimbal to point vertically downward. The first camera was a SONY ILCE-5100 digital
151 RGB camera equipped with a 30 mm focal length lens. It was set on speed priority and auto ISO mode, with
152 speed of 1/1000 sec, and acquired 6000 x 4000 pixel images saved in TIFF format.

153 The second camera was an AIRPHEN multispectral camera (www.hiphen-plant.com/plant-phenotyping/airphen_41.html) equipped with an 8 mm focal length lens and acquiring 1280 x 960 pixel images
154 saved in TIFF format. AIRPHEN is made of six individual cameras equipped with filters centered on 450, 530,
155 560 (in 2017, the 570 nm band replaced the 560 nm one), 675, 730 and 850 nm, with a spectral resolution of
156 10 nm. The integration time of each of the six cameras was adjusted automatically to minimize saturation and
157 maximize the dynamics. Both the RGB and the multispectral cameras acquired images continuously at a 1 Hz
158 frequency.

160 The flight plan was designed to ensure 80% overlap both across- and along-track. The UAV was first flown at
161 40 m altitude with the RGB camera, corresponding to a 6 mm spatial resolution. The AIRPHEN multispectral
162 camera was then flown at 60 m altitude in 2016 (corresponding to a 2.7 cm spatial resolution), and 35 m

163 altitude in 2017 (corresponding to a 1.6 cm spatial resolution). These resolutions were finer than the minimum
164 resolution of 4 cm recommended by Jay et al. (2017a) for optimal C_{ab} estimation in sugar beet crops.

165 Radiometric calibration was performed using a 3 m² carpet reference panel, which could conveniently be used
166 in the field while showing adequate radiometric properties. More specifically, the bidirectional reflectance
167 distribution function of this panel was measured in the laboratory similarly as Verger et al. (2014), and showed
168 a nearly Lambertian behavior for viewing zenith angles lower than 30°, and 8 % reflectance for all of the six
169 bands. Note that the low reflectance of the panel was close to that of soil and vegetation (Fig. 7), which
170 improves the dynamics and signal-to-noise ratio of the imagery. For each UAV flight, this panel was placed
171 horizontally on the ground at a distance of 1.5 times the height of the closest microplot in order to limit
172 adjacency effects. In addition to the radiometric reference panel, nine circular panels of 60 cm diameter were
173 placed within the field and used as ground control points (GCPs). The positions of the GCPs were measured
174 with a RTK GPS providing an accuracy of 2 cm. These different panels are shown in Fig. 1.



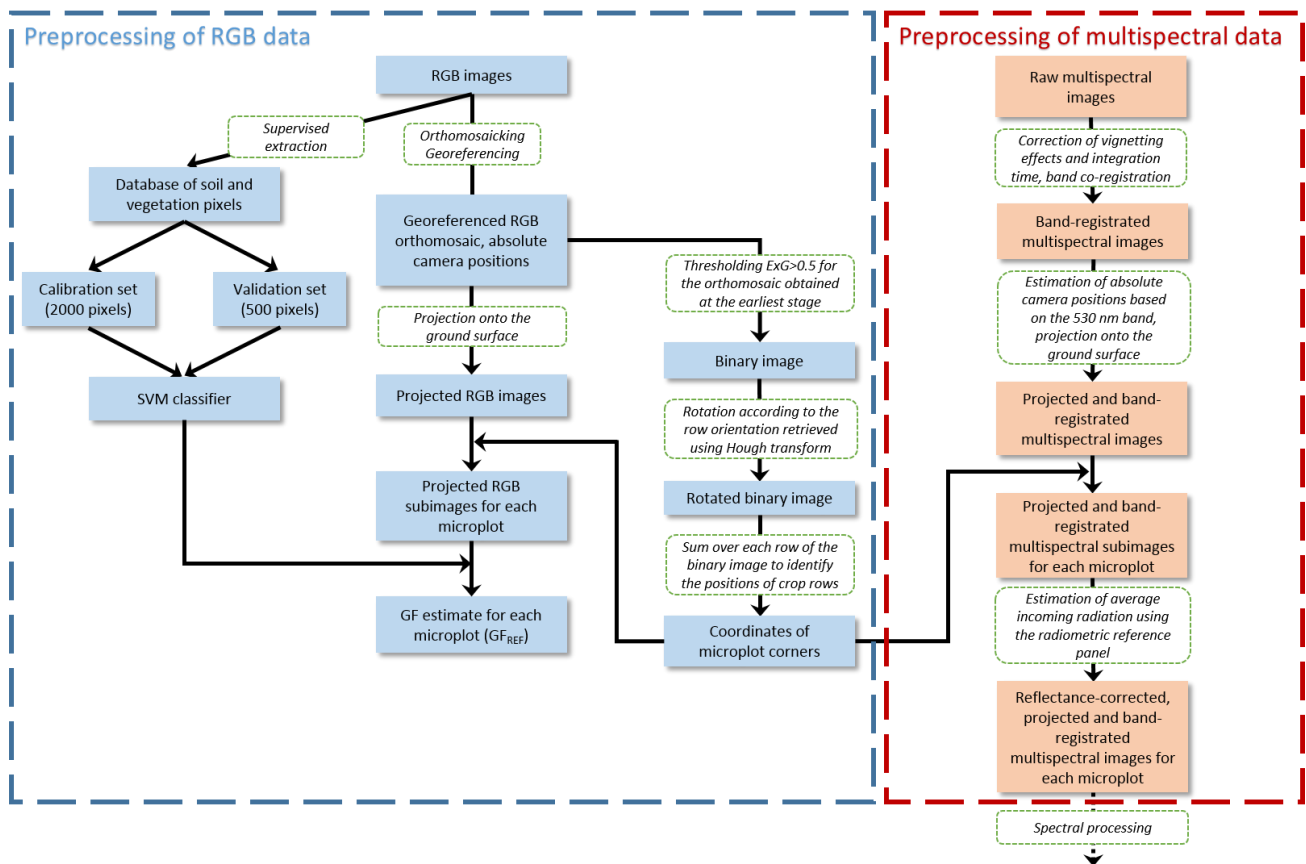
176 Fig. 1 : Examples of RGB images acquired from the UAV over three sites showing differences in growth stages, nitrogen
177 fertilizations and soil properties (Table 1). For each image, the rectangular gray panel is the reference panel used for
178 radiometric calibration, while the smaller circular panels are the GCPs used for georeferencing and orthomosaicking.

179 UAV RGB and multispectral images were generally acquired around solar noon, with an average solar zenith
180 angle between 29° and 55°. Both UAV flights only took a dozen minutes during which illumination was

181 assumed to be stable. The illumination conditions strongly varied across dates of experiments, ranging from a
 182 clear blue sky to a fully overcast one.

183 2.4. Preprocessing of UAV data

184 For the sake of clarity, the complete preprocessing chain detailed in the next sections is illustrated in Fig. 2. It
 185 first consisted in computing the microplot coordinates and estimating the reference GF of each microplot from
 186 RGB images (section 2.4.1). Then, the multispectral bands were co-registered, geometrically and
 187 radiometrically corrected (section 2.4.2).



188
 189 Fig. 2 : Flowchart illustrating the preprocessing of UAV RGB and multispectral images for each trial.

190 2.4.1. Microplot extraction and GF estimation using RGB images

191 Agisoft Photoscan Professional edition (Version 1.2.2, Agisoft LLC., Russia) was used to generate an
 192 orthomosaic of each trial using the GCPs that were automatically detected. The absolute camera position at
 193 the time of each image acquisition was computed, such that each image could be projected onto the ground

194 surface with an accuracy of a few centimeters. For each microplot, 20 to 30 sub-images were then extracted
195 from all the individual projected images containing this microplot. This process ensured a higher image quality
196 as compared to using the orthomosaic (Jin et al., 2017). Note that the microplot coordinates used for sub-
197 image extraction had been automatically computed from the RGB orthomosaic derived from the first flight
198 when the rows were clearly visible, similarly as Jin et al. (2017) to identify the rows and thanks to the
199 knowledge of microplot dimensions and number of rows.

200 Since the rough classification based on the thresholding of the Excess Green Index (Woebbecke et al., 1995)
201 image was sufficient to identify the rows (Fig. 2), but showed limitations to accurately estimate GF (Jay et al.,
202 2015; Lati et al., 2013), a SVM classifier was trained to classify the RGB images. A database of 2500 soil and
203 vegetation pixels was built, encompassing a large variability in crop state and illumination conditions. This
204 database was randomly split into 2000 pixels used for training and 500 pixels used for validation. The trained
205 SVM classifier showed an overall accuracy better than 95% on the validation set and was then applied to each
206 sub-image to derive the corresponding GF. Among all the sub-images available for each microplot, the five
207 ones showing no saturation and no blur, the closest viewing angles from nadir, and full coverage of the
208 microplot, were selected. The GF estimate of each microplot was finally computed as the average GF over the
209 five selected sub-images. This GF value is considered as the reference one and denoted GF_{REF} in this paper.

210 2.4.2. Preprocessing of multispectral images for spectral analysis

211 The six bands were co-registered with an accuracy generally finer than one pixel using the algorithm proposed
212 by Rabatel and Labbé (2016). A master band (530 nm) was then used within Agisoft Photoscan Professional
213 edition (Version 1.2.2, Agisoft LLC., Russia) to derive the camera position for each image acquisition, to project
214 the image onto the ground, and to extract the sub-images corresponding to each microplot in the same way
215 as for RGB imagery. Finally, for each microplot, only sub-images with viewing zenith angles lower than 10°
216 were kept for further analysis to limit bidirectional effects.

217 For each image, the digital number (DN) value for each pixel (x, y) of the i^{th} band (noted $DN^i(x, y)$) was
218 transformed into a bidirectional reflectance factor value (noted $BRF^i(x, y)$) according to Verger et al. (2014):

$$BRF^i(x, y) = \left(\frac{DN^i(x, y) \cdot v^i(x, y)}{t^i} \right) \cdot \left(\frac{t_{ref}^i}{\overline{DN_{ref}^i v^i}} \right) \cdot BRF_{ref}^i \quad (1)$$

219 where t^i and t_{ref}^i are, respectively, the integration times of the images acquired over the target and the
 220 reference panel, v^i the vignetting matrix used to compensate for the darkening observed in the image corners,
 221 $\overline{DN_{ref}^i v^i}$ the pixel-averaged and vignetting-corrected DN value observed over the reference panel of known
 222 BRF value BRF_{ref}^i . Note that, similarly to BRF_{ref}^i (section 2.3), v^i was measured in the laboratory as described
 223 by Verger et al. (2014). All the sub-images containing the reference panel and acquired with viewing zenith
 224 angles lower than 30° were used to get a median value of the $(\overline{DN_{ref}^i v^i} / t_{ref}^i)$ term in Eq. (1). Note that the
 225 radiometric calibration process assumes that the illumination conditions are stable during the flight, which
 226 was generally the case.

