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1 **Effective GAI is best estimated from reflectance observations as**
2 **compared to GAI and LAI: demonstration for wheat and maize**
3 **crops based on 3D radiative transfer simulations**

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10 ***Abstract***

11 The definition of LAI (Leaf Area Index) is important when deriving it from reflectance observation for
12 model application and validation. Canopy reflectance and the corresponding quantities of LAI, PAI (Plant
13 Area Index), GAI (Green Area Index) and effective GAI (GAI_{eff}) are first calculated using a 3D radiative
14 transfer model (RTM) applied to 3D wheat and maize architecture models. A range of phenological stages,
15 leaf optical properties, soil reflectance, canopy structure and sun directions is considered. Several retrieval
16 methods are compared, including vegetation indices (VIs) combined with a semi-empirical model, and 1D
17 or 3D RTM combined with a machine learning inversion approach. Results show that GAI_{eff} is best
18 estimated from remote sensing observations. The RTM inversion using a 3D model provides more
19 accurate GAI_{eff} estimates compared with VIs and the 1D PROSAIL model with RMSE = 0.33 for wheat
20 and RMSE= 0.43 for maize. GAI_{eff} offers the advantage to be easily accessible from ground measurements
21 at the decametric resolution. It was therefore concluded that the most efficient retrieval approach would be

22 to use machine learning algorithms trained over paired GAI_{eff} and the corresponding canopy reflectance
23 derived either from realistic 3D canopy models or from experimental measurements.

24 ***Highlights***

- 25 • Wheat and maize canopy reflectance are simulated with realistic 3D model
- 26 • Effective GAI is best estimated from remote sensing observations
- 27 • 3D model provides the best estimation of effective GAI compared to 1D model and VIs

28 ***Key words***

29 effective GAI, wheat, maize, 3D radiative transfer model, canopy reflectance

30 **1 Introduction**

31 Leaf area index (LAI) was defined by Chen and Black (1992) as half the total developed area of leaves per
32 unit horizontal ground area. LAI is directly involved in vegetation functioning and is therefore widely
33 used in agriculture, ecology or global change research and application domains. As leaves represent the
34 main boundary between the plant and the atmosphere, LAI is a key variable used to evaluate the
35 exchanges of mass and energy (Liang 2004). Furthermore, it reflects the actual plant state and its potential
36 growth (Gonsamo 2009). However, depending on the targeted traits and processes, several definitions of
37 LAI are used:

- 38 • For the aboveground biomass estimation based on allometric relationships (Baret et al. 1989), LAI
39 from the Chen and Black's definition (1992) is relevant. Note that the Green Leaf Area Index (GLAI)
40 is often used in place of LAI, by considering only the green parts of the leaves.
- 41 • For the rainfall interception efficiency of the canopy, all the vegetation elements including leaves,
42 stems, branches and the other aerial organs, either green or senescent should be considered (Domingo
43 et al. 1998; Martello et al. 2015). This leads to using the Plant Area Index (PAI).

- 44 • For transpiration and photosynthesis, all the green parts that potentially exchange carbon and water
45 mainly through the stomata should be considered (Wang and Dickinson 2012). The Green Area Index
46 (GAI) should be used in this case.
- 47 • When estimating the radiation interception efficiency, the spatial arrangement of green vegetation
48 elements needs to be considered since leaf clumping may reduce the interception efficiency by the
49 mutual masking of elements, leading to the effective GAI (GAI_{eff}) definition. GAI_{eff} may be defined
50 as the GAI value of a turbid medium canopy that would provide the closest green fraction to that of
51 the canopy considered.

52 These different quantities are closely related, while their relationship will depend on the species, canopy
53 state, and stage. It is therefore mandatory to use the appropriate quantity to ensure a high degree of
54 consistency the targeted application.

55 Under field conditions, LAI (and GLAI) can be only accessed using direct methods where the (green for
56 GLAI) area of individual leaves is measured for all the leaves present over a given ground area. Similarly,
57 PAI can be measured directly by including the area of all the other elements while only the green parts
58 will be considered for GAI. However, these direct methods are tedious, low-throughput, and generally
59 destructive or at least invasive. This explains why indirect methods are widely used (Gower et al. 1999).
60 Indirect methods are based on instruments measuring canopy gap fraction (the fraction of background sun
61 seen in a given direction) or green fraction (the fraction of green area covered in a given direction) using
62 the same theory that relates the area of canopy elements to the gap (or green) fraction (Jonckheere et al.
63 2004). The simplest techniques are based on canopy transmittance measurements placed at the bottom of
64 the canopy and used as a proxy of the gap fraction. Hemispherical light sensor (Leblanc et al. 2005),
65 mono-directional sensor (Brede et al. 2018), or multidirectional sensors such as LAI2000 instrument
66 (Campbell and Norman 1988) or upward looking digital hemispherical photography (Demarez et al. 2008)
67 are widely used. Those techniques where the sensor is put at the bottom of the canopy, are sensitive to the
68 presence of both green and non-green elements without the possibility to separate them. They provide thus

69 a proxy of PAI (Norman and Campbell 1989). Conversely, techniques based on cameras looking
70 downward from above the canopy allows identifying the green pixels from which GAI is derived. Mono-
71 directional (Baret et al. 2010) or multi-directional (Weiss et al. 2004) views can be used. More recently
72 terrestrial laser scanners (Liu et al. 2017; Soma et al. 2018; Yan et al. 2019) or stereovision (Biskup et al.
73 2007) have been also used to build a 3D point cloud from which the directional canopy transmittance is
74 computed. This leads to estimates of PAI if no distinction is made between the green and non-green
75 elements, or to GAI when the green points are identified.

76 The transformation of the measured directional gap or green fraction into PAI or GAI is generally based
77 on some assumptions on canopy structure, particularly regarding leaf arrangement. One of the main
78 assumptions considers that leaves are randomly distributed within the canopy volume. A distinction is thus
79 made between the true PAI or GAI and the corresponding “effective” values that are derived from gap or
80 green fraction measurements assuming that leaves are randomly distributed (Fang et al. 2018; Nilson
81 1999).

82 PAI and GAI can also be retrieved from reflectance observations using empirically or physically based
83 methods. Empirical methods consist in calibrating relationships between a combination of reflectance in
84 several wavebands and ground measured LAI. The most common method is the use of spectral vegetation
85 indices (VIs) (Broge and Leblanc 2001; Broge and Mortensen 2002; Liu et al. 2012; Richardson et al.
86 1992). While in the past, empirical methods were calibrated, and thus, applicable over very restricted
87 experiments and environmental conditions, recent developments have shown that robust and accurate
88 estimates can be assessed with machine learning techniques providing that the data used to train the
89 algorithms represents well the domain of application (Camacho et al. 2017). Conversely, physically based
90 methods consist in inverting a Radiative Transfer Model (RTM) that simulates the physical processes
91 involved in the photon transport within the canopy (Strahler 1997). Inversion techniques such as
92 optimization (Jacquemoud et al. 2000), Look-Up-Tables (LUT) (Duan et al. 2014; González-Sanpedro et
93 al. 2008) or machine learning (Verrelst et al. 2012; Weiss et al. 2002) are used to estimate the RTM input

94 variables including PAI or GAI from the measured reflectances. The accuracy of such methods depends
95 on the ability of the model to simulate realistically the reflectance of the targeted canopy given a
96 description of the architecture of the canopy and the optical properties of its elements. The 1D RTMs such
97 as PROSAIL (Jacquemoud et al. 2009) assume that the canopy is a horizontally homogeneous layer of
98 randomly distributed leaves. Inverting 1D RTMs has the advantage of being computationally efficient and
99 characterized by a low number of inputs, which eases the setting of numerical experiments and constrains
100 the possible ambiguities between variables during the inversion process (Baret and Buis 2008). However,
101 several 3D radiative transfer models were developed to get more realistic simulations of canopy
102 reflectance: they combine an explicit 3D description of the canopy architecture while accounting for the
103 differences in optical properties of the several vegetation elements. 3D RTMs such as FLIGHT (North
104 1996) based on Monte Carlo ray tracing methods or DART (Gastellu-Etchegorry et al. 2004) based on the
105 discrete ordinate methods have already been used to retrieve canopy structure and biochemical variables
106 from remote sensing data (Banskota et al. 2015; Gascon et al. 2004; Hernández-Clemente et al. 2017;
107 Malenovský et al. 2013). Such 3D models are inverted using LUT or machine learning techniques.
108 However, compared to 1D RTMs, the large computation effort required to populate the LUT or the
109 training dataset, combined with the high number of variables and parameters required for the 3D
110 description of the canopy architecture mainly explain why the space of canopy realization is generally
111 poorly sampled, resulting into possibly less robust PAI or GAI estimates.

112 The objective of this study is to evaluate the retrieval performances from top of canopy reflectance
113 observations of the different xAI (PAI, LAI, GLAI, GAI and GAI_{eff}) state variables of interest. To
114 circumvent the influence of instrument difference and associated measurement errors, the retrieval
115 performances were evaluated with RTM simulations over realistic 3D wheat and maize scenes. To mimic
116 satellite observations using RTM simulations, SENTINEL-2 satellite data which is widely applied in
117 recent crop monitoring applications (Segarra et al. 2020) was selected as an example. We consider a range
118 of phenological stages for wheat and maize crops. We compared the performances of several retrieval

119 methods including VIs combined with a semi-empirical model, and a machine learning based RTM
120 inversion approach using the raw reflectance as inputs and trained with 1D or 3D RTM simulations.

121 **2 Material and methods**

122 We present here how the in-silico experiment was conducted to evaluate the retrieval performances of the
123 several xAI state variables. Realistic 3D wheat and maize scenes (section 2.1 and 2.2) were first combined
124 with 3D RTM simulations (section 2.3) to build a 3D reflectance dataset which was then split into training
125 (70%) and validation (30%). The simulations corresponding to the same training scenes were also
126 conducted with a 1D RTM to train the 1D approach (section 2.4). We then describe the retrieval methods
127 including a neural network machine learning RTM inversion using the raw reflectance as inputs and
128 trained either on the 1D or 3D simulations, and a VIs based approach based on a semi-empirical model
129 (section 2.5). Finally, we present the metrics (section 2.6) that were used to evaluate the retrieval
130 performances of the several state variables and approaches over the 3D reference validation dataset.

