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Assessing impacts of canopy 3D structure on chlorophyll fluorescence radiance and radiative budget of deciduous forest stands using DART

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ABSTRACT

Although remote sensing (RS) of solar-induced chlorophyll fluorescence (SIF) is increasingly used as a valuable source of information about vegetation photosynthetic activity, the RS SIF observations are significantly influenced by canopy-specific structural features (i.e., canopy architecture including leaf area index and presence of woody components), atmospheric conditions during their acquisition (e.g., proportion of direct and diffuse irradiance) and observational geometric configurations (e.g., sun and viewing directions). Radiative transfer (RT) models have the potential to provide a better understanding of the canopy structural effects on the SIF emission and RS signals. Here, we used the DART model to assess the daily influence, from morning to evening, of forest 3D architecture on SIF nadir radiance, emission, escape factor and nadir yield of eight 100 m × 100 m forest study plots established in a temperate deciduous forest of the Smithsonian Environmental Research Center (Edgewater, MD, USA). The 3D architecture of each plot was derived from airborne LiDAR. DART simulations of these 3D forest plots and their 1D (i.e., vertical profile of sun-adapted and shade-adapted leaves) and 0D (i.e., homogeneous layer of sun-adapted leaves above an homogeneous layer of shade-adapted leaves) abstractions were compared to assess the relative errors (ϵ_{1D-3D} and ϵ_{0D-3D}) associated with horizontal and vertical structural heterogeneity, respectively. Forest 3D structure, especially horizontal heterogeneity, had a great influence on forest nadir SIF radiance, resulting in ϵ_{1D-3D} up to 55% at 8:00 and 18:00 (i.e., for oblique sun directions). The key indicators of this impact, in the descending order of importance, were the SIF escape factor (ϵ_{1D-3D} up to 40%), the attenuation of incident photosynthetically active radiation (ϵ_{1D-3D} less than 5%), and the SIF emission yield (ϵ_{1D-3D} less than 2%). The influence of forest architecture on the nadir SIF escape factor and SIF yield (ϵ_{1D-3D} up to 40%) varied over time, with differences in forest stand structure, and per spectral domain, being always larger between 640 and 700 nm than between 700 and 850 nm. In addition, woody elements demonstrated a large influence on forest SIF radiance due to their “shading” effect (ϵ up to 17%) and their “blocking” effect ($\epsilon \approx 10\%$), both of them higher for far-red than for red SIF. These results underline the importance of 3D forest canopy architecture, especially 2D heterogeneity, and inclusion of woody elements in RT modeling used for interpretation of the RS SIF signal, and subsequently for the estimation of gross primary production and detection of vegetation stress.