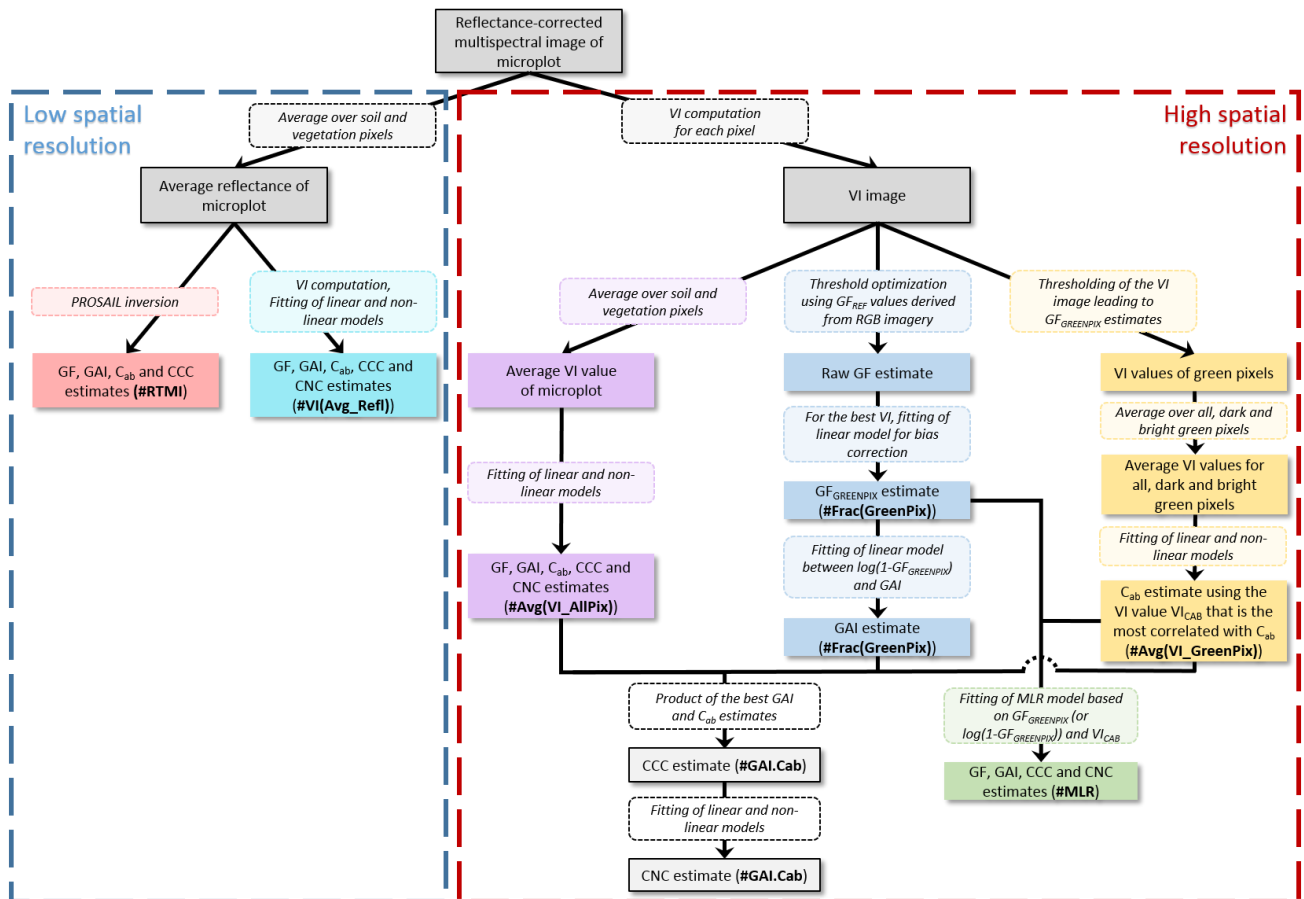
227 2.5. Approaches used to estimate leaf and canopy variables from UAV multispectral 228 imagery

229 In this study, five methods exploiting the centimeter spatial resolution of UAV observations are proposed for
 230 the estimation of the five targeted plant traits (Table 2 and Fig. 3). These methods rely on the calibration of
 231 statistical relationships between each plant trait and one or two VI-based input variable(s) computed from
 232 UAV images. Three of these methods (#Avg(VI_AllPix), #Frac(GreenPix) and #Avg(VI_GreenPix)) mainly differ
 233 in the set of pixels used to compute the VIs, and the way the VI values are used. The other two methods
 234 (#GAI.C_{ab} and #MLR) combine the results obtained with the first three methods. Note that the five variables
 235 cannot be estimated with every method (Table 2). The VIs used are first presented in section 2.5.1. Then, the
 236 five methods designed for centimeter-scale data as well as the two standard remote-sensing approaches
 237 (#RTMI and #VI(Avg_Ref)) serving as baselines for the assessment of the proposed methods are described in
 238 sections 2.5.2 and 2.5.3, respectively.

239 Table 2: Methods used to estimate GF, GAI, C_{ab} , CCC and CNC from UAV multispectral images of microplots. $GF_{GREENPIX}$ is
 240 the best GF estimate obtained with approach #Frac(GreenPix), and VI_{CAB} is the VI value that is computed with
 241 #Avg(VI_GreenPix) and that is the most correlated with C_{ab} .

Spatial resolution	Approach	Description	GF	GAI	C_{ab}	CCC	CNC
Low	#RTMI	Radiative Transfer Model Inversion using PROSAIL.	✓	✓	✓	✓	-
	#VI(Avg_Refl)	VI computed from average microplot reflectance.	✓	✓	✓	✓	✓
High	#Avg(VI_AllPix)	Average VI value over all pixels of the microplot.	✓	✓	✓	✓	✓
	#Frac(GreenPix)	GF given by the fraction of green pixels obtained by thresholding the VI image. The resulting best GF estimate, $GF_{GREENPIX}$, is then transformed into $\log(1 - GF_{GREENPIX})$ for GAI estimation.	✓	✓	-	-	-
	#Avg(VI_GreenPix)	Average VI value over a fraction of green pixels (all, only darkest, or only brightest green pixels).	-	-	✓	-	-
	#GAI. C_{ab}	Product of best GAI and C_{ab} estimates.	-	-	-	✓	✓
	#MLR	Multiple Linear Regression using $\log(1 - GF_{GREENPIX})$ (or $GF_{GREENPIX}$ for GF estimation) and VI_{CAB} as inputs.	✓	✓	-	✓	✓

242



243

244 Fig. 3: Flowchart illustrating the seven methods used to estimate GF, GAI, C_{ab} , CCC and CNC from UAV multispectral
 245 images of microplots. The blue (resp., red) panel on the left-hand (resp., right-hand) side corresponds to methods to be
 246 used with low (resp., high) spatial resolution data.

247

248 2.5.1. Selection of VIs

249 A number of VIs were selected from the literature based on their sensitivity to GF, GAI, C_{ab} , CCC and CNC
 250 (Table 3). All of them were expressed as ratios of two or three wavebands. Such VIs indeed minimized the
 251 influence of multiplicative factors, including possible variation in the illumination conditions during the flights.
 252 An extensive discussion of the properties of the selected VIs can be found in Jay et al. (2017a). In this study,
 253 the Visible Atmospherically Resistant Index (*VARI*) was also included in the comparison, as it was
 254 demonstrated to be strongly related to GF (Gitelson et al., 2002).

255 All the six VIs selected were originally designed using wavebands that may not be available on the band set
 256 chosen for the AIRPHEN multispectral camera. Therefore, each band in the original formulation of each VI was

257 replaced by the closest band available (Table 3). Note that the 560 nm band used in 2016 and the 570 nm
 258 band used in 2017 were not considered to prevent potential artifacts between years.

259 Table 3 : Ratio VIs selected from the literature.

VI name	References	VI formulation used in this study
<i>VARI</i>	Gitelson et al. (2002)	$\frac{R_{530} - R_{675}}{R_{530} + R_{675} - R_{450}}$
<i>NDVI</i>	Rouse et al. (1973)	$\frac{R_{850} - R_{675}}{R_{850} + R_{675}}$
<i>CI_{green}</i>	Gitelson et al. (2006a, 2005, 2003)	$\frac{R_{850}}{R_{530}} - 1$
<i>CI_{re}</i>	Gitelson et al. (2006a, 2005, 2003)	$\frac{R_{850}}{R_{730}} - 1$
<i>MTCI</i>	Dash and Curran (2004)	$\frac{R_{850} - R_{730}}{R_{730} - R_{675}}$
<i>mND_{blue}</i>	Jay et al. (2017a)	$\frac{R_{450} - R_{730}}{R_{450} + R_{850}}$

260

261 2.5.2. Estimation approaches exploiting the centimeter resolution of UAV multispectral
 262 imagery

263 - *#Avg(VI_AllPix): using the average VI value over all the pixels of the microplot.* Here, the VI value was
 264 the average of the VI values computed for all the soil and vegetation pixels of the UAV image of the
 265 microplot (Fig. 3). This average was computed using a 1 % trimmed mean to remove possible outliers
 266 present in the tails of the VI distributions. Four linear and non-linear (second-degree polynomial,
 267 power and exponential functions) prediction models were then built using all the UAV multispectral
 268 images available for each targeted variable.

269 - *#Frac(GreenPix): estimating GF and GAI using a fraction of green pixels derived from VI thresholding.*
 270 For each microplot, green pixels were identified by thresholding the six VI images. For each VI, the
 271 threshold value was optimized to get the best match between the reference GF value GF_{REF} derived
 272 from the RGB image classification (section 2.4.1), and the GF value given by the fraction of green pixels
 273 after VI image thresholding (Fig. 3). Furthermore, the raw estimated GF value obtained by
 274 thresholding the VI image could be linearly related to GF_{REF} to remove possible bias. This corrected GF

275 estimate is called $GF_{GREENPIX}$, and is also used in the following #MLR approach. In the case of GAI
276 estimation, $GF_{GREENPIX}$ was transformed into $\log(1-GF_{GREENPIX})$ and linearly related to GAI according to
277 Nilson (1971) and Weiss et al. (2004).

278 - *#Avg(VI_GreenPix): estimating C_{ab} using the average VI value computed over a fraction of green pixels.*
279 Similarly to Jay et al. (2017a), VIs were here computed based on three subsets of green pixels extracted
280 using the available centimeter-scale UAV multispectral imagery, i.e., (i) all the green pixels, (ii) the 50
281 % darkest green pixels or (iii) the 50 % brightest green pixels. The green pixels were first identified
282 using the optimal threshold leading to the $GF_{GREENPIX}$ estimates obtained with the previous
283 #Frac(GreenPix) approach (Fig. 3). However, the threshold value leading to optimal C_{ab} estimation may
284 differ from the value leading to optimal GF estimation due to the detrimental influence of mixed pixels
285 containing both soil and vegetation. Therefore, the performance of C_{ab} estimation was also
286 investigated for other selections of green pixels obtained for several threshold values around the
287 optimal value leading to $GF_{GREENPIX}$ estimates. Then, for each selected fraction of green pixels, the 50 %
288 darkest and 50 % brightest pixels were identified based on the value in the near-infrared (NIR) band.
289 For each subset of pixels considered, the average VI values were computed using a 1 % trimmed mean
290 as for #Avg(VI_Refl), and linearly and non-linearly related to C_{ab} . Note that this approach focusing on
291 green pixels was only used for C_{ab} estimation. The VI computed over the selected fraction of green
292 pixels that provides the best C_{ab} estimation performance is called VI_{CAB} when used in the following
293 #MLR approach.