131 **2.1 The 3D canopy architecture models**

132 We selected two species characterized by different architectures: (1) wheat with small spacing between
133 rows and plants, and (2) maize with taller plants, larger row, and plant spacing. Wheat canopies shows a
134 clear row structure at early stages, its structure becomes similar to a turbid medium later in the vegetation
135 cycle. Maize canopy is characterized by a row structure that persists up to the latest stages. Leaf
136 inclination varies differently during the growth cycle for both species.

137 The 3D ADEL-Wheat model (Fournier et al. 2003) was selected to simulate the time course of the 3D
138 architectural growth of wheat. It is an up-to-date model calibrated over a range of experimental conditions
139 (Abichou et al. 2013), where leaf undulation and curvature are considered. For maize, we used the 3D
140 model created by López-Lozano et al. (2007) where plants are described by simple geometric shapes
141 (triangles for leaves and pyramids for stems), Even though this model does not account for leaf undulation
142 and curvature, maize canopies are much better represented than when using a turbid medium model (Casa

143 et al. 2010). As little knowledge is available on ear and flowers optical properties, both wheat and maize
 144 were simulated from emergence to the last stage before earing (wheat) or male flowering (maize). For
 145 both species, the fraction of senescent leaves appears marginal during this first part of the growth cycle. In
 146 such conditions, PAI \approx GAI and LAI \approx GLAI. The thermal time ($^{\circ}\text{Cd}$) is used to drive the wheat and
 147 maize development (Hallett and Jones 1993). It corresponds to the accumulated average daily air
 148 temperature since emergence.

149 For each species, 729 canopies were generated according to the variables listed in Table 1. The range of
 150 values considered for the input variables were derived from previous experiments (Abichou et al. 2013;
 151 López-Lozano et al. 2007; Liu et al. 2017). Each input variable was equally distributed between its
 152 minimum and maximum values (Table 1). Five development stages evenly distributed from 100°Cd to
 153 900°Cd for wheat, and from 150°Cd to 950°Cd for maize. The LAI, GLAI, PAI and GAI were calculated
 154 from the corresponding area of mock-ups. For LAI, the area of both green and senescent leaves were
 155 considered. For PAI, all elements including leaves and stems independently from their colour were
 156 considered, while only the area of green parts were considered for GAI. Since around 40% canopies had a
 157 GAI smaller than 1.0, 89 canopies with $\text{GAI} < 1$ were randomly eliminated from the wheat and maize
 158 canopies to avoid some oversampling of low GAI values. Therefore, 640 square scenes of 4.5m side for
 159 both wheat and maize were used for the 3D simulations. A typical 3D scene of wheat and maize canopy
 160 simulated with ADEL-Wheat and 3D maize models is shown in Figure 1.

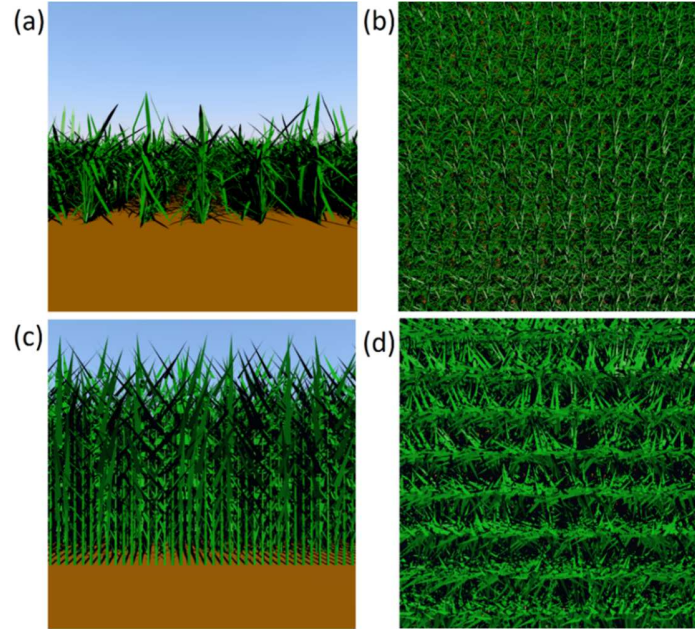
161 **Table 1** Parameters of ADEL-Wheat and 3D maize model used in this study.

	Variables		Unit	Min	Typical	Max	Steps
ADEL-Wheat	D	Plant density	plants/m ²	150	250	350	3
	N _{tiller}	Number of tillers per plant	-	3			1
	N _{leaf.main}	Number of leaves on the main stem	-	11			1
	TT _{phy}	Phyllochron	$^{\circ}\text{Cd}$	80	100	120	3
	L _{lamina}	Length of lamina one	cm	8	12	16	3
	Ang _{shift}	Rotation of leaf basal inclination	$^{\circ}$	-30	0	30	3
	Ang _{tiller}	Inclination of the base of the tiller	$^{\circ}$	20			1
3D	D	Plant density	plants/m ²	9			1
	d _{rows}	Distance between rows	m	0.6	0.7	0.8	3
	N _{max}	Maximum number of leaves per plant	-	18	20	22	3

	TT_{phy}	Phyllochron	$^{\circ}Cd$	50			1
	S_{max}	Maximum leaf area per plant	m^2	0.5	0.75	0.75	3
	H_{max}	Maximum plant height	m	2			1
	Θ_{max}	Inclination of largest leaf	$^{\circ}$	30	50	60	3

162

163



164

165 **Figure 1** Typical 3D scenes of wheat ((a) front view; (b) top view) and maize ((c) front view; (d) top view)

166 canopy simulated with ADEL-Wheat (LAI=2.26, GAI=2.34, GAI_{eff} I=2.15, PAI=2.56) and 3D maize

167 models. (LAI=4.78, GAI=6.51, GAI_{eff} =4.12, PAI=6.51)

168 2.2 GAI_{eff} computation

169 GAI_{eff} was defined consistently with the output of indirect ground measurement methods using

170 hemispherical photography (Weiss et al. 2004). GAI_{eff} was therefore computed from Welles and Norman

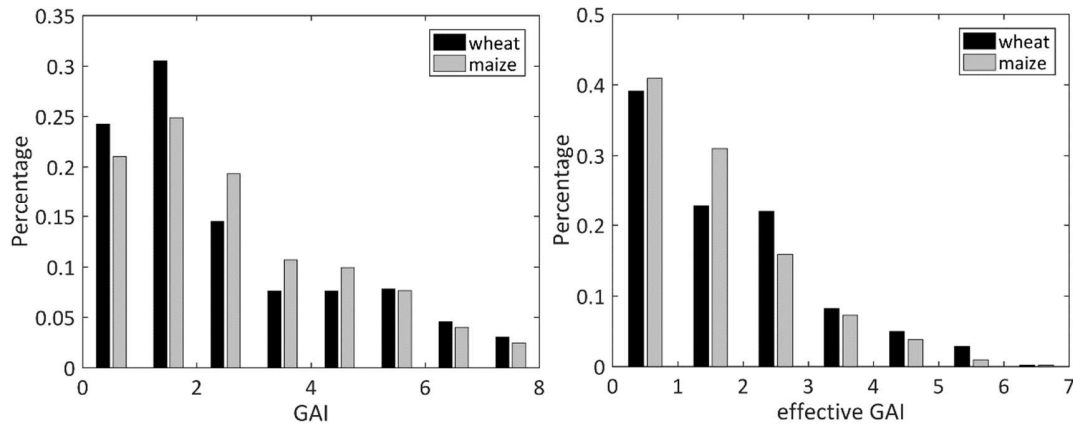
171 (1991) which corresponds to a close approximation of Miller's formula (Miller 1967) applied to the green

172 fraction. It relates GAI to the directional green fraction, $GF(\theta)$, assuming that the leaves are randomly

173 distributed in the canopy volume:

$$174 \quad GAI_{eff} = 2 \int_0^{\pi/2} -\ln(1 - GF(\theta)) \cos\theta \sin\theta \, d\theta \quad (1)$$

175 Where θ is the view zenith angle. The green fraction was thus simulated on each scene with
 176 LuxCoreRender for six view zenith angles spanning from 0° to 60° and averaged over all the azimuths.
 177 Even though part of the small GAI and GAI_{eff} values were discarded, the low values are still the most
 178 represented for the two crops (Figure 2).



179

180 **Figure 2** Distribution of GAI (left) and GAI_{eff} (right) of simulated wheat and maize.

181 2.3 LuxCoreRender reflectance simulations

182 Canopy reflectance was simulated using the LuxCoreRender 3D render engine (LuxCoreRender 2018)
 183 based on the 3D scenes generated by the crop architecture models. LuxCoreRender is an open source
 184 software (LuxCoreRender 2018; Pharr et al. 2016), which was validated against a set of state-of-the-art
 185 models by Jiang et al. (2020) using the RAMI Online Model Checker (ROMC) (Widlowski et al. 2008) .

186 The LuxCoreRender ray-tracing integrator was used with 1.36×10^3 samples of light and 16 path depths per
 187 pixel to guarantee the accuracy of the rendering of the simulated reflectance. The sun was the only light
 188 source with no adjacency contributions nor diffuse incoming radiation. The bidirectional reflectance factor
 189 was computed as the ratio of reflected photons in the view direction to those reflected by a perfect
 190 lambertian scatterer placed horizontally under the same illumination conditions. Finally, to minimize
 191 possible border effects, the 4.5m square scenes were replicated three times on each side to be large enough
 192 compared to the footprint of the camera.

193 Since reflectance simulation with LuxCoreRender is time consuming because of the ray-tracing process,
194 we used the method proposed by Jiang et al. (2020) to speed up the computations of LuxCoreRender: for a
195 given canopy structure and observational configuration, the method allows to accurately compute canopy
196 reflectance for any soil reflectance and any leaf properties (wavelength and biochemical composition) by
197 simulating canopy reflectance for two contrasted backgrounds and six value of the absorption coefficient
198 of the leaf that drives leaf reflectance and transmittance.