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1 **1. Introduction**

2 Solar-induced chlorophyll fluorescence (SIF) is a photoprotective electromagnetic radiation
3 emitted by chlorophyll molecules in response to absorption of photosynthetically active
4 radiation (PAR) by green vegetation. Since the energy emitted as SIF is complementary to the
5 energy entering the photochemical processes and the excessive energy dissipated as heat (Baker,
6 2008; Mohammed et al., 2019), it is considered as an indicator of the functional state of plant
7 photosynthesis (Baker, 2008). SIF measurements are complicated by the fact that SIF represents
8 only a small fraction of absorbed PAR and spectrally overlaps with radiation reflected by Earth
9 surface elements and the atmosphere. However, the improvement of remote sensing (RS)
10 optical sensors and techniques for retrieving the SIF signal (Meroni et al., 2009; Mohammed et
11 al., 2019) has opened new avenues for monitoring the functional state of vegetation. SIF can be
12 used to track actual photosynthetic efficiency (Rossini et al., 2015; Campbell et al., 2019; Yang
13 et al., 2021), to improve assessment of plant gross primary production (Guanter et al., 2014; Z.
14 Liu et al., 2019), and to detect vegetation stress (Ač et al., 2015). This diverse potential of SIF
15 for vegetation monitoring spurred the development of methods for space-borne measurements
16 and new satellite missions, such as the FLuorescence EXplorer (FLEX) selected by the
17 European Space Agency (ESA) as its 8th Earth explorer scientific mission (Drusch et al., 2017).
18 Besides plant photosynthetic activity, SIF observations are impacted by other confounding
19 factors, notably the structure of vegetation canopies (Fournier et al., 2012; Migliavacca et al.,
20 2017) and PAR availability. They are of SIF also influenced by sun-canopy-sensor angular and
21 directional effects (Zhang, Zhang, Porcar-Castell, et al., 2020; Zhang, Zhang, Zhang, et al.,
22 2020), and are driven by wavelength-dependent phenomena of SIF emission, scattering, and re-
23 absorption. For instance, Fournier et al. (2012) found that the red-to-far-red fluorescence ratio
24 could decrease by a factor of two between the leaf level and the canopy level, due to a higher
25 absorption of red SIF by the vegetation canopy. Therefore, accurate interpretation and use of
26 SIF RS observations require understanding of three consecutive processes: i) interception of
27 photosynthetically active radiation (PAR; 400 - 750 nm) and its absorption by foliar elements
28 ($APAR_{green}$; $W.m^{-2}$), due to chlorophyll pigments in leaves, ii) leaf SIF emission from
29 photosystems I and II (PSI and PSII) in thylakoid membranes, due to $APAR_{green}$, and iii)
30 propagation of the SIF radiation through the canopy, including its scattering and absorption by
31 different canopy elements, *i.e.*, leaves, woody elements, litter, bare soil, and others (van der Tol
32 et al., 2019).

33 Radiative transfer models (RTMs) are powerful tools used for various vegetation RS
34 applications, ranging from sensitivity analyses (Malenovský et al., 2008) to quantitative
35 retrievals of models' biophysical inputs (Brede et al., 2020; Verrelst et al., 2019). The
36 increasing need for understanding and interpreting the SIF signal at canopy level resulted in
37 coupling canopy RTMs with a leaf-level SIF model, most frequently with Fluspect (Vilfan et
38 al., 2016). The pioneer in one-dimensional (1D) SIF canopy modeling is SCOPE (van der Tol
39 et al., 2009). Based on SAIL RTM (Verhoef, 1984) and coupled with leaf-level SIF and
40 biochemistry models, SCOPE models photosynthesis and the full energy balance (Damm et al.,
41 2015; Migliavacca et al., 2017; Verrelst et al., 2015, 2016). Despite its extension to vertically
42 heterogeneous canopies (Yang et al., 2017), SCOPE's 1D formulation makes it less suitable for
43 structurally complex and spatially heterogeneous canopies, such as forests. This explains the
44 recent development of three-dimensional (3D) SIF RTMs, such as FluorFLIGHT (Hernández-
45 Clemente et al., 2017), based on the 3D FLIGHT model (North, 1996), FLiES-SIF (Sakai et al.,
46 2020) based on the FLiES model (Kobayashi & Iwabuchi, 2008) that simulate SIF for tree
47 canopies, FluorWPS (Zhao et al., 2016) based on the WPS model (Zhao et al., 2015) designed
48 to simulate SIF of structurally complex canopies and the FluLCVRT model (Kallel, 2020) that
49 simulates SIF for 3D canopies including 3D leaf-level SIF modeling. The work presented in
50 this paper was carried out with the 3D discrete anisotropic radiative transfer (DART) model
51 (Gastellu-Etchegorry et al., 2017) coupled with Fluspect-Cx (Vilfan et al., 2018). DART
52 simulates both the 3D SIF radiative budget (*i.e.*, interception, absorption, emission and
53 scattering) and the SIF signal remotely sensed at the bottom of atmosphere (BOA) and top of
54 atmosphere (TOA) for forest or crop canopies. It upscales leaf-level SIF to canopy SIF, while
55 considering the user-defined leaf biochemistry and fluorescence quantum yield efficiencies of
56 PSI and PSII, and accounting for the actual 3D vegetation architecture. DART has been cross
57 compared with the SCOPE modeling of the same 1D vegetation scenarios (Malenovský et al.,
58 2021), and used in various studies for sensitivity analyses of the SIF signal in architecturally
59 complex forest canopies (W. Liu et al., 2019; Malenovský et al., 2021), scaling canopy-level
60 SIF down to the level of photosystems (X. Liu et al., 2019), and studying the escape probability
61 of far-red SIF from discontinuous forest canopies (W. Liu et al., 2020).