294 - *#GAI.C_{ab}: estimating CCC and CNC using the product of the best GAI and C_{ab} estimates.* CCC could be
295 estimated either directly as in approach #Avg(VI_AllPix), or as the product of the best GAI and C_{ab}
296 estimates (Fig. 3). Since leaf nitrogen content shows some correlation with leaf chlorophyll content
297 (Jay et al., 2017b; Schlemmer et al., 2013), CNC was also linearly and non-linearly related to this
298 product (Fig. 3).

299 - *#MLR: estimating GF, GAI, CCC and CNC using Multiple Linear Regression.* In the #MLR approach, a
300 Multiple Linear Regression (MLR) model was built, combining (i) $GF_{GREENPIX}$ OR $\log(1- GF_{GREENPIX})$ derived

301 from approach #Frac(GreenPix) and carrying information on canopy structure, and (ii) VI_{CAB} derived
 302 from approach #Avg($VI_{GreenPix}$) and carrying information on leaf chlorophyll content (Fig. 3). These
 303 two input variables were assumed to bring complementary information on the targeted plant traits.
 304 These input variables were first standardized according to:

$$X_i = \frac{(x_i - \bar{x}_i)}{\sigma_{x_i}} \quad (2)$$

305 where \bar{x}_i and σ_{x_i} are, respectively, the average and standard deviation values of input variable x_i in
 306 the calibration set, with $[x_1, x_2] = [GF_{GREENPIX}, VI_{CAB}]$. Note that, in the case of GAI, CCC and CNC
 307 estimation, we took $x_1 = \log(1 - GF_{GREENPIX})$. A MLR model was then built according to:

$$Y = \alpha_0 + \sum_{i=1}^2 \alpha_i X_i \quad (3)$$

308 where Y is the variable to be estimated, and α_i the MLR coefficients to be calibrated.

309

310 2.5.3. Standard remote-sensing approaches using the average reflectance of the microplot

311 - *#RTMI: inverting the PROSAIL model.* The #RTMI (standing for Radiative Transfer Model Inversion,
 312 Table 2 and Fig. 3) approach consists in inverting the PROSAIL radiative transfer model (Baret et al.,
 313 1992; Jacquemoud et al., 2009), combining the PROSPECT model (Jacquemoud and Baret, 1990) with
 314 the SAIL model (Verhoef, 1985, 1984). PROSAIL simulates the canopy bidirectional reflectance of a
 315 turbid medium canopy as a function of leaf biochemical and canopy structural variables for a given
 316 sun-sensor geometry. Although PROSAIL may not be fully optimal for modeling the reflectance of row-
 317 structured sugar beet canopies, a number of studies have demonstrated that it enables accurate
 318 retrievals of GAI, C_{ab} and CCC for such vegetation arrangements (Dorigo, 2012; Duan et al., 2014;
 319 Jacquemoud et al., 1995; Jay et al., 2017b; Verger et al., 2014).

320 The PROSPECT 3 model (Baret and Fourty, 1997) was used in this study, as Jiang et al. (2018) showed
 321 that this PROSPECT version generally shows similar performance as the latest versions (Feret et al.,
 322 2008; Féret et al., 2017) while having less variables to be inverted. It simulates the leaf directional-

323 hemispherical reflectance and transmittance as a function of a structure parameter (N , unitless) as
324 well as leaf chlorophyll (C_{ab} , in $\mu\text{g}/\text{cm}^2$), dry matter (C_m , in g/cm^2), water (C_w , in g/cm^2) and brown
325 pigment (C_{bp} , unitless) contents. SAIL accounts for the effects of leaf reflectance and transmittance,
326 green area index (GAI, unitless), average leaf angle (ALA, in $^\circ$), soil brightness factor (B_s , unitless),
327 viewing zenith angle (θ_v , in $^\circ$), solar zenith angle (θ_s , in $^\circ$) and relative azimuth angle (ϕ_{sv} , in $^\circ$). A
328 parameter (s_L , unitless) was also included to account for the hotspot effect (Kuusk, 1991; Verhoef,
329 1998).

330 In this paper, each UAV-measured canopy reflectance obtained by averaging all the vegetation and
331 soil pixels of each microplot was inverted using a PROSAIL inversion approach based on artificial neural
332 network. Following Verger et al. (2014), the inputs of the neural network were the solar zenith and
333 azimuth angles, the viewing zenith angle, and the first five bands normalized by the 850 nm band so
334 as to better handle possible variation in the illumination conditions. More details on the neural
335 network architecture and training data base can be found in Weiss et al. (2002), Verger et al. (2011)
336 and Li et al. (2015). Note that GF and CCC can be directly estimated using this inversion method. In
337 the case of CCC, the obtained estimate may differ from the product of GAI and C_{ab} estimated values.
338 Note also that it is not possible to estimate directly CNC since leaf nitrogen content is not explicitly
339 accounted for by the leaf PROSPECT model.

340 - *#VI(Avg_Refl): using the VI value computed from the average microplot reflectance.* The six VIs were
341 computed from the canopy reflectance obtained by averaging over all the vegetation and soil pixels
342 of the UAV image of the microplot (Fig. 3). The VIs were then linearly and non-linearly related to each
343 targeted variable, similarly as #Avg(VI_AllPix) (section 2.5.2). Note that approach #VI(Avg_Refl) does
344 not exploit the centimeter resolution of UAV multispectral images, unlike the previous #Avg(VI_AllPix)
345 approach for which each VI was computed by averaging pixel-level VI values. As the six VIs tested are
346 non-linear functions of reflectance, these two approaches may obtain different results (Jay et al.,
347 2017a; Steven et al., 2015).

348 2.5.4. Performance assessment

349 A cross-validation process was used to quantify the performances of the six VI-based approaches (Table 2). It
 350 consisted in calibrating a prediction model using N-1 dates out of the N available (Table 1) and using the last
 351 date for the validation. This process was repeated N times to use every date available for the validation. Note
 352 that in the case of approach #MLR, each of the N calibration and validation sets was standardized using the \bar{x}_i
 353 and σ_{x_i} values computed over the corresponding calibration set (Eq. (2)). Four indicators of the prediction
 354 performance were then computed, namely, the root mean square error of prediction (RMSEP), the relative
 355 RMSEP (RRMSEP) being defined as the ratio of the RMSEP to the mean measured value, the squared Pearson's
 356 correlation coefficient (r^2) between estimated and measured values, and the coefficient of determination
 357 defined as $R^2 = 1 - \frac{RMSEP^2}{\sigma_{tot}^2}$, where σ_{tot}^2 is the total variance of the measured variable.

358 3. Results

359 3.1. Ground-based measurements

360 Table 4 : Statistics of GF, GAI, C_{ab}, CCC and CNC measurements.

Variable	Unit	Number of microplots	Min - Max	Mean	Standard deviation	Coefficient of variation (%)
GF	-	238	0.18 - 0.97	0.61	0.25	40
GAI	-	135	0.13 - 4.57	1.50	1.00	67
C _{ab}	µg/cm ²	177	21.2 - 51.1	33.7	7.0	21
CCC	g/m ²	92	0.04 - 1.46	0.52	0.39	74
CNC	g/m ²	114	0.7 - 16.8	6.4	3.9	61

361

362 A large variability is observed for each structural and biochemical variable of interest (Table 4). Importantly,
 363 C_{ab} and canopy structure variables (GAI and GF) poorly correlate (Table 5), which ensures that any correlation
 364 between VIs and C_{ab} will not derive from the covariance with either GF or GAI. Conversely, strong correlations
 365 are observed between GF and GAI (Table 5), as already outlined by Andrieu et al. (1997) for sugar beet crops.
 366 Note that, as expected, the linear correlation between GF and GAI slightly increases when transforming GF
 367 into log(1-GF) to better account for the saturation observed for high GAI values (Andrieu et al., 1997; Nilson,

1971; Weiss et al., 2004). GAI strongly correlates with CCC (Table 5) because of the larger variability in GAI as compared to that in C_{ab} (Table 4). Table 5 also shows strong correlations between CNC and GAI, as well as between CNC and CCC. However, these correlations should be taken with caution due to the low number of samples considered (24) and to the poorer correlations between CNC and $\log(1-GF)$ obtained with a larger number of samples (96).

Table 5 : Squared Spearman's (ρ^2 , lower diagonal) and Pearson's (r^2 , upper diagonal) correlation coefficients between the five variables targeted. The variable $\log(1-GF)$ is also included to show the gain in linear correlation obtained with this transformation. For each pair of variables, the number of microplots available to compute the correlation is indicated in parentheses. Colors show the level of correlation, ranging from pale yellow for low correlation to red for high correlation.

$\rho^2 \backslash r^2$	GF	$\log(1-GF)$	GAI	C_{ab}	CCC	CNC
GF	-	0.87 (238)	0.81 (117)	0.11 (159)	0.79 (86)	0.58 (96)
$\log(1-GF)$	1.00 (238)	-	0.83 (117)	0.03 (159)	0.81 (86)	0.50 (96)
GAI	0.89 (117)	0.89 (117)	-	0.07 (87)	0.91 (92)	0.82 (24)
C_{ab}	0.07 (159)	0.07 (159)	0.11 (87)	-	0.21 (87)	0.10 (113)
CCC	0.86 (86)	0.86 (86)	0.95 (92)	0.24 (87)	-	0.84 (24)
CNC	0.62 (96)	0.62 (96)	0.83 (24)	0.04 (113)	0.87 (24)	-

377

3.2. Correlations between VIs

The correlations between VIs computed over soil and vegetation pixels shows that $VARI$ and $NDVI$ are strongly related, with squared Spearman's correlation coefficients (ρ^2) higher than 0.93 (Table 6). These two VIs show high to intermediate correlations with CI_{green} and CI_{re} ($0.49 \leq \rho^2 \leq 0.83$), both of which are themselves strongly related ($\rho^2 = 0.87$). On the other hand, mND_{blue} and $MTCI$ generally poorly correlate with other VIs ($\rho^2 \leq 0.53$). Note that the Spearman's and Pearson's correlation coefficients are generally similar, indicating that the relationships are approximately linear.

385

386

Table 6 : Squared Spearman's (ρ^2 , lower diagonal) and Pearson's (r^2 , upper diagonal) correlation coefficients between VIs computed over all soil and vegetation pixels and over all the 274 microplots. For each microplot, each VI is computed

389 from the average of pixel-level VI values. Colors show the level of correlation, ranging from pale yellow for low correlation
 390 to red for high correlation.

$\rho^2 \backslash r^2$	<i>VARI</i>	<i>NDVI</i>	<i>CI_{green}</i>	<i>CI_{re}</i>	<i>MTCI</i>	<i>mND_{blue}</i>
<i>VARI</i>	-	0.94	0.65	0.49	0.01	0.55
<i>NDVI</i>	0.93	-	0.80	0.63	0.06	0.53
<i>CI_{green}</i>	0.64	0.83	-	0.90	0.32	0.18
<i>CI_{re}</i>	0.49	0.66	0.87	-	0.56	0.04
<i>MTCI</i>	0.00	0.03	0.19	0.40	-	0.15
<i>mND_{blue}</i>	0.53	0.42	0.21	0.07	0.17	-

391

392 *VARI* and *NDVI* still strongly correlate ($\rho^2 = 0.80$) when computed over vegetation pixels (Table 7). However,
 393 in this case, only *NDVI* shows significant correlations with the other VIs tested, with maximum ρ^2 values of
 394 0.73 and 0.49 with *CI_{green}* and *CI_{re}*, respectively. *MTCI*, *CI_{re}*, *CI_{green}* and, to a lesser extent, *mND_{blue}*,
 395 strongly correlate with each other, with a maximum correlation between *MTCI* and *CI_{re}* ($\rho^2 = 0.97$), and a
 396 minimum correlation between *CI_{green}* and *mND_{blue}* ($\rho^2 = 0.20$). Here again, the similar Spearman's and
 397 Pearson's correlation coefficients indicate that the relationships are approximately linear.