199 Five typical soil spectra with a variability in soil brightness (B_s) were selected to represent a large range of
200 soil background, assumed flat and lambertian (Table 2). Leaves were also assumed lambertian and
201 characterized by their reflectance and transmittance. Stems were characterized by the same reflectance as
202 the leaf with no transmittance. Their optical properties were simulated using the PROSPECT3 model
203 (Baret and Fourty 1997; Jacquemoud and Baret 1990) by considering the contents of four main absorbing
204 element: chlorophyllian pigments (C_{abc}), dry matter (C_{dm}), water (C_w) and brown pigments (C_{bp}). Their
205 distribution laws were defined similarly to Li et al (2015), based on a full factorial experimental plan to
206 sample more evenly the space of canopy realization (Table 2).

207 We selected six SENTINEL-2A bands in the visible, red-edge, and near infrared domains characterized by
208 the following central wavelengths: 450 nm, 560 nm, 665 nm, 705 nm, 740 nm and 865 nm. For each band,
209 the reflectance was spectrally integrated to take into account the SENTINEL-2A spectral response
210 function.

211 For each of the 640 scenes considered for each crop (Table 1), the camera was set at a nadir (View Zenith
212 Angle, $VZA=0^\circ$) corresponding to the most common observational configuration for decametric satellites
213 such as SENTINEL-2. The sun position varied by considering eight Sun Zenith Angles (SZA) and four
214 Sun Azimuth Angles (SAA) defined relatively to the row orientation (Table 2). Note that the row
215 orientation is here linked to the sun azimuthal direction which is made possible because of the nadir view
216 direction.

217 The 640 scenes were evenly divided into 18 classes according to the value of GAI and the averaged leaf
 218 angle (ALA). Finally, for each of the 20 illumination directions considered, a total of
 219 $18 \times 5 \times 5 \times 5 \times 3 \times 5 = 33750$ simulations were computed (Table 2). The simulated cases were randomly split
 220 into 70% used for the training database and 30% used to validate the retrieval performances of the several
 221 state variables and retrieval methods.

222
 223 **Table 2** Distribution of input variables used to generate canopy reflectance with 3D RTM simulations.
 224 The column Nb_Class corresponds to the number of levels used for the full factorial experiment design.
 225 VZA, SZA, SAA correspond to view zenith angle, sun zenith angle and sun azimuth angle. C_{ab} , C_{dm} ,
 226 C_{w_Rel} and B_s represent the chlorophyll content, the dry matter content, the relative water content and soil
 227 brightness.

		Input variable	Minimum	Maximum	Mode	Std	Nb_Class	Law
	Observation geometry	VZA(°)	0					
		SZA(°)	20, 35, 50, 65					
		SAA(°)	0, 25, 45, 67, 90					
(Jiang et al. 2020; Koetz et al. 2005; Li et al. 2015)	Leaf optical properties	Refractive Index n	1.4					
		Mesophyll, N	1.5					
		$C_{ab}(\mu\text{g}\cdot\text{cm}^{-2})$	20	90	45	30	5	Gauss
		$C_{dm}(\text{g}\cdot\text{cm}^{-2})$	0.003	0.011	0.005	0.005	5	Gauss
		C_{w_Rel}	0.6	0.85	0.75	0.08	5	Uniform
	C_{bp}	0.0	2.0	0.0	0.3	3	Gauss	
Soil background	B_s	0.5	3.5	1.2	2.0	5	Gauss	

228 2.4 1D PROSAIL simulations

229 The PROSAIL model (Baret et al. 1992) was generated from the combination of the PROSPECT leaf
 230 optical properties model (Jacquemoud and Baret 1990) and the SAIL (Scattering by Arbitrary Inclined
 231 Leaves) canopy reflectance model (Verhoef 1984) which assumes the canopy as a turbid medium, i.e.
 232 homogeneous infinitely extended horizontal layer of infinitely small leaves randomly distributed. A

233 hotspot parameter was introduced by Kuusk (1985) to account for the fact that leaves have finite
 234 dimensions. PROSAIL has been widely used to estimate canopy biophysical and structural variables for
 235 applications at different scales (Jacquemoud et al. 2009).

236 We used the same input variables for PROSPECT and soil background (Table 2) and generated canopy
 237 structure variables consistent with those used previously for the 3D models (Table 3). A total of
 238 $3 \times 6 \times 5 \times 5 \times 5 \times 3 \times 5 = 33750$ cases were simulated for both wheat and maize. A total of 70% of the simulated
 239 cases were randomly selected to match what was done for the 3D training database.

240 **Table 3** Distribution of input variables used to generate the learning database with PROSAIL model.

	Input variable	Minimum	Maximum	Mean	Std	Class	Law
Canopy structure	GAI	0.0	8.0	2.0	3.0	6	Gauss
	ALA (°)	30	70	45	30	3	Gauss
	hotspot	0.1	0.5	0.2	0.5	1	Gauss

241 2.5 Retrieval methods

242 2.5.1 Model inversion using neural networks

243 For each variable, based on the architecture defined by Li et al. (2015), two back-propagation NNs were
 244 trained, one using 3D LuxCoreRender and the other one using 1D PROSAIL simulations. This technique
 245 was applied operationally to derive kilometeric resolution (Baret et al. 2007) or decametric biophysical
 246 products (Delloye et al. 2018; Li et al. 2015; Verrelst et al. 2018; Weiss et al. 2002).

247 For the 3D RTM inversion, the inputs of NN were the canopy reflectance in the six selected SENTINEL-
 248 2A bands simulated from 3D model and the associated geometrical configurations including the cosine of
 249 SZA and the cosine of relative azimuth angle between SAA and the row direction. The considered outputs
 250 were either LAI, GAI or GAI_{eff} . For the 1D PROSAIL inversion, the inputs of the NN were the PROSAIL
 251 simulated canopy reflectance in the six selected SENTINEL-2A bands and the cosine of SZA. The
 252 corresponding outputs were GAI that indeed equals LAI since no other elements than the green leaves
 253 were considered in such a model, and GAI_{eff} that is in agreement with the 1D turbid medium assumption.

254 **2.5.2 VI based empirical retrieval**

255 Many vegetation indices based on the combination of a few spectral bands have been developed to
 256 retrieve variables related to the plant photosynthetic activity, such as GAI, fAPAR, and chlorophyll
 257 content (Myneni et al. 1995). We selected three vegetation indices among those proposed in the literature
 258 (Henrich et al. 2009): the Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974) which is
 259 the most widely used, the optimized Soil-Adjusted Vegetation Index (OSAVI) (Rondeaux et al. 1996)
 260 which was designed to minimize the effect from the soil background, and finally, the modified triangular
 261 vegetation index (MTVI2) which was found less sensitive to the saturation effect and thus provides more
 262 accurate estimates of high GAI values while reducing the influence of the soil background (Haboudane et
 263 al. 2004).

264
$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \quad (2)$$

265
$$OSAVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red} + 0.16} \quad (3)$$

266
$$MTVI2 = 1.5 \frac{1.2(\rho_{NIR} - \rho_{red}) - 2.5(\rho_{red} - \rho_{green})}{\sqrt{(2\rho_{NIR} + 1)^2 - (6\rho_{NIR} - 5\sqrt{\rho_{red}}) - 0.5}} \quad (4)$$

267 To relate VIs to different definitions of LAI, the modified version of Beer's Law describing VI as an
 268 exponential function of the foliage amount F (Broge and Mortensen 2002; Weiss et al. 2002) was
 269 selected:

270
$$VI = VI_{\infty} + (VI_g - VI_{\infty}) \exp^{K_{VI} \cdot xAI} \quad (5)$$

271 where xAI refers either to LAI, GAI, or GAI_{eff} . VI_{∞} represents the VI value for a very dense canopy
 272 ($xAI \rightarrow \infty$) and VI_g represents the bare soil value ($xAI = 0$) of VI; K_{VI} is equivalent to the extinction
 273 coefficient in the Beer Law. For each case, parameters [VI_{∞} , VI_g , K_{VI}] were fitted based on Eq.5 with
 274 VIs (NDVI, OSAVI, MTVI2) and LAI (or GAI, GAI_{eff}) calculated from the training database which were
 275 generated to train the 3D RTM neural networks.

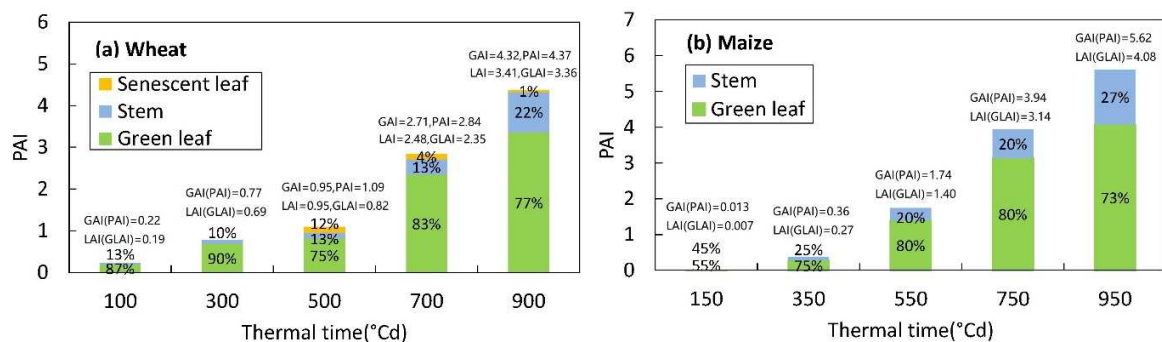
276 **2.6 Performance metrics**

277 The validation dataset generated from 3D simulation was used to evaluate the inversion results from NNs
 278 trained with 1D or 3D simulations. The root mean square error (RMSE) and the coefficient of
 279 determination (R^2) are used to evaluate the agreement between the original F value and the estimated one.