62 The main objective of this paper is to assess the impact of temperate deciduous forest
63 architecture on the diurnal variability in the nadir SIF RS signal and within-canopy SIF
64 emission by green leaves. SIF canopy signals were simulated with a new Monte Carlo mode of

65 DART, called DART-Lux, whereas the radiative budget of within canopy SIF emission was
66 simulated using the standard flux tracking mode of DART, called DART-FT. (cf. section 2.1).

67 2. Material and methods

68 2.1. Discrete anisotropic radiative transfer (DART) modeling approaches

69 DART (<https://dart.omp.eu>) is a comprehensive physically based 3D RTM developed by the
70 CESBIO Laboratory (Toulouse, France) since 1993 (Gastellu-Etchegorry et al., 1996, 2015). It
71 is continuously improved both scientifically (*e.g.*, light polarization and radiative coupling
72 between the atmosphere and Earth surfaces) and technically (*e.g.*, computational efficiency in
73 terms of simulation time and computer memory). It simulates the radiative budget (RB) as well
74 as TOA, BOA, and in-situ RS observations (*i.e.*, LiDAR and imaging spectroradiometer data,
75 either pushbroom scanner, hemispherical or frame camera) of urban and natural landscapes
76 from the visible to the thermal infrared spectral domains, for any experimental and instrumental
77 configuration (solar illumination, viewing direction, atmosphere condition, spatial and spectral
78 resolutions, etc.). DART is made of three radiative transfer modeling modules:

- 79 1. DART-FT (Flux Tracking) simulates passive optical RS signals and 3D RB, including SIF,
80 using an adaptation of the N-flux discrete ordinates' method (Yin et al., 2013, 2015).
81 Landscapes are simulated as the juxtaposition of planar triangular facets in 3D arrays of
82 voxels that contain fluid and turbid medium (*i.e.*, vegetation volume statistically
83 characterized by a leaf angular distribution (LAD) and a leaf area index (LAI) equivalent
84 to a volume filled with an infinite number of infinitely small planar surfaces).
- 85 2. DART-RC (Ray Carlo) combines Monte Carlo (MC) and FT methods in order to simulate
86 LiDAR signals (Gastellu-Etchegorry et al., 2016; Yin et al., 2016). 3D landscapes are
87 simulated in the same way as for DART-FT module.
- 88 3. DART-Lux is a new module that broadens the application domain of DART to large
89 landscapes through the introduction of a bidirectional MC modeling approach adapted from
90 the physically based and unbiased rendering engine called LuxCoreRender (Georgiev et
91 al., 2012; *LuxCoreRender – Open Source Physically Based Renderer*). It greatly improves
92 the computational efficiency of simulations for large and complex landscapes. For example,
93 the reduction of simulation time and computer memory can be over 100-times. Indeed, this
94 DART mode only tracks radiation that impacts the signal forming the sensor observation.

95 Landscapes are simulated as the juxtaposition of facets and volumes filled with fluids and
96 turbid medium. Volumes in DART-Lux can be defined independently from the 3D arrays
97 of voxels, unlike DART-FT and RC. Although still under intensive testing, DART-Lux
98 already simulates most RS products of DART-FT and DART-RC, including SIF and
99 LiDAR. Presently, TOA signals are simulated using DART-FT based atmosphere
100 modeling (Wang & Gastellu-Etchegorry, 2021). MC-based modeling of atmosphere
101 thermal radiative transfer, as well as radiative budget are under development.
102