398 Table 7 : Squared Spearman's (ρ^2 , lower diagonal) and Pearson's (r^2 , upper diagonal) correlation coefficients between
 399 VIs computed over all green pixels and over all the 274 microplots. For each microplot, each VI is computed from the
 400 average of pixel-level VI values. Colors show the level of correlation, ranging from pale yellow for low correlation
 401 for high correlation.

$\rho^2 \backslash r^2$	<i>VARI</i>	<i>NDVI</i>	<i>CI_{green}</i>	<i>CI_{re}</i>	<i>MTCI</i>	<i>mND_{blue}</i>
<i>VARI</i>	-	0.79	0.30	0.19	0.13	0.00
<i>NDVI</i>	0.80	-	0.69	0.52	0.43	0.07
<i>CI_{green}</i>	0.33	0.73	-	0.87	0.81	0.38
<i>CI_{re}</i>	0.21	0.49	0.81	-	0.99	0.70
<i>MTCI</i>	0.12	0.36	0.72	0.97	-	0.77
<i>mND_{blue}</i>	0.01	0.02	0.20	0.51	0.63	-

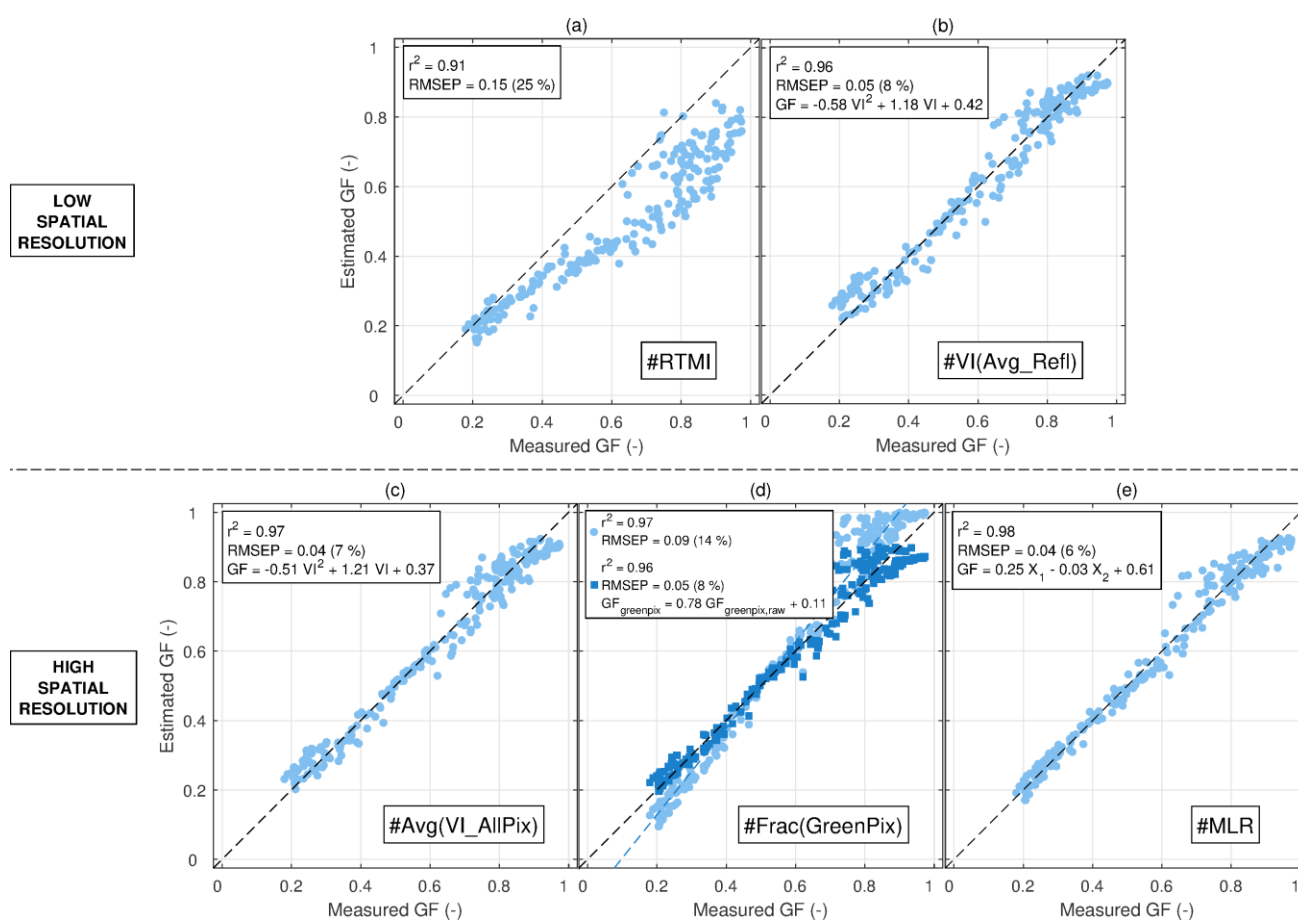
402

403 3.3. Estimation of canopy structure

404 3.3.1. GF estimation

405 Since GF may play a particular role in the estimation of the other variables when exploiting the centimeter
 406 resolution of UAV images, emphasis is first put on it.

407 When using the average microplot reflectance, the GF values estimated using PROSAIL inversion (approach
 408 #RTMI) strongly correlate with the measured ones ($r^2 = 0.91$) (Fig. 4.a). However, the results are penalized
 409 by a significant underestimation for the largest GF values, resulting in $RMSEP = 0.15$ ($RRMSEP = 25\%$). The
 410 bias is removed when using #VI(Avg_Refl) based on VIs computed over average microplot reflectances
 411 (Fig. 4.b). Significantly better predictions are obtained using *VARI* and a second-degree polynomial, with
 412 $RMSEP = 0.05$ ($RRMSEP = 8\%$, Table 8, Fig. 4.b).



413

414 Fig. 4 : GF estimation results obtained using low and high spatial resolution approaches: (a) #RTMI based on PROSAIL
 415 inversion, (b) #VI(Avg_Refl) with *VARI* and a second-degree polynomial, (c) #Avg(VI_AllPix) with *VARI* and a second-
 416 degree polynomial, (d) #Frac(GreenPix) with *VARI* and a threshold of 0.14 before (disks in light blue) and after (squares
 417 in dark blue) correcting for the bias affecting the raw GF estimate $GF_{GREENPIX,RAW}$, and (e) #MLR based on standardized
 418 $GF_{GREENPIX}$ (Fig. 4.d) and VI_{CAB} (Fig. 6.d) values. For each method, the squared Pearson's correlation coefficient (r^2) and the
 419 RMSEPs in absolute and relative (in %) are indicated. The regression equation is also shown for empirical approaches.

420

421 Table 8 : RMSEPs obtained for the estimation of GF (unitless), GAI (unitless), C_{ab} (in $\mu\text{g}/\text{cm}^2$), CCC (in g/m^2) and CNC (in
 422 g/m^2) using VIs computed either from the average microplot reflectance (#VI(Avg_Refl)) or from the average of pixel-
 423 level VI values over all microplot pixels (#Avg(VI_AllPix)). For each method, each variable and each VI, only the RMSEP

424 obtained with the best model is shown (results obtained with the four linear and non-linear models tested are provided
 425 in supplementary material). For each column, the best result is in bold.

VI	#VI(Avg_Refl)					#Avg(VI_AllPix)				
	GF	GAI	C _{ab}	CCC	CNC	GF	GAI	C _{ab}	CCC	CNC
<i>VARI</i>	0.05	0.42	7.4	0.19	2.7	0.04	0.40	7.7	0.19	2.7
<i>NDVI</i>	0.07	0.46	7.6	0.20	2.2	0.07	0.44	7.6	0.19	2.2
<i>CI_{green}</i>	0.18	0.69	6.9	0.24	2.1	0.18	0.70	6.9	0.24	2.1
<i>CI_{re}</i>	0.21	0.74	5.4	0.20	3.2	0.20	0.74	5.2	0.20	3.1
<i>MTCI</i>	0.25	0.93	4.2	0.25	3.6	0.29	1.10	4.2	0.32	4.8
<i>mND_{blue}</i>	0.21	0.87	7.7	0.41	5.3	0.19	0.82	7.4	0.40	5.1

426
 427 When exploiting the centimeter resolution of UAV images through approach #Avg(VI_AllPix) for which each VI
 428 value is the average of the VI image, a slight improvement is observed when using *VARI* ($RMSEP = 0.04$,
 429 Fig. 4.c), followed by *NDVI* ($RMSEP = 0.07$) (Table 8). When using approach #Frac(GreenPix), GF is given by
 430 the fraction of green pixels computed by thresholding the VI image. The optimal threshold used here is
 431 determined using the reference GF derived from RGB image classification. The best GF estimation results are
 432 obtained using *VARI* images and an optimal threshold of $VARI = 0.14$ ($RMSEP = 0.09$, Table 9), followed
 433 by *NDVI* images and an optimal threshold of $NDVI = 0.62$ ($RMSEP = 0.11$, Table 9). It is worth noting that
 434 similarly accurate results are obtained for a range of *VARI* values around the optimal value of 0.14, e.g., the
 435 $RMSEP$ remains lower than 0.11 when taking a *VARI* threshold between 0 and 0.25 (see the figure in
 436 supplementary material). However, these results show some underestimation for low GF values and some
 437 overestimation for large GF values (Fig. 4.d). A linear regression was thus applied to correct for this bias,
 438 leading to improved performance with $RMSEP = 0.05$ (Table 9, Fig. 4.d). The resulting GF estimates are called
 439 $GF_{GREENPIX}$ and used as complementary information to improve the estimation of canopy variables through the
 440 #MLR approach. Further, green pixels selected by thresholding the *VARI* images will be used in the following
 441 sections.

442 Here, approach #MLR consists in combining the two input variables [$GF_{GREENPIX}$, VI_{CAB}], where VI_{CAB} is the
 443 *mND_{blue}* value averaged over the 50 % darkest green pixels (the green pixels being defined by $VARI > 0.20$,
 444 see section 3.4.1). Using VI_{CAB} as additional explanatory variable within #MLR slightly improves the GF
 445 estimation results obtained with #Frac(GreenPix), with $RMSEP = 0.04$ ($RRMSEP = 6\%$) (Fig. 4.e).

446

447 Table 9 : Results obtained for the estimation of GF using the #Frac(GreenPix) approach, consisting in retrieving the
 448 fraction of green pixels by thresholding the VI images. For each VI, the RMSEP (unitless) before and after bias correction
 449 is shown, and the best result is in bold.