280 **3 Results**

281 **3.1 Contribution of the stems and senescent parts to PAI**

282 For the early stages (thermal time lower than 300°Cd), the stem area is negligible. After this period, the
 283 stem area is increasing and can have a PAI between 1 or 2 (Figure 3) representing almost one fourth of the
 284 total plant area. The maize simulated canopies have greater PAI than the wheat ones. The several scenes
 285 simulated by ADEL-Wheat and the 3D maize architecture models show a marginal fraction of senescent
 286 elements as already pointed out (Figure 3). Further, the senescent elements are mainly located at the
 287 bottom of the canopy, with a marginal contribution to canopy reflectance (Figure S1 provides an example
 288 of wheat canopy reflectance with or without senescent leaves in red and NIR). As a consequence,
 289 $LAI=GLAI$ and $PAI=GAI$, thus $GLAI$ and PAI will not be explicitly considered in the following of this
 290 study.



291 **Figure 3** Plant Area Index and the corresponding proportion of green leaves (green), senescent leaves
 292 (yellow) and stems (blue) of typical wheat (a) and maize (b) canopies during the vegetative stages.
 293

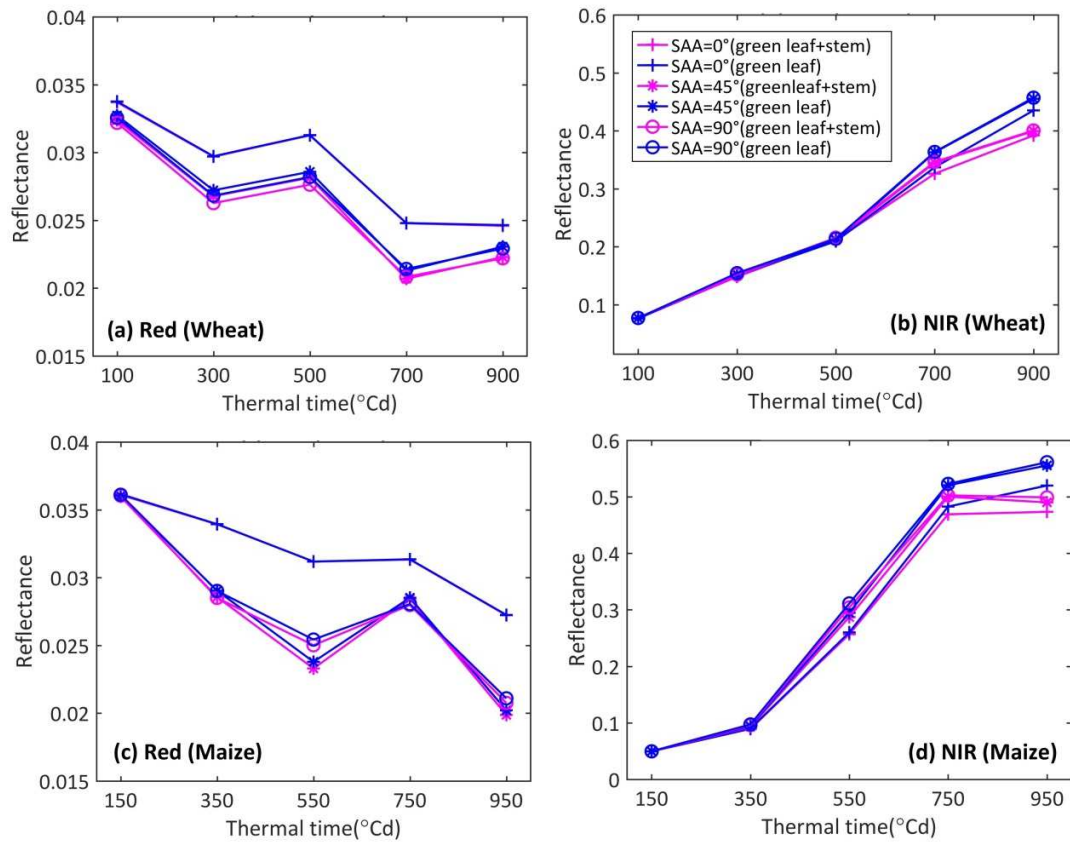
294 3.2 Impact of canopy structure assumptions on reflectance

295 We investigated the contribution of the stems to canopy reflectance as well as the role of the spatial
296 distribution of the elements. One 3D scene of wheat and maize were randomly selected from the 3D wheat
297 and maize architecture models (Section 2.1). The statistics of PAI, LAI, GLAI and GAI of those scenes
298 were described in Figure 3. Based on the LuxCoreRender reflectance simulations (Section 2.3), we
299 simulated the 3D scenes canopy reflectance in the Red (665nm) and NIR (865nm) bands. For the sake of
300 simplicity, constant optical properties of the canopy elements and soil background were used (Table 4).
301 The view direction was set at nadir with SZA=45° and SAA= [0°, 45°, 90°].

302 **Table 4** Optical properties of the different elements (leaves, stem, and soil background) used to analyze
303 the impact of wheat and maize canopy architecture assumptions on reflectance in the red and NIR domain.

	Reflectance		Transmittance	
	Red	NIR	Red	NIR
Green leaf	0.063	0.463	0.018	0.522
Stem	0.063	0.463	0.000	0.000
Senescent leaf	0.347	0.474	0.287	0.432
Soil	0.140	0.191	-	-

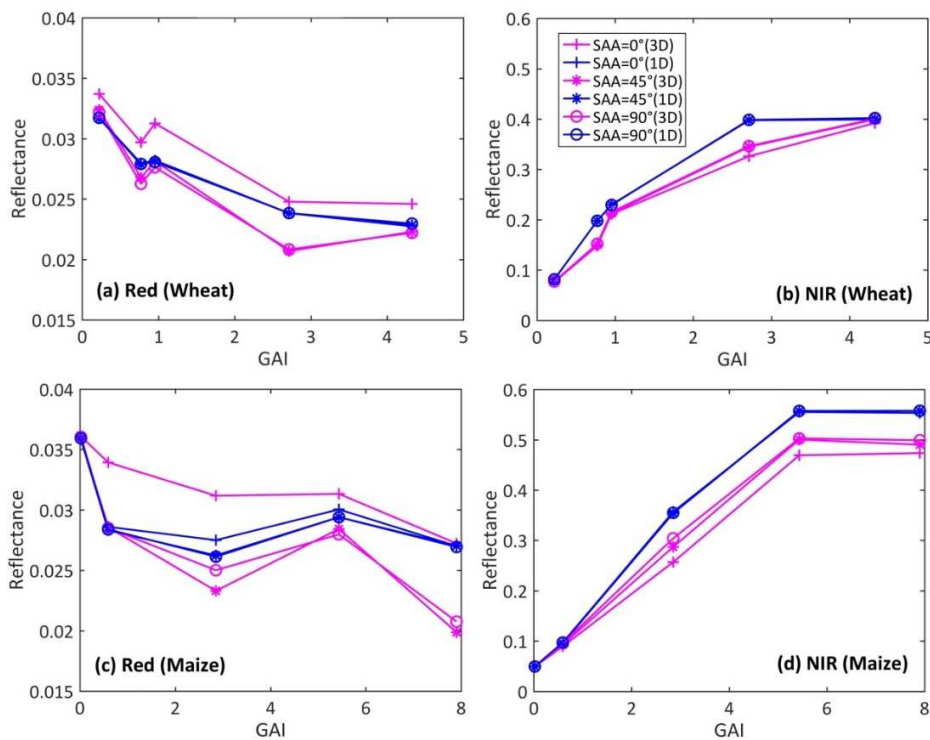
304 Results show that the stems have almost no influence on canopy reflectance in the red domain (Figure 4a
305 and Figure 4c) especially when the soil contribution is the highest (SAA=0°). This is explained by the low
306 value of leaf and stem reflectance and transmittance. Conversely, in the NIR domain, stems showed
307 significant impact on canopy reflectance, particularly for the later stages when the contribution of stems to
308 GAI increases (Figure 4b and Figure 4d). The decrease of canopy reflectance due to the stems in the NIR
309 is mainly explained by the strong stem absorption (null transmittance) that reduces the multiple scattering.
310



311
 312 **Figure 4** Comparison of canopy nadir reflectance (3D structure) between canopy with leaves and stems
 313 (red) and canopy with only leaves (blue) in red (left) and NIR (right) for wheat (top) and maize (bottom)
 314 for three sun azimuth angles values SAA = 0° (+), 45° (*) and 90° (○) and a sun zenith angle at 45°.

315 We then simulated a turbid medium version of each scene by keeping the same canopy elements with their
 316 corresponding optical properties and original orientation, and distributed them randomly in the canopy
 317 volume. This allowed performing a fair comparison between a random medium (1D) and the actual 3D
 318 crop architecture. Because of this random distribution of the elements in the 1D canopy structure
 319 description of wheat and maize (Figure 5), reflectance is independent from the sun azimuthal position.
 320 Conversely, canopy reflectance of the 3D realistic canopy architecture shows significant variations with
 321 sun azimuth, especially when the sun is parallel to the row direction and under its nominal zenith angle
 322 (SZA=45°).