VI	Optimal threshold value	RMSEP before bias correction (-)	RMSEP after bias correction (-)
<i>VARI</i>	0.14	0.09	0.05
<i>NDVI</i>	0.62	0.11	0.06
<i>CI_{green}</i>	2.20	0.16	0.12
<i>CI_{re}</i>	0.15	0.16	0.16
<i>MTCI</i>	0.22	0.23	0.24
<i>mND_{blue}</i>	-0.68	0.37	0.30

450

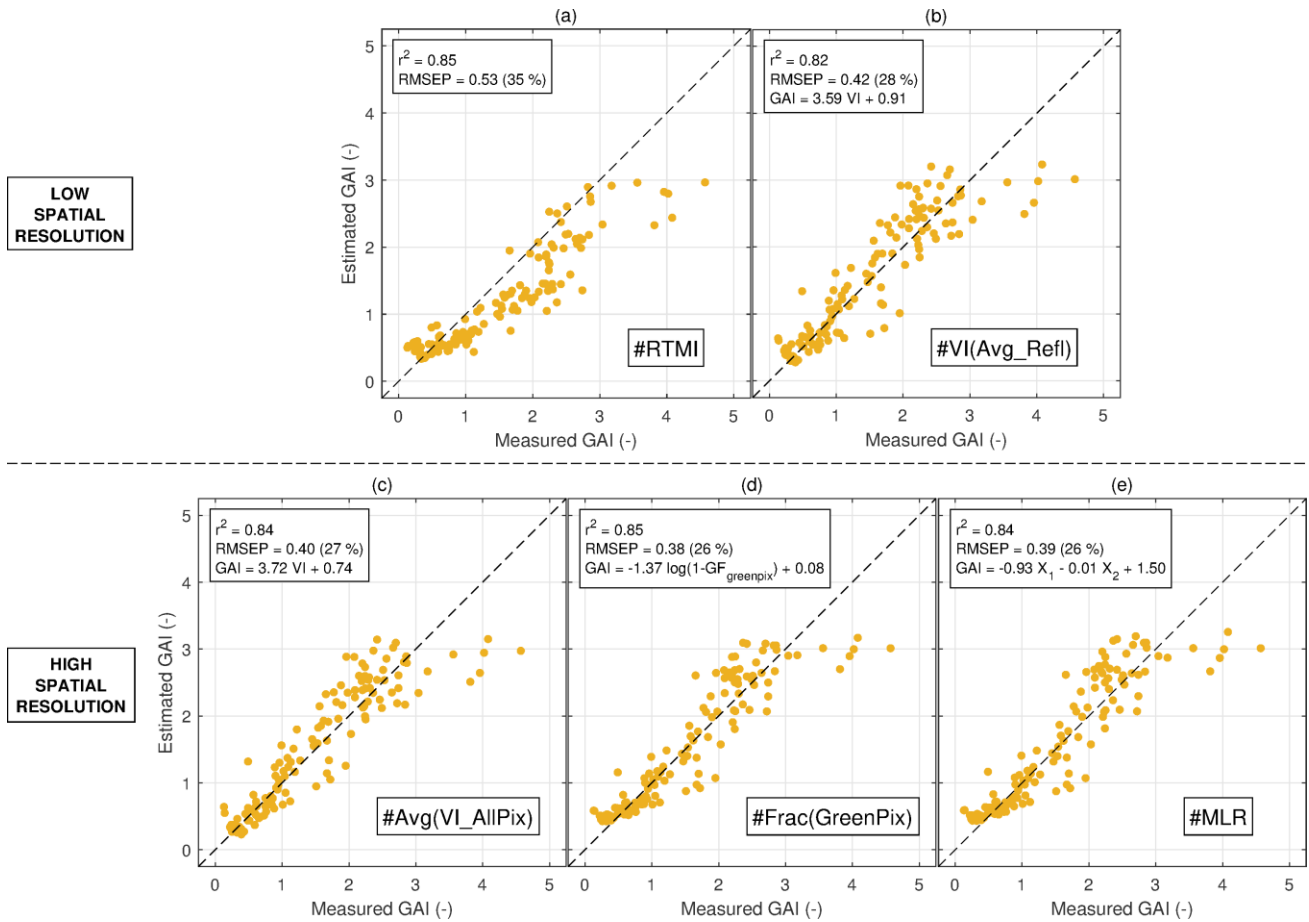
451 3.3.2. GAI estimation

452 The GAI estimation results obtained when using the average microplot reflectance show similar characteristics
 453 as the GF estimation results. In the case of approach #RTMI, the measured and estimated GAI values strongly
 454 correlate ($r^2 = 0.85$); however, #RTMI significantly underestimates GAI for the largest values, leading to
 455 $RMSEP = 0.53$ ($RRMSEP = 35\%$) (Fig. 5.a). The retrieval accuracy improves when using #VI(Avg_Refl), with
 456 the same hierarchy between VIs being observed for GF and GAI (Table 8). The best predictions are obtained
 457 with *VARI* and a linear model ($RMSEP = 0.42$) (Fig. 5.b). Note, however, that GAI is still underestimated for
 458 $GAI \geq 3.00$ (Fig. 5.b).

459 Similarly to GF, exploiting the image centimeter resolution through approach #Avg(VI_AllPix) slightly improves
 460 the best performance obtained with approach #VI(Avg_Refl) based on the average microplot reflectance
 461 (Table 8). The best predictions are obtained using *VARI* ($RMSEP = 0.40$ with a linear model, Fig. 5.c),
 462 followed by *NDVI* ($RMSEP = 0.44$ with an exponential model, Table 8). Approach #Frac(GreenPix) for which
 463 GAI is linearly related to $\log(1 - GF_{GREENPIX})$ further improves GAI estimation, with $RMSEP = 0.38$ (Fig. 5.d).
 464 Finally, similar GAI estimates ($RMSEP = 0.39$, Fig. 5.e) are obtained when using approach #MLR based on the
 465 two input variables [$\log(1 - GF_{GREENPIX})$, VI_{CAB}], where VI_{CAB} is the *mND_{blue}* value averaged over the 50 % darkest
 466 green pixels (the green pixels being defined by $VARI > 0.20$, see section 3.4.1). Note that the three methods
 467 exploiting the centimeter resolution still show some underestimation for $GAI \geq 3.00$, similarly to approaches
 468 based on average microplot reflectance (Fig. 5).

469

470



471

472 Fig. 5 : GAI estimation results obtained using low and high spatial resolution approaches: (a) #RTMI based on PROSAIL
 473 inversion, (b) #VI(Avg_Refl) with *VARI* and a linear model, (c) #Avg(VI_AllPix) with *VARI* and a linear model, (d)
 474 #Frac(GreenPix) with $\log(1-GF_{GREENPIX})$ and a linear model, and (e) #MLR based on standardized $\log(1-GF_{GREENPIX})$ (Fig. 4.d)
 475 and V_{CAB} (Fig. 6.d) values. For each method, the squared Pearson's correlation coefficient (r^2) and the RMSEPs in absolute
 476 and relative (in %) are indicated. The regression equation is also shown for empirical approaches.

477

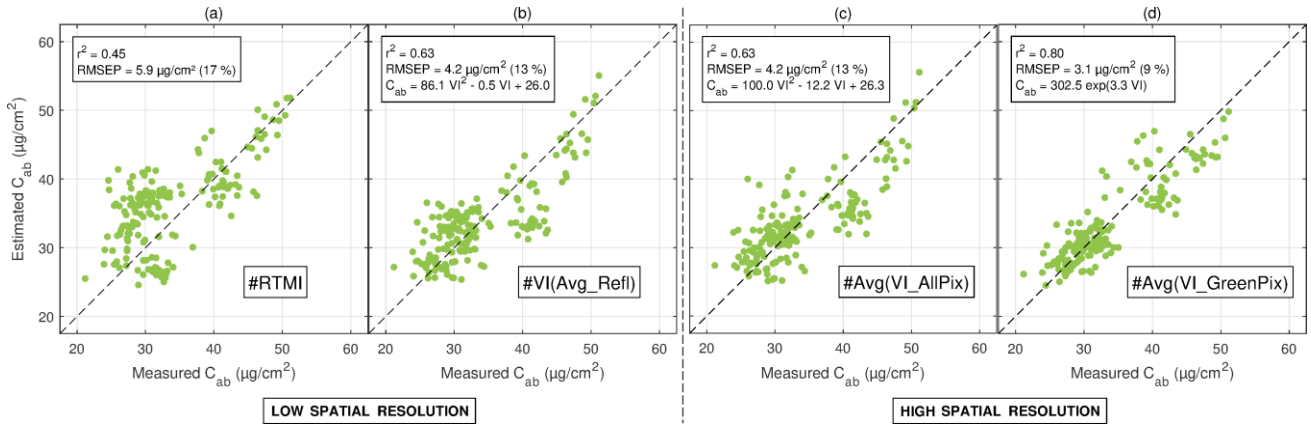
478 3.4. Estimation of canopy biochemistry

479 3.4.1. C_{ab} estimation

480 For C_{ab} estimation, inverting PROSAIL based on the average microplot reflectance results in relatively poor
 481 performance ($RMSEP = 5.9 \mu\text{g}/\text{cm}^2$, Fig. 6.a). Note that the dispersion around the 1:1 line is greater for
 482 samples with C_{ab} values around $30 \mu\text{g}/\text{cm}^2$ (Fig. 6.a). Further investigation shows that, although having similar
 483 C_{ab} values, these samples are characterized by strongly different canopy structures, with GF ranging from 0.20
 484 to 0.97 and a standard deviation of 0.28. Using VIs through approach #VI(Avg_Refl) significantly improves C_{ab}

485 estimation, with $MTCI$ and, to a lesser extent, CI_{re} , performing better than the other VIs tested (Table 8). The
 486 best predictions are obtained using $MTCI$ and a second-degree polynomial ($RMSEP = 4.2 \mu\text{g}/\text{cm}^2$, Fig. 6.b).

487



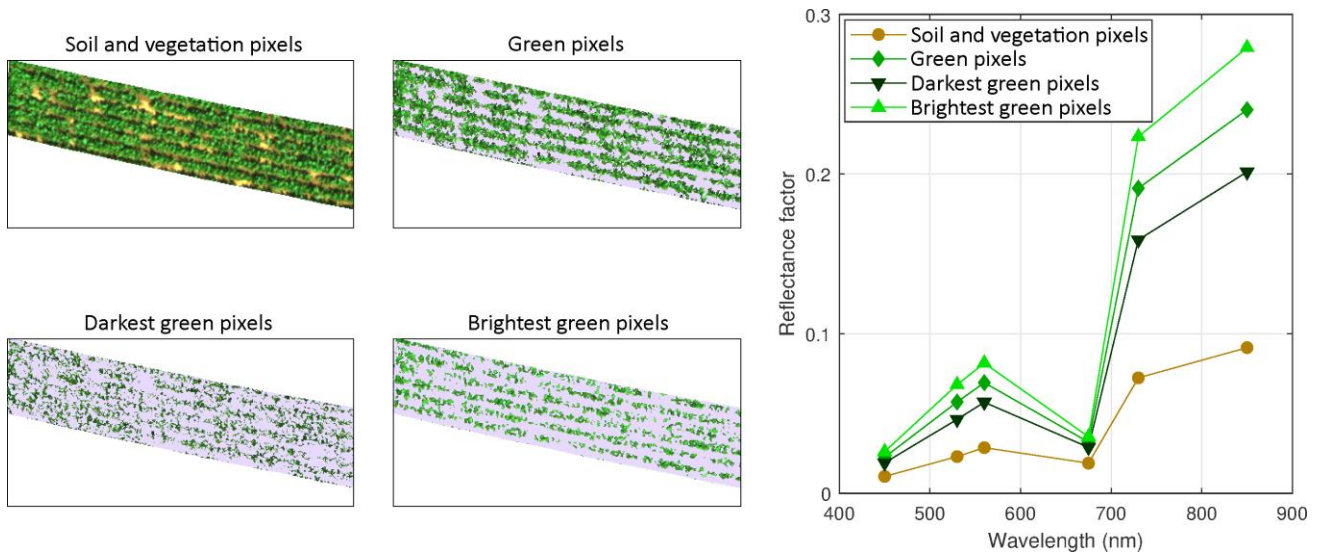
488

489 Fig. 6 : C_{ab} estimation results obtained using low and high spatial resolution approaches: (a) #RTMI based on PROSAIL
 490 inversion, (b) #VI(Avg_Refl) with $MTCI$ and a second-degree polynomial, (c) #Avg(VI_AllPix) with $MTCI$ and a second-
 491 degree polynomial, and (d) #Avg(VI_GreenPix) with a $VARI$ threshold of 0.20, and an exponential model relating C_{ab} and
 492 mND_{blue} values averaged over the darkest green pixels. For each method, the squared Pearson's correlation coefficient
 493 (r^2) and the RMSEPs in absolute and relative (in %) are indicated. The regression equation is also shown for empirical
 494 approaches.

495

496 Approach #Avg(VI_AllPix) based on the average VI value of the microplot (Fig. 6.c) shows nearly the same
 497 performances as approach #VI(Avg_Refl) based on the average microplot reflectance (Table 8). A similar
 498 hierarchy between VIs is observed, with $MTCI$ leading to the best performance ($RMSEP = 4.2 \mu\text{g}/\text{cm}^2$), and
 499 $VARI$, $NDVI$ and mND_{blue} to the worst ones ($RMSEP \geq 7.4 \mu\text{g}/\text{cm}^2$).

500 Focusing on any of the three selections of green pixels identified using the $VARI$ image (using the threshold
 501 $VARI = 0.14$) and the near-infrared band (section 2.5.2), makes the measured optical signature get closer to
 502 a typical leaf signature, e.g., with a sharper increase in reflectance observed in the red-edge region (Fig. 7).



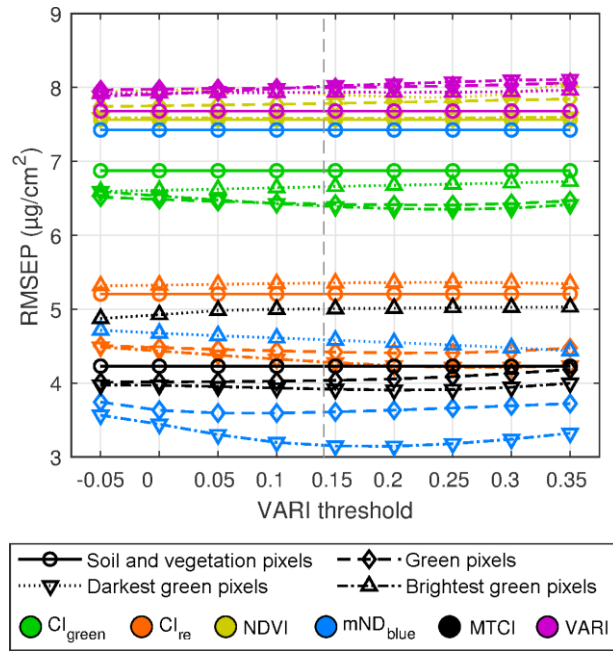
503

504 Fig. 7 : Subsets of pixels extracted from a multispectral image of a single microplot, and corresponding average
 505 reflectance spectra. Pixels are here discriminated using a $VARI$ threshold of 0.14 (section 3.3.1). Purple areas show the
 506 pixels excluded from the spectral average for each subset.

507

508 Consequently, approach #Avg(VI_GreenPix) generally improves the C_{ab} estimation results obtained with
 509 approach #Avg(VI_AllPix) (Fig. 8). For example, the results obtained with $MTCI$ slightly improves when
 510 focusing on the 50 % darkest green pixels ($RMSEP = 3.9 \mu\text{g}/\text{cm}^2$). However, in the case of mND_{blue} , this
 511 improvement is much more significant, with $RMSEP = 3.2 \mu\text{g}/\text{cm}^2$ obtained when considering the 50 %
 512 darkest green pixels (Fig. 8). Note that $VARI$, $NDVI$ and CI_{green} provide significantly poorer performances
 513 than CI_{re} , $MTCI$ and mND_{blue} , and show no to little improvement when focusing on either selection of green
 514 pixels (Fig. 8).

515 The threshold value $VARI = 0.14$ leading to optimal green segmentation (section 3.3.1) also appears to be
 516 appropriate for C_{ab} estimation (Fig. 8). Varying the threshold value around 0.14 shows little impact on the
 517 performances for the six VIs, especially for $VARI$ values between 0.05 and 0.35. The best C_{ab} estimation results
 518 are obtained using a threshold value $VARI = 0.20$, mND_{blue} computed over the darkest green pixels, and an
 519 exponential model ($RMSEP = 3.1 \mu\text{g}/\text{cm}^2$, Fig. 6.d). Note that using a linear model leads to similar
 520 performance ($RMSEP = 3.3 \mu\text{g}/\text{cm}^2$, not shown). For each microplot, the VI_{CAB} input variable used within the
 521 #MLR approach thus corresponds to the mND_{blue} value averaged over the 50 % darkest green pixels (the
 522 green pixels being defined by $VARI > 0.20$).



523

524 Fig. 8 : RMSEPs obtained for the estimation of C_{ab} using VIs computed as the average of pixel-level VI values over all
 525 microplot pixels ($\#Avg(VI_AllPix)$), or over one of the three subsets of green pixels ($\#Avg(VI_GreenPix)$) identified using
 526 various $VARI$ thresholds. The vertical dashed line shows the optimal $VARI$ threshold of 0.14 leading to $GF_{GREENPIX}$
 527 (Table 9). For each combination of $VARI$ thresholds, VIs and subsets of pixels, only the RMSEP obtained with the best
 528 model (linear or non-linear) is shown.

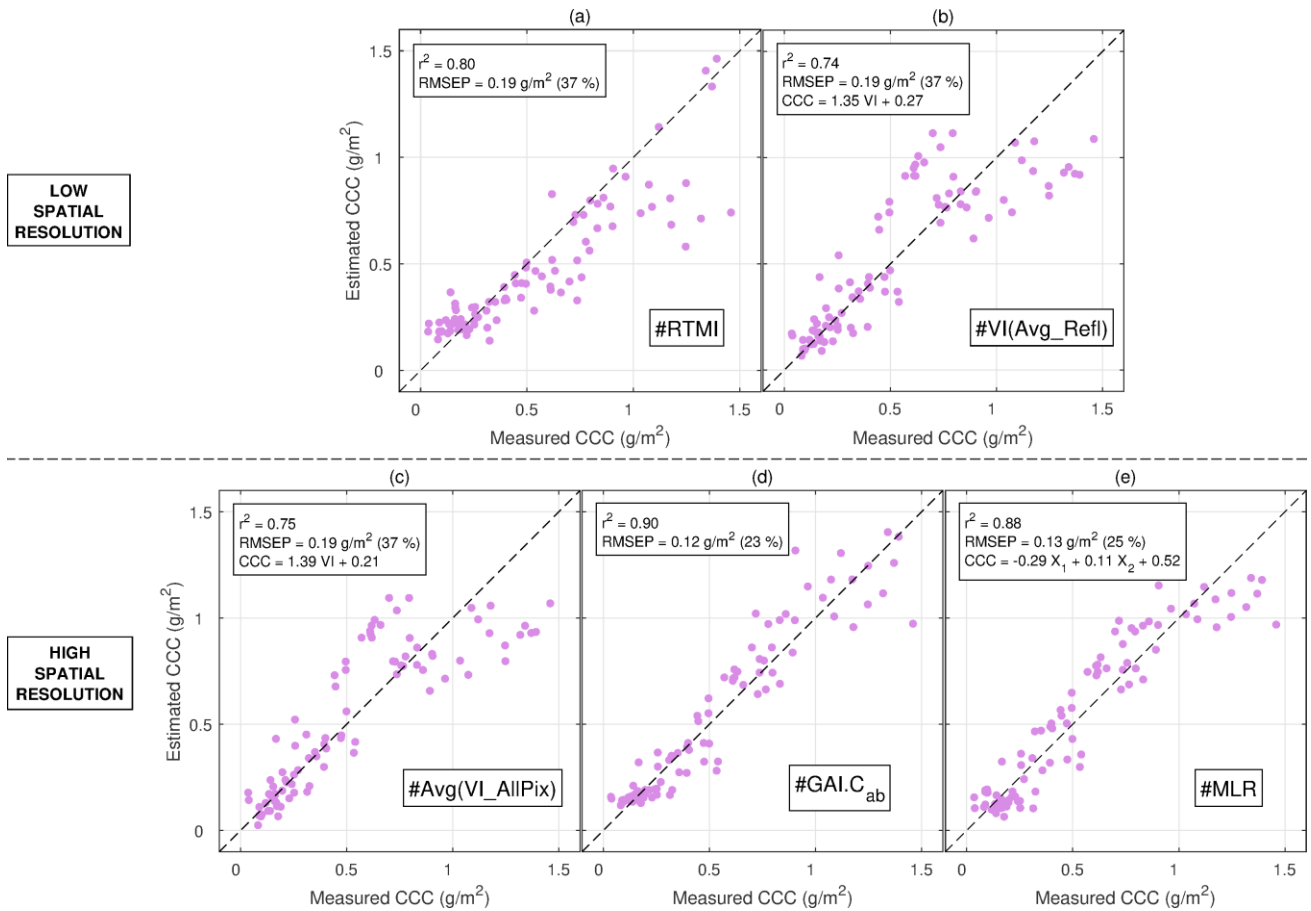
529

530 3.4.2. CCC estimation

531 Despite a similar bias as for GF and GAI, #RTMI based on PROSAIL inversion provides relatively accurate CCC
 532 estimates, with $RMSEP = 0.19 \text{ g/m}^2$ (Fig. 9.a). When using VIs computed from average microplot reflectances
 533 ($\#VI(Avg_Refl)$), all the VIs except mND_{blue} provides rather similar performances, with RMSEP ranging from
 534 0.19 g/m^2 for $VARI$ to 0.25 g/m^2 for $MTCI$ (Table 8, Fig. 9.b). Both approaches #RTMI and $\#VI(Avg_Refl)$
 535 generally show a strong dispersion for the highest CCC values (Figs. 9.a-b), corresponding to contrasted
 536 combinations of GAI and C_{ab} . For example, in the case of #RTMI and $CCC \geq 1.00 \text{ g/m}^2$, the most
 537 underestimated CCC values correspond to $GAI \geq 3.00$ and $C_{ab} \leq 40 \text{ µg/cm}^2$, while the most accurate CCC
 538 estimates correspond to $GAI \approx 2.80$ and $C_{ab} \geq 46 \text{ µg/cm}^2$.