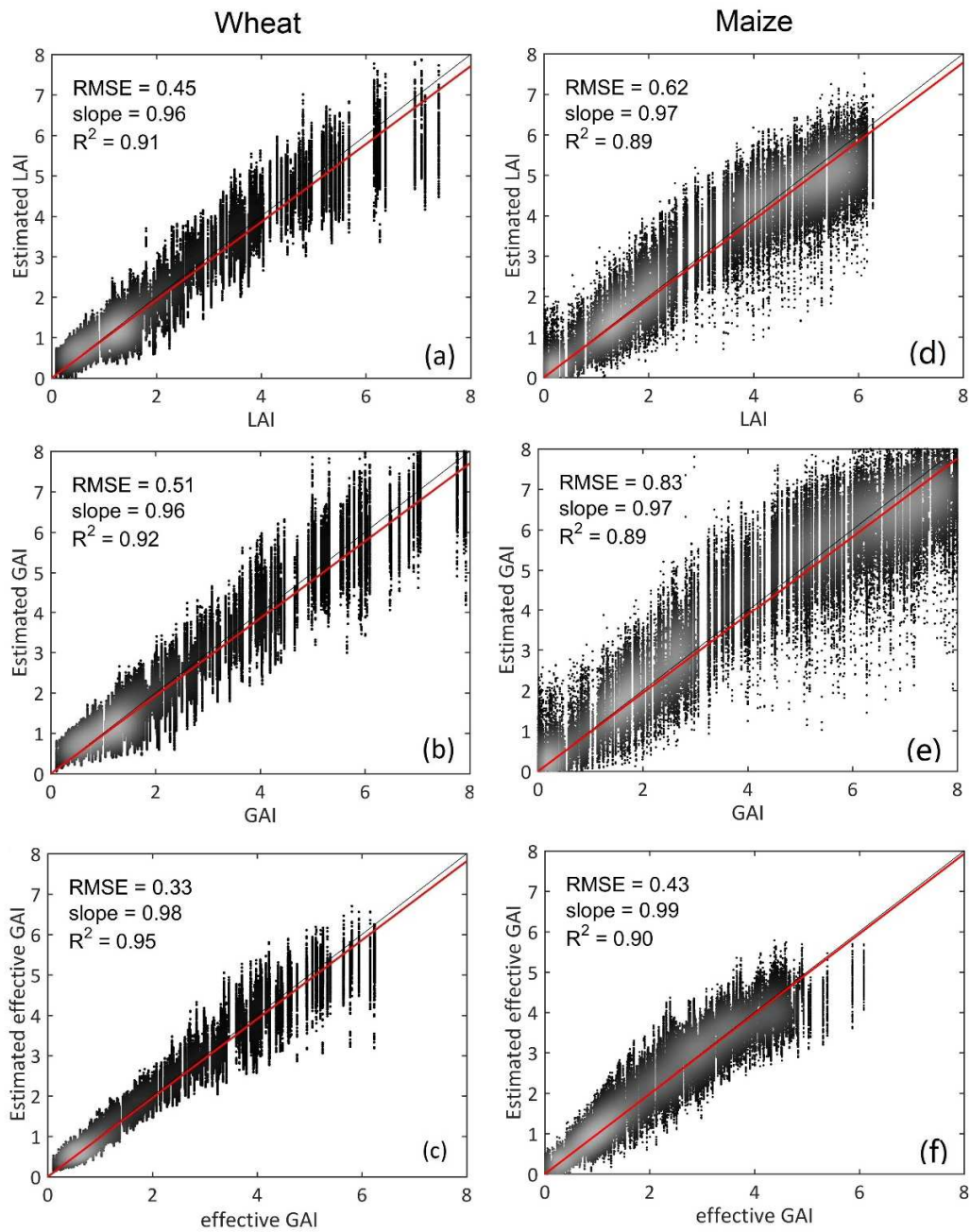
323 In the NIR, the 1D canopy always shows a higher crop reflectance than the 3D one (Figure 5b and Figure
 324 5d). This is mainly due to a higher probability for a photon to interact with a leaf in the absence of
 325 clumping (Duthoit et al. 2008). This boosts multiple scattering and lowers the soil contribution, the soil
 326 being less reflective in the NIR than the leaves (Table 4). Conversely in the red domain, the soil is more
 327 reflective in the red as compared to leaves (Table 4). When the sun is parallel to the row direction
 328 ($SAA=0^\circ$), the higher proportion of soil illuminated between the rows in the 3D description explains that
 329 canopy reflectance is higher than that of the 1D description (Figure 5a and Figure 5c). When canopy
 330 develops, the difference in reflectance between 1D and 3D assumptions increases for maize while
 331 remaining almost constant for wheat. This demonstrates that, conversely to maize, for the latest stages, the
 332 structure of the wheat canopy becomes closer to a turbid medium, with a decreasing row effect.



333
 334 **Figure 5** Comparison of canopy nadir reflectance between turbid medium assumption (magenta) and 3D
 335 realistic structure (blue) in red (left) and NIR (right) for wheat (top) and maize (bottom) for three sun
 336 azimuth angles values $SAA = 0^\circ$ (+), 45° (*) and 90° (○) and a sun zenith angle at 45° .

337 **3.3 GAI_{eff} is better estimated than LAI and GAI**

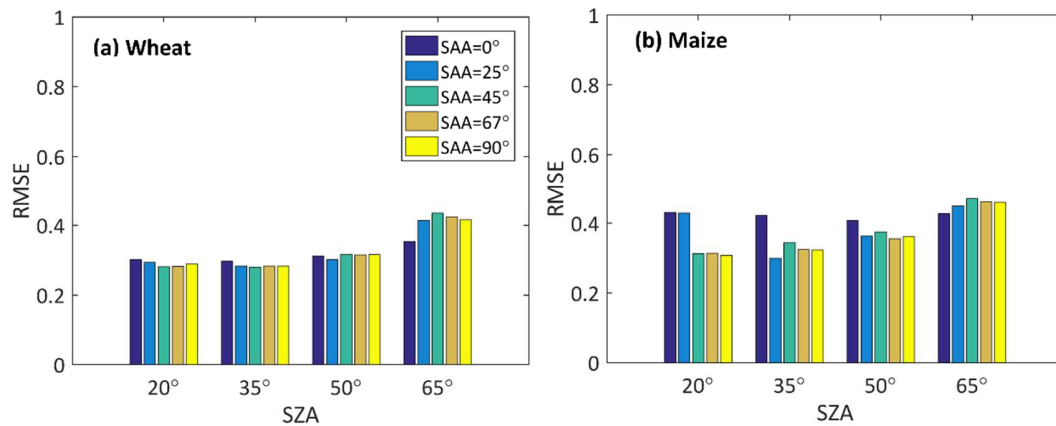
338 NN were trained on the 3D wheat or maize canopies to estimate either LAI, GAI or GAI_{eff} . The retrieval
339 performances were evaluated on the 3D simulated validation dataset that was not used during the training
340 process. Results showed that LAI and GAI are estimated with similar performances in terms of R^2 (Figure
341 6). However, RMSE values for GAI are slightly larger mainly because of the larger range of variation of
342 GAI as compared to LAI that does not include the area of green stems. Slight systematic underestimation
343 is observed for the high LAI and GAI values, which is due to the combined effect of reflectance saturation
344 (Price and Bausch 1995) and the fact that, conversely to Li et al (2015), the training dataset is limited by
345 the fewer representative cases of LAI or GAI above 6 (Figure 6). The estimation of GAI_{eff} showed the best
346 performance with the highest R^2 and the smallest RMSE (RMSE = 0.33, $R^2 = 0.95$ for wheat and RMSE =
347 0.43, $R^2 = 0.90$ for maize). Here again, the smaller values of RMSE are partly explained by the smaller
348 range of variation of the GAI_{eff} as compared to LAI and GAI. The scattering around the 1:1 line slightly
349 increases with LAI, GAI or GAI_{eff} because of the decreasing sensitivity of reflectance to variation in the
350 amount of green area as already observed in Figure 4 and Figure 5. Therefore, GAI_{eff} appears as a
351 pertinent variable when using reflectance observations over typical crops. Furthermore, it offers the
352 advantage of being more directly comparable to estimates of the GAI_{eff} derived from indirect ground
353 measurements techniques (Jonckheere et al. 2004). This will allow to validate GAI_{eff} values estimated
354 from remote sensing without explicitly handling the complex problem of accounting for the leaf clumping
355 (Leblanc and Fournier 2014).



356
 357 **Figure 6** Scatter plots between state variables estimated from neural networks trained over 3D model
 358 simulations and wheat LAI (a), wheat GAI (b), wheat GAI_{eff} (c), maize LAI (d), maize GAI (e), and
 359 maize GAI_{eff} (f). The lighter color increases with the point density. The black line corresponds to the 1:1
 360 line. The red line is the best linear fit with no intercept.

361 **3.4 Performances of GAI_{eff} estimates are almost insensitive to the sun position**

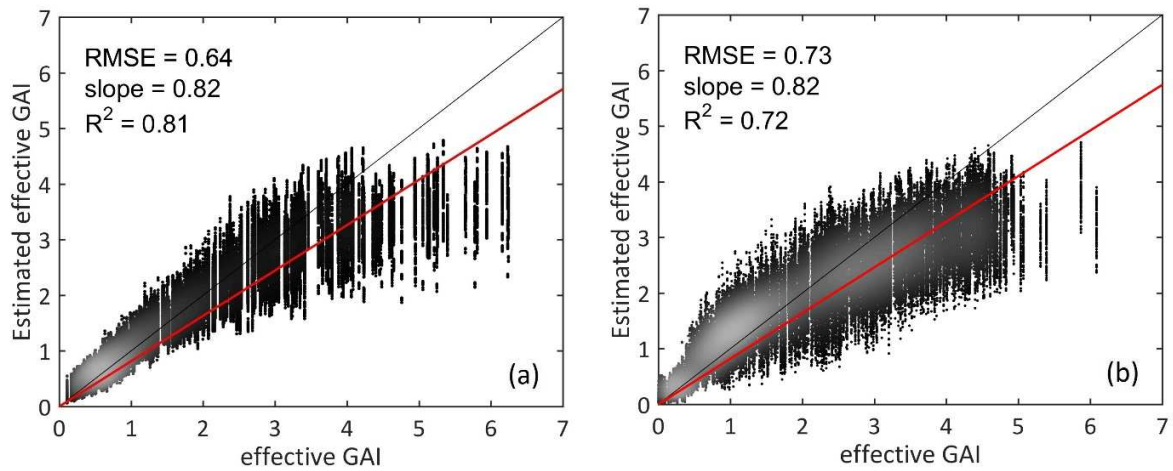
362 Retrieval of GAI_{eff} from ground measurements of the green fraction exploits all the directions of the
363 hemisphere (Eq. 1). Conversely, canopy reflectance depends on the sun and view directions which are
364 explicitly used as inputs into the retrieval process. We therefore investigated here the possible residual
365 impact of the sun position on the retrieval performances of GAI_{eff} under near nadir viewing direction that
366 corresponds to the most common observational configuration for decametric satellites such as
367 SENTINEL-2. Results show that GAI_{eff} estimation performances are little sensitive to the sun position
368 (Figure 7), with RMSE between 0.3 and 0.4. However, a slight degradation of GAI_{eff} retrieval
369 performances is observed when SZA increases. This may be explained by the larger optical depth in the
370 canopy for the more inclined illumination directions that makes canopy reflectance less sensitive to the
371 elements placed at the bottom of the canopy. The change in SAA marginally impacts performances for
372 wheat, in agreement with the small row effect and closeness to the turbid medium assumption.
373 Nevertheless, some small effect is observed for $SZA=65^\circ$, where slightly better performances are
374 observed when the sun is parallel to the rows. This may be due to the enhanced reflectance sensitive to
375 changes in GAI in the inter-row spacing for the higher GAI values while saturation occurs earlier on the
376 row. The same is observed for maize (Figure 7). However, significant degradation of performances are
377 observed for maize for $SZA < 40^\circ$ and sun directions close to that of the row. This may be due to the
378 combined effect of the higher sensitivity to the background properties when the soil is well illuminated,
379 and an earlier saturation of reflectance to changes in GAI on the row.