539 Exploiting the centimeter resolution by using the average VI value of the microplot ($\#Avg(VI_AllPix)$) shows
 540 negligible difference with the previous $\#VI(Avg_Refl)$ approach (Table 8), $VARI$ and a linear model still
 541 providing the best performance ($RMSEP = 0.19 \text{ g/m}^2$, Fig. 9.c). On the other hand, combining the best GAI
 542 and C_{ab} estimates within approach $\#GAI.C_{ab}$ leads to a significant 37 % gain in estimation accuracy ($RMSEP =$

543 0.12 g/m²) as compared to previous approaches that do not differentiate between green and non-green pixels
 544 (Fig. .d). Similarly, the #MLR approach combining log(1-GF_{GREENPIX}) and VI_{CAB} also achieves very good
 545 performance, with RMSEP = 0.13 g/m² (Fig. .e).



546
 547 Fig. 9 : CCC estimation results obtained using low and high spatial resolution approaches: (a) #RTMI based on PROSAIL
 548 inversion, (b) #VI(Avg_Refl) with *VARI* and a linear model, (c) #Avg(VI_AllPix) with *VARI* and a linear model, (d) #GAI.C_{ab},
 549 and (e) #MLR based on standardized log(1-GF_{GREENPIX}) (Fig. 4.d) and VI_{CAB} (Fig. 6.d) values. For each method, the squared
 550 Pearson's correlation coefficient (*r*²) and the RMSEPs in absolute and relative (in %) are indicated. The regression
 551 equation is also shown for empirical approaches.

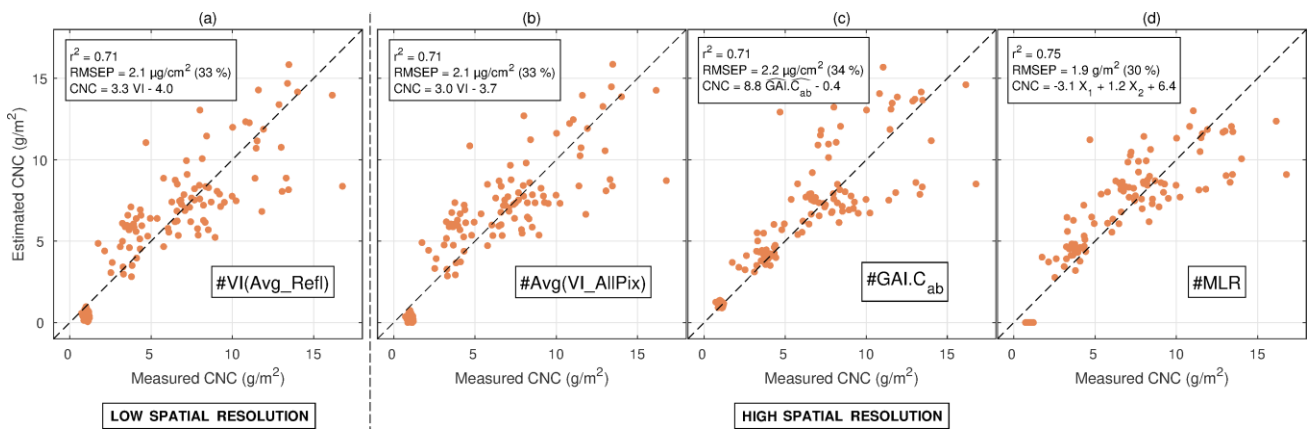
552

553 3.4.3. CNC estimation

554 As outlined in section 2.5.3, approach #RTMI could not be used to estimate CNC, since leaf nitrogen content
 555 is not an input variable of the PROSAIL model. When using approach #VI(Avg_Refl) based on average microplot
 556 reflectance, *CI_{green}*, *NDVI* and *VARI* provide the most accurate estimates (Table 8). The best results are
 557 obtained using *CI_{green}* and a linear model, with RMSEP = 2.1 g/m² (Fig. 10.a).

558 Except for *MTCI*, approach #Avg(VI_AllPix) shows comparable performances as approach #VI(Avg_Refl)
 559 (Table 8): CI_{green} still performs the best, with $RMSEP = 2.1 \text{ g/m}^2$ and a linear model (Fig. 10.b). Similar
 560 results are also obtained using approach #GAI.C_{ab} based on the best GAI and C_{ab} estimates (Fig. 10.c). Further
 561 inspection of the results however indicates that #GAI.C_{ab} provides more accurate CNC estimates for $CNC \leq$
 562 5 g/m^2 . However, for higher CNC values, poor estimates are obtained with the three approaches. Finally, a
 563 slight improvement is observed when using approach #MLR, which achieves $RMSEP = 1.9 \text{ g/m}^2$ (Fig. 10.d).

564



565

566 Fig. 10 : CNC estimation results obtained using low and high spatial resolution approaches: (a) #VI(Avg_Refl) with
 567 CI_{green} and a linear model, (c) #Avg(VI_AllPix) with CI_{green} and a linear model, (d) #GAI.C_{ab} and a linear model relating
 568 CNC and the product of the best GAI and C_{ab} estimates (denoted \widehat{GAI} and \widehat{C}_{ab}), and (e) #MLR based on standardized
 569 $\log(1-GF_{GREENPIX})$ (Fig. 4.d) and VI_{CAB} (Fig. 6.d) values. For each method, the squared Pearson's correlation coefficient (r^2)
 570 and the RMSEPs in absolute and relative (in %) are indicated. The regression equation is also shown for empirical
 571 approaches.

572

573 4. Discussion

574 All the results presented in sections 3.3 and 3.4 are summarized in Table 10 that will serve as a basis for the
 575 following discussion.

576

577 Table 10 : Summary of best performances obtained with the seven approaches tested for the estimation of GF, GAI, C_{ab} ,
578 CCC and CNC. Performances are here evaluated using the coefficient of determination (R^2). The best VI (when necessary)
579 and best performance are indicated in bold.

Spatial resolution	Approach	GF		GAI		C_{ab}		CCC		CNC	
		VI	R^2	VI	R^2	VI	R^2	VI	R^2	VI	R^2
Low	#RTMI	-	0.63	-	0.72	-	0.30	-	0.75	-	-
	#VI(Avg_Refl)	<i>VARI</i>	0.96	<i>VARI</i>	0.82	<i>MTCI</i>	0.63	<i>VARI</i>	0.75	<i>CI_{green}</i>	0.70
	#Avg(VI_AllPix)	<i>VARI</i>	0.97	<i>VARI</i>	0.84	<i>MTCI</i>	0.64	<i>VARI</i>	0.75	<i>CI_{green}</i>	0.70
High	#Frac(GreenPix)	<i>VARI</i>	0.96	<i>VARI</i>	0.85	-	-	-	-	-	-
	#Avg(VI_GreenPix)	-	-	-	-	<i>mND_{blue}</i>	0.80	-	-	-	-
	#GAI. C_{ab}	-	-	-	-	-	-	-	0.90	-	0.68
	#MLR	-	0.98	-	0.84	-	-	-	0.88	-	0.75

580

581 4.1. PROSAIL inversion provides less accurate estimates than empirical approaches

582 When inverting PROSAIL based on average microplot reflectance (approach #RTMI), significant biases are
583 observed for the estimation of GF and GAI (Figs. 4.a and 5.a). Such results are probably due to the turbid
584 medium assumption used to describe the canopy structure within the SAIL model (Verhoef, 1985, 1984). As
585 with ground-based spectro-radiometric measurements (Jay et al., 2017b), this assumption seems to be a
586 limiting factor to accurately characterize the row structure of sugar beet canopies based on UAV observations.
587 Further, the biases observed for GF and GAI affect C_{ab} estimation through a compensation effect well known
588 in optical remote sensing (Baret et al., 2007; Baret and Buis, 2008; Jay et al., 2017b). In particular, the GAI
589 underestimation (Fig. 5.a) is partly compensated for by the C_{ab} overestimation generally observed for samples
590 with similar C_{ab} values around 30 $\mu\text{g}/\text{cm}^2$ but with strongly different canopy structures (Fig. 6.a). Because of
591 these compensations, the bias observed for the product of GAI and C_{ab} , namely, CCC, is less marked than those
592 observed for GF and GAI. Overall, PROSAIL inversion performs similarly or poorer than empirical approaches
593 for every targeted variable (Table 10). However, when properly exploited, the centimeter-resolution imagery
594 makes it possible to improve the performance for every variable, as we will see in the next sections.

595 4.2. Exploiting the centimeter resolution to compute VIs leads to more accurate 596 estimates than using VIs computed from average microplot reflectance

597 Empirical approaches can be applied to VIs computed from average microplot reflectances (#VI(Avg_Refl)), or
598 to VIs averaged over VI images (#Avg(VI_AllPix)) when exploiting the high spatial resolution imagery.

599 Approaches #VI(Avg_Refl) and #Avg(VI_AllPix) perform similarly (Table 10), although a slight improvement is
600 observed for canopy structure variables (GF, GAI) with #Avg(VI_AllPix). This agrees with the results of Jay et
601 al. (2017a) who suggested that approach #Avg(VI_AllPix) enhances the influence of the heterogeneity due to
602 shadowing and soil effects, which relate to the canopy structure. Another reason is that, unlike #VI(Avg_Refl),
603 approach #Avg(VI_AllPix) used with ratio-based VIs is insensitive to multiplicative variations observed at the
604 pixel level and due mainly to soil brightness (Kauth and Thomas, 1976) and leaf orientation (Jay et al., 2016).
605 Besides enabling the use of VIs averaged over VI images, the centimeter resolution makes it possible to focus
606 on a subset of pixels of interest. For example, approach #Frac(GreenPix) relates the fraction of green pixels to
607 GF and GAI, while #Avg(VI_GreenPix) uses VI values averaged over the selected darkest green pixels to provide
608 the best C_{ab} estimates (Table 10).

609 4.3. The *VARI* index provides the most accurate estimates of canopy structure variables 610 (GF, GAI)

611 Canopy structure variables (GF and GAI) are best estimated using *VARI* or *NDVI* (Tables 8 and 9). The strong
612 correlation between both VIs (Table 6) indicates that they convey similar information for the ranges of GF and
613 GAI values investigated. The remarkable relationship between GF and *VARI* averaged over all soil and
614 vegetation pixels is consistent with the literature (Gitelson et al., 2002) and makes this VI the most appropriate
615 for accurately retrieving GF in this study. *VARI* also leads to $GF_{GREENPIX}$, defined as the fraction of green pixels
616 obtained by thresholding the *VARI* image (approach #Frac(GreenPix)). As GF and GAI are closely but non-
617 linearly related in sugar beet crops (Table 5), GAI can be accurately derived from $\log(1 - GF_{GREENPIX})$.
618 Because *VARI* is based only on visible bands (Table 3) for which leaf and soil reflectances are minimum, it is
619 significantly less affected by multiple scattering caused by surrounding elements as compared to other VIs
620 using a NIR band. Using *VARI* within approach #Avg(VI_AllPix) thus leads to very accurate and stable GF and
621 GAI estimates, especially when considering a highly heterogeneous data set such as the one used in this study.
622 However, when the canopy reaches nearly full cover for $GAI \geq 3.00$, *VARI* saturates and becomes insensitive
623 to GAI, especially because it does not use a NIR band that saturates for much higher GAI values (Jacquemoud

624 et al., 2009). This saturation effect and the associated GAI underestimation are clearly visible in Fig. 5 and are
625 consistent with the findings of Andrieu et al. (1997).

626 Overall, approaches #Avg(VI_AllPix) and #Frac(GreenPix) provide very similar GF and GAI estimation
627 performances (Table 10), especially when considering that GAI reference measurements are also affected by
628 some level of uncertainty (section 2.2). However, approach #Frac(GreenPix) is expected to be more robust
629 than #Avg(VI_AllPix) because it is not based on the whole distribution of *VARI* values in the image, but only
630 on the number of green pixels whose *VARI* values exceed 0.14. Therefore, #Frac(GreenPix) is less affected
631 than #Avg(VI_AllPix) by possible non-multiplicative variations in soil reflectance (e.g., between different sites
632 or due to shadows cast by leaves) and illumination conditions (e.g., under variable cloud coverage). The
633 beneficial influence of such robustness properties on the results could have certainly been more visible if the
634 illumination had been more variable during the flights. Yet, these properties are critical in the perspective of
635 applying a unique prediction model over a wide range of soil properties and illumination conditions, e.g., in a
636 phenotyping context.

637 4.4. The best C_{ab} estimates are obtained using the mND_{blue} index computed over the 638 darkest green pixels

639 When using average microplot reflectances (#VI(Avg_Refl)), the best performance obtained with *MTCI*
640 confirms its strong potential for retrieving C_{ab} from meter- to decameter-scale observations (Haboudane et
641 al., 2008; Hunt et al., 2012; Jay et al., 2017b, 2017a). The improved sensitivity to C_{ab} observed when computing
642 the VIs over a selection of green pixels (#Avg(VI_GreenPix)) is mainly due to the reduction of the soil influence,
643 as reported in the literature (Jay et al., 2017a; Moorthy et al., 2008; Zarco-Tejada et al., 2004, 2013, 2001).
644 This gain is very important for mND_{blue} that is extremely sensitive to this detrimental influence (Jay et al.,
645 2017a). Therefore, mND_{blue} performs the best when the *VARI* threshold used to extract green pixels is
646 sufficiently high to remove most of the soil pixels, including mixed pixels containing both soil and vegetation.
647 In this study, the optimal *VARI* threshold of 0.14 leading to optimal green segmentation (Table 9) may
648 therefore be slightly increased up to 0.20 to remove more mixed pixels, thus reaching best C_{ab} estimation.

649 Further, focusing on the dark green pixels rather than on the bright ones appears to be more effective for C_{ab}
650 estimation, which is inconsistent with previous studies (Jay et al., 2017a; Moorthy et al., 2008; Zarco-Tejada
651 et al., 2004, 2013, 2001). Leaf surface contribution that does not contain information on C_{ab} may explain the
652 poorer performance obtained with bright pixels, for which the importance and variability of the surface
653 reflectance is large. Further inspection shows that the poorer results obtained with bright green pixels are also
654 due to small errors in the co-registration of multispectral bands. These pixels are indeed not only located at
655 the top of canopy, but also on the plant/soil boundaries where the accuracy of the co-registration is the most
656 critical. An error of a few pixels is likely to induce unrealistic VI values at these boundaries, which may have a
657 critical influence on the average VI value. On the other hand, the use of dark green pixels is less affected by
658 errors in the co-registration as these pixels are usually located in the inner part of the canopy and thus
659 surrounded by other green pixels anyway. These results suggest that some improvements are required to
660 allow full exploitation of bright green pixels, hence improving C_{ab} estimation. Three avenues could be explored:
661 (i) improving the co-registration algorithm, (ii), using another multispectral camera technology for which the
662 different wavebands natively overlap, e.g., the one presented by Lee et al. (2014) or (iii) excluding pixels on
663 plant/soil boundaries (this would, however, require a significant increase in spatial resolution to make the
664 number of excluded pixels negligible compared to the total number of bright green pixels).

665 4.5. Using covariables improves the estimation of canopy biochemistry (CCC, CNC)

666 The addition of the information on C_{ab} derived from $\#Avg(VI_GreenPix)$ to that of $GF_{GREENPIX}$ within the $\#MLR$
667 approach does not significantly improve the estimation of single canopy structure variables such as GF and
668 GAI (Table 10). The $GF_{GREENPIX}$ estimates already provide very accurate GF estimates. The same applies to GAI
669 estimates based on $\log(1 - GF_{GREENPIX})$ because of the very strong relationship between GAI and GF (Table 5).

670 Conversely, in the case of CCC estimation, the $\#GAI.C_{ab}$ and $\#MLR$ approaches substantially outperform the
671 other approaches based on a single input variable ($\#VI(Avg_Refl)$, $\#Avg(VI_AllPix)$) (Table 10). In fact, when
672 directly related to CCC, VIs may not simultaneously detect CCC variations due to GAI and C_{ab} with sufficient
673 accuracies. For example, $VARI$ and $NDVI$ are strongly sensitive to GAI (up to $GAI \approx 3.00$) but nearly

674 insensitive to C_{ab} (Table 8), which partly explains the scatters observed for CCC in Figs. 9.b-c. Similarly, CI_{r-e}
675 is more sensitive to C_{ab} than $VARI$ and $NDVI$, but less sensitive to GAI (Table 8). As a result, these three VIs
676 obtain a similar accuracy of 0.19 g/m² for CCC. On the other hand, #GAI. C_{ab} exploits independently the two
677 optimal configurations for estimating the two components of CCC, namely, using $VARI$ and all the pixels of
678 the microplot image for GAI, and using mND_{blue} and only the darkest green pixels for C_{ab} . #GAI. C_{ab} thus makes
679 it possible to accurately capture the two sources of CCC variations, e.g., the variations due to C_{ab} that were
680 not detected with $VARI$ or $NDVI$ alone. This yields a significant 37 % gain in accuracy over #VI(Avg_Refl) and
681 #Avg(VI_AllPix). Note that #GAI. C_{ab} performs slightly better than #MLR since it directly combines the best
682 estimates of GAI and C_{ab} in a multiplicative way, as opposed to #MLR for which the two input variables are
683 combined in an additive way.

684 The case of CNC appears to be more complex than that of CCC. #GAI. C_{ab} does not bring any improvement as
685 compared to #VI(Avg_Refl) and #Avg(VI_AllPix), while the #MLR approach leads to the best performance
686 (Table 10). In fact, nitrogen does not absorb light at the six wavebands sampled by the camera (Curran, 1989),
687 which means that CNC can mainly be retrieved through its presumed correlation with CCC. Therefore, the
688 strong improvements obtained for C_{ab} and CCC when exploiting the centimeter resolution, do not result in a
689 strong improvement for CNC because CCC and CNC show a poorer correlation for $CNC \geq 5.0$ g/m², as already
690 suggested by Jay et al. (2017b) between different years. The more comprehensive data set used here thus
691 indicates that CCC is generally not an accurate proxy of CNC for large CNC values in sugar beet crops. Actually,
692 a significant amount of the nitrogen uptake is stored in the root for the latest stages (Draycott, 2006), which
693 could explain the loose relationship between leaf nitrogen content and C_{ab} for such stages.

694 5. Conclusions and perspectives

695 This study aims to quantify the benefits of centimeter-resolution multispectral imagery as acquired from a
696 UAV for the estimation of GF, GAI, C_{ab} , CCC and CNC in sugar beet crops. Besides testing classical methods
697 (#Avg(VI_AllPix) and #Avg(VI_GreenPix)) that relate each targeted plant trait and the average VI value
698 computed over a particular subset of pixels, we propose several novel methods (#Frac(GreenPix), #GAI. C_{ab} and

699 #MLR) that exploit the centimeter resolution to improve the estimation of canopy-level variables.

700 #Frac(GreenPix) exploits the GF estimate (denoted $GF_{GREENPIX}$) obtained by thresholding the *VARI* image to

701 identify the green pixels. $GF_{GREENPIX}$ is shown to be at least as accurate as GF estimates derived from other

702 approaches based on VI values averaged over the microplots, while being less dependent from soil optical

703 properties and variable illumination conditions leading to poor reflectance correction. Further, the logarithmic

704 transformation of $GF_{GREENPIX}$, $\log(1 - GF_{GREENPIX})$, provides the best GAI estimate at least up to $GAI \geq 3.00$. For

705 larger GAI values corresponding to $GF_{GREENPIX} \approx 1$, #Frac(GreenPix) should be combined with another approach

706 exploiting the red-edge and/or near infrared band(s) that should be still sensitive to GAI variations. In the case

707 of C_{ab} estimation, the results show the superiority of mND_{blue} computed over the darkest green pixels

708 (denoted VI_{CAB}), as compared to other approaches using all the pixels of the microplot. By simply multiplying

709 these C_{ab} estimates by the #Frac(GreenPix) GAI estimates, the chlorophyll content at the leaf level can be

710 upscaled to the canopy level, leading to the best CCC estimates (#GAI. C_{ab} approach). Similarly, combining

711 $\log(1 - GF_{GREENPIX})$ and VI_{CAB} within a multiple linear regression model (#MLR) leads to the best CNC estimates.

712 Compared to two standard remote-sensing approaches applied to average microplot reflectances, the

713 centimeter-resolution methods always improve the estimation performance, with a minimum gain of 8 % for

714 GAI and CNC, and maximum gains of 26 and 37 % for C_{ab} and CCC, respectively. It is worth noting here that the

715 centimeter-resolution methods based on $GF_{GREENPIX}$ would have led to even stronger gains if the illumination

716 conditions had strongly varied during the flights (this was not the case here). Since $GF_{GREENPIX}$ and VI_{CAB} are

717 sufficient to retrieve all the five targeted plant traits and can be computed using a low-cost multispectral (or

718 even RGB for $GF_{GREENPIX}$ only) camera, these two variables are promising for important agricultural applications

719 such as precision agriculture and phenotyping. In addition, the methods presented in this study might be

720 useful for the calibration and/or validation of vegetation land products derived from satellite imagery.

721 Despite the diversity of the data set used in this study, the robustness of the proposed empirical models should

722 be further assessed using a larger and more contrasted data set. Also, because some of the results presented

723 in this paper may be specific to sugar beet crops, they should be re-evaluated for other species. For example,

724 the two *VARI* thresholds leading to optimal GF and C_{ab} estimates may change with the canopy structure and
725 spatial resolution of the multispectral images. That said, the strong discrimination abilities of *VARI* suggest
726 that finely tuning these thresholds is not critical and that a unique threshold between 0.05 and 0.25 may be
727 sufficient for most cases if the spatial resolution is fine enough. The accuracy of GAI and C_{ab} estimation should
728 also be confirmed by using direct reference measurements, e.g., as provided using a pigment extraction
729 method for C_{ab} . A variety of other machine learning algorithms (Feilhauer et al., 2015; Verrelst et al., 2016)
730 could be tested to better handle possible non-linearities between $GF_{GREENPIX}$ (or $\log(1 - GF_{GREENPIX})$), VI_{CAB} and the
731 targeted variables. Finally, note that exploiting the high-resolution imagery through the $GF_{GREENPIX}$ and VI_{CAB}
732 variables requires a very accurate registration between the several images constituting the multispectral
733 image. Refining the co-registration process thus represents another way of improvement.

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