380
 381 **Figure 7** RMSE between GAI_{eff} and estimated GAI_{eff} from NN trained with 3D datasets for wheat (a) and
 382 maize (b). Results are evaluated using the validation dataset for several sun azimuth angles (SAA) and sun
 383 zenith angles (SZA).

384 3.5 3D structure description improves estimates of GAI_{eff} as compared to a 1D 385 description

386 The same GAI_{eff} value may correspond to a range of canopy structure associated to a range of radiometric
 387 response. We therefore compared the performances of GAI_{eff} estimation using either a 1D radiative
 388 transfer model such as PROSAIL, or the realistic 3D models of wheat or maize. Results show that for both
 389 wheat and maize, accounting for the 3D structure description (Figure 6c and Figure 6f) provides more
 390 accurate estimates of GAI_{eff} than the turbid medium assumption (Figure 8). Conversely to the GAI_{eff}
 391 derived from NN trained with the 3D model, the 1D model inversion resulted in a systematic
 392 underestimation for both crops when GAI_{eff} is higher than 4. For GAI_{eff} lower than 4, the estimated GAI_{eff}
 393 from PROSAIL model shows good agreement with GAI_{eff} for wheat (Figure 8a), while more outliers are
 394 observed for maize. Similar results are observed by Duveiller et al. (2011) and Camacho et al. (2017) who
 395 compared indirect GAI_{eff} measurements with estimates from NN trained on PROSAIL.



396
 397 **Figure 8** Scatter plots between estimated GAI_{eff} from NN trained over PROSAIL model simulations and
 398 GAI_{eff} for (a) wheat and (b) maize. The grey level intensity increases with the density of points. The black
 399 line corresponds to the 1:1 line. The red line is the best linear fit with no intercept.

400 **3.6 Using raw reflectance values and machine learning performs better than**
 401 **vegetation indices and a semi-empirical model**

402 The parameters of the empirical model (Eq. 5) describing the relationship between VIs and GAI_{eff} were
 403 fitted over the training database made of 3D model simulations. Since Eq. 5 does not account explicitly for
 404 the illumination direction, parameters $[VI_{\infty}, VI_g, K_{VI}]$ were tuned for each sun zenith and azimuth angles,
 405 and when considering all the sun angles together. The values of K_{VI} with different sun directions were
 406 showed in Table S1. Results showed better GAI_{eff} estimates (higher R^2) for most of the sun angles when
 407 the parameters $[VI_{\infty}, VI_g, K_{VI}]$ are tuned for each illumination direction (Table 5). The R^2 are
 408 significantly lower for maize as compared to wheat. OSAVI and MTVI2 are performing better than NDVI
 409 since they were designed to be less sensitive to the soil background and the canopy structure (Liu et al.
 410 2012; Nguy-Robertson et al. 2012). Highest R^2 are observed when the sun is parallel to the rows ($SAA=0^\circ$)
 411 similarly to what was observed in Figure 7 when using the raw reflectances from 3D simulations and a
 412 machine learning inversion.

413 **Table 5.** Determination coefficients (R^2) associated to the goodness of fit of Eq. 5 between VIs (NDVI,
414 OSAVI and MTVI2) observed on the training database made of 3D model simulations. The several sun
415 directions [SZA, SAA] are either considered separately or grouped together. Red color indicates the
416 poorest performances while green corresponds to the best ones.

		NDVI				OSAVI				MTVI2			
		20°	35°	50°	65°	20°	35°	50°	65°	20°	35°	50°	65°
Wheat	SZA 0°	0.68	0.69	0.68	0.67	0.73	0.74	0.74	0.7	0.83	0.84	0.83	0.79
	25°	0.69	0.69	0.69	0.36	0.74	0.75	0.75	0.71	0.84	0.81	0.73	0.58
	45°	0.7	0.7	0.58	0.26	0.76	0.74	0.74	0.66	0.84	0.74	0.66	0.64
	67°	0.69	0.68	0.53	0.26	0.76	0.76	0.75	0.66	0.83	0.73	0.64	0.64
	90°	0.7	0.68	0.53	0.27	0.75	0.76	0.75	0.66	0.82	0.72	0.65	0.62
	All angles	0.54				0.7				0.65			
Maize	SZA 0°	0.55	0.56	0.54	0.46	0.55	0.56	0.58	0.61	0.66	0.68	0.69	0.66
	25°	0.63	0.54	0.18	0.11	0.62	0.66	0.53	0.16	0.67	0.64	0.62	0.48
	45°	0.59	0.41	0.15	0.11	0.66	0.6	0.48	0.1	0.65	0.57	0.61	0.43
	67°	0.52	0.42	0.15	0.1	0.63	0.59	0.47	0.1	0.61	0.59	0.6	0.42
	90°	0.5	0.43	0.18	0.1	0.64	0.59	0.47	0.14	0.6	0.59	0.59	0.46
	All angles	0.21				0.46				0.42			

417
418 Eq. 5 fitted for each illumination direction over the 3D training dataset was then evaluated over the 3D
419 validation database to estimate GAI_{eff} . For both wheat and maize crops, OSAVI appears to perform
420 slightly better than MTVI2, and significantly better than NDVI (Table 6). However, using the raw
421 reflectances from 3D model simulations as input to the NN for GAI_{eff} estimation outperforms VIs with
422 RMSE values divided by almost a factor of two (Table 6). The higher degree of flexibility of the model
423 inversion approach based on machine-learning explains most of these improved performances. Indeed,
424 about 50 coefficients were tuned in case of the NN while only three are fitted in Eq. 5. for the VI based
425 approach. Furthermore, VIs are using only two to three wavebands as compared to the six wavebands used
426 in the machine learning based inversion approach.

427 **Table 6** GAI_{eff} retrieval performances using VIs (NDVI, OSAVI and MTVI2), or neural networks trained
 428 on raw reflectances from 3D model simulations. Colors are coded according to the RMSE or R^2 values
 429 from best (green) to worst (red).

	Wheat		Maize	
	RMSE	R^2	RMSE	R^2
NDVI	0.95	0.54	1.21	0.21
OSAVI	0.77	0.70	1.00	0.46
MTVI2	0.83	0.65	1.02	0.42
Raw reflectances	0.33	0.95	0.43	0.90

430 **4 Discussion**

431 In this study, we investigated the several ways to characterize the area of canopy elements from remote
 432 sensing observations based on 3D simulation. The question is complex since at least two aspects should be
 433 tackled concurrently: First, among PAI, LAI, GLAI, GAI and GAI_{eff} , which quantity is best estimated
 434 from reflectance data? Second, is this quantity useful for given applications? Our simulations conducted
 435 over wheat and maize crops clearly demonstrated that the GAI_{eff} is the quantity that is best estimated from
 436 nadir reflectance observations in 6 bands corresponding to a standard configuration of decametric
 437 resolution satellite observations as provided since 2015 by SENTINEL-2. However, in this study, the
 438 amount of senescent elements was marginal, which implies that $PAI \approx GAI$ and $LAI \approx GLAI$. Further
 439 simulations should be conducted for later stages where the senescent elements are increasingly present.
 440 The results we obtained over two major crops should be extended to other vegetation types to verify the
 441 robustness and the validity of our results. The second aspect, i.e. the pertinence of the GAI_{eff} for
 442 applications, requires more attention. Indeed, considering all the green vegetation elements (GAI) that are
 443 potentially active appears well suited when monitoring the capacity of the crop to grow, or to quantify its
 444 past growth. However, GAI_{eff} is better suited to quantify the light interception efficiency according to the
 445 proposed definition based on the directional green fraction. Additionally, this offers the advantage to get a
 446 definition that is fully consistent with indirect ground methods that can be used for the validation. It can
 447 also be used for the calibration of machine learning algorithms over ground experiments if empirical

448 approaches such as those conducted by Camacho et al. (2017) are further investigated. Ultimately, the use
449 of GAI_{eff} that is clearly defined and more robustly estimated, may also help when integrating remote
450 sensing observations into crop growth models for which canopy structure is generally described in a very
451 simple way.

452 The next question that we investigated was related to the best canopy architecture description required to
453 get accurate estimates of the targeted GAI_{eff} variable from reflectance observations. We thus compared
454 realistic 3D canopy architecture description with the 1D counterpart that is consistent with the turbid
455 medium nature used to define the ‘effective’ GAI. We used a neural network machine learning algorithm
456 to invert both the 1D and 3D models. Results obtained over an independent set of 3D canopy architecture
457 simulations clearly demonstrated the importance of using a realistic 3D canopy architecture description to
458 get reflectance simulations as close as possible to the observed ones.

459 Finally, we also investigated the best GAI_{eff} retrieval approach by comparing the use of VIs and a semi-
460 empirical model versus the use of raw reflectances with a machine learning based RTM inversion. Results
461 clearly demonstrated that VIs have strong limitations due to at least three factors: First, the fact that they
462 are not exploiting the whole spectral information available since they generally use two to three bands as
463 compared to the six ones that were used in the radiative transfer model inversion; Second, the simple
464 combination of bands used to compute VIs results into a loss in information as compared to using the
465 original reflectance wavebands as inputs in the retrieval algorithm; Third, the semi-empirical model
466 relating the GAI_{eff} to VIs is using only three parameters to account for the variability in canopy
467 architecture, leaf and soil properties, even if the illumination conditions are accounted for by adjusting the
468 three parameters for each conditions.

469 **5 Conclusion**

470 In this study, canopy reflectance and the corresponding variables including LAI, PAI, GAI and GAI_{eff}
471 were first calculated using a 3D RTM applied to 3D wheat and maize architecture models. Different
472 inversion methods including VIs, 1D RTM PROSAIL and 3D RTM LuxCoreRender are compared.

473 Results show that GAI_{eff} is best estimated from remote sensing observations and is better suited with
474 indirect ground measurements at the decametric scale. The outcomes also indicate that the best GAI_{eff}
475 retrieval approach would be to train machine learning algorithms using a training database where accurate
476 GAI_{eff} values are paired with accurate corresponding reflectance values. The 3D model simulations as
477 completed in this study is a possible solution that requires the canopy architecture models to be very
478 realistic, and the distribution of their input parameters and variables very well designed to represent the
479 actual ones. However, the retrieval methods based on 3D model simulations presented in this study should
480 be extended to other types of vegetation and then evaluated using actual observations. Alternatively,
481 empirical approaches based on accurate GAI_{eff} values measured from indirect ground methods and on
482 concurrent corresponding canopy reflectance measured by the satellite are very appealing. They need
483 however to sample a large range of canopy state and illumination conditions. This is now possible for
484 decametric resolution, where the ground measurement effort is affordable over decametric pixel size.

485 **Declaration of Competing Interest**

486 The authors declare that they have no known competing financial interests or personal relationships that
487 could have appeared to influence the work reported in this paper.

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492 **References**

493 Abichou, M., Fournier, C., Dornbusch, T., CHAMBON, C., Baccar, R., Bertheloot, J., Vidal, T., Robert, C.,
494 Gouache, D., & Andrieu, B. (2013). Re-parametrisation of Adel-wheat allows reducing the experimental

495 effort to simulate the 3D development of winter wheat. In, *7. International Conference on Functional*
496 *Structure Plant Models* (p. np). Saariselkä, Finland: Finnish Society of Forest Science

497 Banskota, A., Serbin, S.P., Wynne, R.H., Thomas, V.A., Falkowski, M.J., Kayastha, N., Gastellu-Etchegorry,
498 J.-P., & Townsend, P.A. (2015). An LUT-based inversion of DART model to estimate forest LAI from
499 hyperspectral data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *8*,
500 3147-3160

501 Baret, F., & Buis, S. (2008). Estimating Canopy Characteristics from Remote Sensing Observations: Review
502 of Methods and Associated Problems. In S. Liang (Ed.), *Advances in Land Remote Sensing* (pp. 173-201):
503 Springer Netherlands

504 Baret, F., de Solan, B., Lopez-Lozano, R., Ma, K., & Weiss, M. (2010). GAI estimates of row crops from
505 downward looking digital photos taken perpendicular to rows at 57.5 degrees zenith angle: Theoretical
506 considerations based on 3D architecture models and application to wheat crops. *Agricultural and Forest*
507 *Meteorology*, *150*, 1393-1401

508 Baret, F., & Fourty, T. (1997). Estimation of leaf water content and specific leaf weight from reflectance
509 and transmittance measurements. *Agronomie*, *17*, 455-464

510 Baret, F., Guyot, G., & Major, D.J. (1989). Crop biomass evaluation using radiometric measurements.
511 *Photogrammetria (PRS)*, *43*, 241-256

512 Baret, F., Hagolle, O., Geiger, B., Bicheron, P., Miras, B., Huc, M., Berthelot, B., Nino, F., Weiss, M.,
513 Samain, O., Roujean, J.L., & Leroy, M. (2007). LAI, fAPAR and fCover CYCLOPES global products derived
514 from VEGETATION: Part 1: Principles of the algorithm. *Remote Sensing of Environment*, *110*, 275-286

515 Baret, F., Jacquemoud, S., Guyot, G., & Leprieur, C. (1992). Modeled analysis of the biophysical nature of
516 spectral shifts and comparison with information content of broad bands. *Remote Sensing of*
517 *Environment*, *41*, 133-142

518 Berger, M., Moreno, J., Johannessen, J.A., Levelt, P.F., & Hanssen, R.F. (2012). ESA's sentinel missions in
519 support of Earth system science. *Remote Sensing of Environment*, *120*, 84-90

520 Biskup, B., Scharr, H., Schurr, U., & Rascher, U. (2007). A stereo imaging system for measuring structural
521 parameters of plant canopies. *Plant, Cell & Environment*, *30*, 1299-1308

522 Brede, B., Gastellu-Etchegorry, J.-P., Lauret, N., Baret, F., Clevers, J., Verbesselt, J., & Herold, M. (2018).
523 Monitoring Forest Phenology and Leaf Area Index with the Autonomous, Low-Cost Transmittance Sensor
524 PASTiS-57. *Remote Sensing*, *10*, 1032

525 Broge, N.H., & Leblanc, E. (2001). Comparing prediction power and stability of broadband and
526 hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density.
527 *Remote Sensing of Environment*, *76*, 156-172

528 Broge, N.H., & Mortensen, J.V. (2002). Deriving green crop area index and canopy chlorophyll density of
529 winter wheat from spectral reflectance data. *Remote Sensing of Environment*, *81*, 45-57

530 Camacho-Collados, J., Pilehvar, M.T., Collier, N., & Navigli, R. (2017). Semeval-2017 task 2: Multilingual
531 and cross-lingual semantic word similarity. In, *Proceedings of the 11th International Workshop on*
532 *Semantic Evaluation (SemEval-2017)* (pp. 15-26)

533 Campbell, G.S., & Norman, J.M. (1988). The description and measurements of plant canopy structure. In
534 B.M.a.P.G.J.G. Russell (Ed.), *Plant canopies: their growth, form and function* (pp. 1-19): Cambridge
535 University Press

536 Casa, R., Baret, F., Buis, S., Lopez-Lozano, R., Pascucci, S., Palombo, A., & Jones, H.G. (2010). Estimation of
537 maize canopy properties from remote sensing by inversion of 1-D and 4-D models. *Precision agriculture*,
538 *11*, 319-334

539 Chen, J.M., & Black, T. (1992). Defining leaf area index for non - flat leaves. *Plant, Cell & Environment*,
540 *15*, 421-429

541 Delloye, C., Weiss, M., & Defourny, P. (2018). Retrieval of the canopy chlorophyll content from Sentinel-2
542 spectral bands to estimate nitrogen uptake in intensive winter wheat cropping systems. *Remote Sensing
543 of Environment, 216*, 245-261

544 Demarez, V., Duthoit, S., Baret, F., Weiss, M., & Dedieu, G. (2008). Estimation of leaf area and clumping
545 indexes of crops with hemispherical photographs. *Agricultural and Forest Meteorology, 148*, 644-655

546 Domingo, F., Sánchez, G., Moro, M., Brenner, A., & Puigdefábregas, J. (1998). Measurement and
547 modelling of rainfall interception by three semi-arid canopies. *Agricultural and Forest meteorology, 91*,
548 275-292

549 Duan, S.-B., Li, Z.-L., Wu, H., Tang, B.-H., Ma, L., Zhao, E., & Li, C. (2014). Inversion of the PROSAIL model
550 to estimate leaf area index of maize, potato, and sunflower fields from unmanned aerial vehicle
551 hyperspectral data. *International Journal of Applied Earth Observation and Geoinformation, 26*, 12-20

552 Duthoit, S., Demarez, V., Gastellu-Etchegorry, J.-P., Martin, E., & Roujean, J.-L. (2008). Assessing the
553 effects of the clumping phenomenon on BRDF of a maize crop based on 3D numerical scenes using DART
554 model. *Agricultural and Forest Meteorology, 148*, 1341-1352

555 Duveiller, G., Weiss, M., Baret, F., & Defourny, P. (2011). Retrieving wheat Green Area Index during the
556 growing season from optical time series measurements based on neural network radiative transfer
557 inversion. *Remote Sensing of Environment, 115*, 887-896

558 Fang, H., Liu, W., Li, W., & Wei, S. (2018). Estimation of the directional and whole apparent clumping
559 index (ACI) from indirect optical measurements. *ISPRS Journal of Photogrammetry and Remote Sensing*,
560 144, 1-13

561 Fournier, C., Andrieu, B., Ljutovac, S., & Saint-Jean, S. (2003). ADEL-wheat: a 3D architectural model of
562 wheat development. In: Springer Verlag

563 Gascon, F., Gastellu-Etchegorry, J.-P., Lefevre-Fonollosa, M.-J., & Dufrene, E. (2004). Retrieval of forest
564 biophysical variables by inverting a 3-D radiative transfer model and using high and very high resolution
565 imagery. *International Journal of Remote Sensing*, 25, 5601-5616

566 Gastellu-Etchegorry, J., Martin, E., & Gascon, F. (2004). DART: a 3D model for simulating satellite images
567 and studying surface radiation budget. *International Journal of Remote Sensing*, 25, 73-96

568 Gonsamo, A. (2009). *Remote sensing of leaf area index: enhanced retrieval from close-range and*
569 *remotely sensed optical observations*. University of Helsinki, Department of Geography

570 González-Sanpedro, M., Le Toan, T., Moreno, J., Kergoat, L., & Rubio, E. (2008). Seasonal variations of
571 leaf area index of agricultural fields retrieved from Landsat data. *Remote Sensing of Environment*, 112,
572 810-824

573 Gower, S.T., Kucharik, C.J., & Norman, J.M. (1999). Direct and indirect estimation of leaf area index,
574 fAPAR, and net primary production of terrestrial ecosystems. *Remote Sensing of Environment*, 70, 29-51

575 Haboudane, D., Miller, J.R., Pattey, E., Zarco-Tejada, P.J., & Strachan, I.B. (2004). Hyperspectral
576 vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and
577 validation in the context of precision agriculture. *Remote Sensing of Environment*, 90, 337-352

578 Hallett, S.H., & Jones, R.J. (1993). Compilation of an accumulated temperature database for use in an
579 environmental information system. *Agricultural and Forest Meteorology*, 63, 21-34

580 Henrich, V., Götze, E., Jung, A., Sandow, C., Thürkow, D., & Gläßer, C. (2009). Development of an Online
581 indices-database: motivation, concept and implementation. *EARSeL proceedings, EARSeL, Tel Aviv*

582 Hernández-Clemente, R., North, P., Hornero, A., & Zarco-Tejada, P. (2017). Assessing the effects of forest
583 health on sun-induced chlorophyll fluorescence using the FluorFLIGHT 3-D radiative transfer model to
584 account for forest structure. *Remote Sensing of Environment*, 193, 165-179

585 Jacquemoud, S., Bacour, C., Poilve, H., & Frangi, J.-P. (2000). Comparison of four radiative transfer
586 models to simulate plant canopies reflectance: Direct and inverse mode. *Remote Sensing of*
587 *Environment*, 74, 471-481

588 Jacquemoud, S., & Baret, F. (1990). PROSPECT : A model of leaf optical properties spectra. *Remote*
589 *Sensing of Environment*, 34, 75-91

590 Jacquemoud, S., Verhoef, W., Baret, F., Bacour, C., Zarco-Tejada, P.J., Asner, G.P., François, C., & Ustin,
591 S.L. (2009). PROSPECT + SAIL models: A review of use for vegetation characterization. *Remote Sensing of*
592 *Environment*, 113, S56-S66

593 Jiang, J., Weiss, M., Liu, S., Rochdi, N., & Baret, F. (2020). Speeding up 3D radiative transfer simulations: a
594 physically based metamodel of canopy reflectance dependency on wavelength, leaf biochemical
595 composition and soil reflectance. *Remote Sensing of Environment*, 237, 111614

596 Jonckheere, I., Fleck, S., Nackaerts, K., Muys, B., Coppin, P., Weiss, M., & Baret, F. (2004). Review of
597 methods for in situ leaf area index determination: Part I. Theories, sensors and hemispherical
598 photography. *Agricultural and Forest Meteorology*, 121, 19-35

599 Koetz, B., Baret, F., Poilvé, H., & Hill, J. (2005). Use of coupled canopy structure dynamic and radiative
600 transfer models to estimate biophysical canopy characteristics. *Remote Sensing of Environment*, 95, 115-
601 124

602 Kuusk, A. (1985). The hot spot effect on a uniform vegetative cover. *Sov J Remote Sens*, 3, 645-658

603 López-Lozano, R., Baret, F., Chelle, M., Rochdi, N., & España, M. (2007). Sensitivity of gap fraction to
604 maize architectural characteristics based on 4D model simulations. *Agricultural and Forest Meteorology*,
605 143, 217-229

606 Leblanc, S., Chen, J., Fernandes, R., Deering, D.W., & Conley, A. (2005). Methodology comparison for
607 canopy structure parameters extraction from digital hemispherical photography in boreal forests.
608 *Agricultural and Forest Meteorology*, 129, 187-207

609 Leblanc, S.G., & Fournier, R.A. (2014). Hemispherical photography simulations with an architectural
610 model to assess retrieval of leaf area index. *Agricultural and Forest Meteorology*, 194, 64-76

611 Li, W., Weiss, M., Waldner, F., Defourny, P., Demarez, V., Morin, D., Hagolle, O., & Baret, F. (2015). A
612 generic algorithm to estimate LAI, FAPAR and FCOVER variables from SPOT4_HRVIR and landsat sensors:
613 evaluation of the consistency and comparison with ground measurements. *Remote Sensing*, 7, 15494-
614 15516

615 Liang, S. (2004). *Quantitative remote sensing of land surfaces*. (1st ed.). New York, the USA: John Wiley &
616 Sons

617 Liu, J., Pattey, E., & Jégo, G. (2012). Assessment of vegetation indices for regional crop green LAI
618 estimation from Landsat images over multiple growing seasons. *Remote Sensing of Environment*, 123,
619 347-358

620 Liu, S., Baret, F., Abichou, M., Boudon, F., Thomas, S., Zhao, K., Fournier, C., Andrieu, B., Irfan, K., &
621 Hemmerlé, M. (2017). Estimating wheat green area index from ground-based LiDAR measurement using
622 a 3D canopy structure model. *Agricultural and Forest meteorology*, 247, 12-20

623 Lord, D., Desjardins, R.L., & Dubé, P.A. (1988). Sun-angle effects on the red and near infrared reflectances
624 of five different crop canopies. *Canadian Journal of Remote Sensing*, 14, 46-55

625 LuxCoreRender (2018). LuxCoreRender Wiki. https://wiki.luxcorerender.org/LuxCoreRender_Wiki. In
626 Malenovský, Z., Homolová, L., Zurita-Milla, R., Lukeš, P., Kaplan, V., Hanuš, J., Gastellu-Etchegorry, J.-P., &
627 Schaepman, M.E. (2013). Retrieval of spruce leaf chlorophyll content from airborne image data using
628 continuum removal and radiative transfer. *Remote Sensing of Environment*, 131, 85-102

629 Martello, M., Ferro, N., Bortolini, L., & Morari, F. (2015). Effect of incident rainfall redistribution by maize
630 canopy on soil moisture at the crop row scale. *Water*, 7, 2254-2271

631 Miller, J. (1967). A formula for average foliage density. *Australian Journal of Botany*, 15, 141-144

632 Myneni, R.B., Hall, F.G., Sellers, P.J., & Marshak, A.L. (1995). The interpretation of spectral vegetation
633 indexes. *IEEE transactions on Geoscience and Remote Sensing*, 33, 481-486

634 Nguy-Robertson, A., Gitelson, A., Peng, Y., Viña, A., Arkebauer, T., & Rundquist, D. (2012). Green leaf
635 area index estimation in maize and soybean: Combining vegetation indices to achieve maximal
636 sensitivity. *Agronomy Journal*, 104, 1336-1347

637 Nilson, T. (1999). Inversion of gap frequency data in forest stands. *Agricultural and Forest meteorology*,
638 98, 437-448

639 Norman, J.M., & Campbell, G.S. (1989). Canopy structure. *Plant physiological ecology* (pp. 301-325):
640 Springer

641 North, P.R. (1996). Three-dimensional forest light interaction model using a Monte Carlo method. *IEEE*
642 *transactions on Geoscience and Remote Sensing*, 34, 946-956

643 Pharr, M., Jakob, W., & Humphreys, G. (2016). *Physically based rendering: From theory to*
644 *implementation*. Morgan Kaufmann

645 Price, J.C., & Bausch, W.C. (1995). Leaf area index estimation from visible and near-infrared reflectance
646 data. *Remote Sensing of Environment*, 52, 55-65

647 Richardson, A., Wiegand, C., Wanjura, D., Dusek, D., & Steiner, J. (1992). Multisite analyses of spectral-
648 biophysical data for sorghum. *Remote Sensing of Environment*, 41, 71-82

649 Rondeaux, G., Steven, M., & Baret, F. (1996). Optimization of soil-adjusted vegetation indices. *Remote*
650 *Sensing of Environment*, 55, 95-107

651 Rouse, J., Haas, R.H., Schell, J.A., & Deering, D.W. (1974). Monitoring vegetation systems in the Great
652 Plains with ERTS. *NASA special publication*, 351, 309

653 Segarra, J., Buchailot, M.L., Araus, J.L., & Kefauver, S.C. (2020). Remote sensing for precision agriculture:
654 Sentinel-2 improved features and applications. *Agronomy*, 10, 641

655 Soma, M., Pimont, F., Durrieu, S., & Dupuy, J.-L. (2018). Enhanced Measurements of Leaf Area Density
656 with T-LiDAR: Evaluating and Calibrating the Effects of Vegetation Heterogeneity and Scanner Properties.
657 *Remote Sensing*, *10*, 1580

658 Strahler, A.H. (1997). Vegetation canopy reflectance modeling—Recent developments and remote
659 sensing perspectives. *Remote Sensing Reviews*, *15*, 179-194

660 Verhoef, W. (1984). Light scattering by leaf layers with application to canopy reflectance modeling: the
661 SAIL model. *Remote Sensing of Environment*, *16*, 125-141

662 Verrelst, J., Malenovský, Z., Van der Tol, C., Camps-Valls, G., Gastellu-Etchegorry, J.-P., Lewis, P., North,
663 P., & Moreno, J. (2018). Quantifying vegetation biophysical variables from imaging spectroscopy data: A
664 review on retrieval methods. *Surveys in Geophysics*, 1-41

665 Verrelst, J., Muñoz, J., Alonso, L., Delegido, J., Rivera, J.P., Camps-Valls, G., & Moreno, J. (2012). Machine
666 learning regression algorithms for biophysical parameter retrieval: Opportunities for Sentinel-2 and-3.
667 *Remote Sensing of Environment*, *118*, 127-139

668 Wang, K., & Dickinson, R.E. (2012). A review of global terrestrial evapotranspiration: Observation,
669 modeling, climatology, and climatic variability. *Reviews of Geophysics*, *50*

670 Weiss, M., Baret, F., Leroy, M., Hauteœur, O., Bacour, C., Prevol, L., & Bruguier, N. (2002). Validation of
671 neural net techniques to estimate canopy biophysical variables from remote sensing data. *Agronomie-*
672 *Sciences des Productions Vegetales et de l'Environnement*, *22*, 547-554

673 Weiss, M., Baret, F., Smith, G., Jonckheere, I., & Coppin, P. (2004). Review of methods for in situ leaf area
674 index (LAI) determination: Part II. Estimation of LAI, errors and sampling. *Agricultural and Forest*
675 *meteorology*, *121*, 37-53

676 Widlowski, J.-L., Robustelli, M., Disney, M., Gastellu-Etchegorry, J.-P., Lavergne, T., Lewis, P., North, P.,
677 Pinty, B., Thompson, R., & Verstraete, M. (2008). The RAMI On-line Model Checker (ROMC): A web-based
678 benchmarking facility for canopy reflectance models. *Remote Sensing of Environment*, *112*, 1144-1150

679 Yan, G., Hu, R., Luo, J., Weiss, M., Jiang, H., Mu, X., Xie, D., & Zhang, W. (2019). Review of indirect optical
680 measurements of leaf area index: Recent advances, challenges, and perspectives. *Agricultural and Forest*
681 *Meteorology*, 265, 390-411

682 Zhao, F., Gu, X., Verhoef, W., Wang, Q., Yu, T., Liu, Q., Huang, H., Qin, W., Chen, L., & Zhao, H. (2010). A
683 spectral directional reflectance model of row crops. *Remote Sensing of Environment*, 114, 265-285

684