103 SIF modeling was initially introduced in DART-FT for vegetation canopies represented explicitly
104 with facets (Gastellu-Etchegorry et al., 2017) and later for canopies simulated with 3D turbid
105 voxels (Regaieg et al., 2020). More recently, SIF modeling was also implemented in DART-Lux,
106 for both facet-based as well as turbid canopies (Regaieg et al., in preparation). As indicated above,
107 compared to the standard DART-FT mode, DART-Lux is much more efficient in terms of
108 computation time and required memory to simulate RS images, including SIF images. However,
109 up to now it does not simulate the landscape RB. Therefore, in this work, we simulated SIF image
110 observations at the spatial resolution of 1m in DART-Lux, whereas the forest RB was simulated
111 in DART-FT at a lower spectral resolution to reduce computational demand.

112 The leaf radiative transfer model Fluspect-Cx, which was embedded in DART and tested by
113 (Malenovsky et al., 2021), simulates additionally to leaf spectral reflectance and transmittance
114 optical properties the forward and backward fluorescence excitation-emission matrices per
115 photosystem (PSI and PSII). Its inputs include contents of foliar pigments, water and dry matter,
116 a structural parameter characterizing the leaf optical thickness, and leaf fluorescence quantum
117 efficiencies fqe (*i.e.*, fraction of $APAR_{green}$ emitted as fluorescence) of a dark-adapted leaf, that
118 are in DART referred to as PSI and PSII fluorescence yields. Leaf physiology and local
119 climatology influence fqe . However, unlike the SCOPE model, DART does not contain a leaf
120 biochemical model, and therefore cannot simulate the canopy climatic weights that condition leaf
121 fqe . Therefore, in DART, fqe is an input parameter that can be specified per individual foliage
122 facet, per group of foliage facets, per type of turbid medium, or as a single value for all leaf
123 facets and turbid medium types. Groups of foliage facets can correspond, for instance, to sunlit
124 and shaded leaves (*i.e.*, leaves irradiated by direct sun or not at a certain time), or to sun- and
125 shade-adapted leaves (*i.e.*, leaves that have grown under and adapted to high or low light
126 intensity such that biochemical contents vary), knowing that a sun-adapted leaf can be

127 momentarily a shaded leaf and vice versa. In this work, forest *fqe* values published in (W. Liu
 128 et al., 2019) are used. Although very likely differing from actual values of the study forest sites,
 129 these values are sufficiently representative to investigate the impact of forest architecture and
 130 different structures (*e.g.*, wood components) on canopy SIF signal and emission. We also note
 131 that although sun-adapted and shade-adapted *fqe*'s are considered, the actual light and temperature
 132 modulations are not. Consequently, a leaf emitted SIF is given by APAR and *fqe* per leaf
 133 adaptation.

134

135 2.2. Study sites

136 Eight deciduous forest sites in the Smithsonian Environmental Research Center (SERC,
 137 Edgewater, MD, USA) were selected as the study sites. The stands mainly consist of mixed-
 138 species deciduous forests of *Liquidambar styraciflua* and *Liriodendron tulipifera* for the
 139 overstory, and *C. tomentosa*, *Quercus alba*, and *F. grandifolia* for the understory (Kamoske et
 140 al., 2019; Parker, 1995). Descriptions of forest stands and management characteristics can be
 141 found in (Brush et al., 1980, Parker et al., 2001, McMahon et al., 2010). Four forest stand types
 142 were selected from the combinations of both canopy development categories [“intermediate”
 143 (I) or “mature” (M)] and experimental status categories [“control” (C) or “logged” (L)], and
 144 two sites of each type (indexed 1 and 2) were used for this study (Table 1). Therefore, the eight
 145 study sites (Figure 1) have different canopy architectures, as illustrated by their height maps
 146 (Figure 2) and LAI vertical profiles. The forest plots LI2, LM1, LM2, and, to a lesser extent,
 147 LI2, have a larger horizontal heterogeneity than the other plots. These plots also have
 148 pronounced heterogeneity, with foliage density being larger (*i.e.*, larger LAI voxel values in
 149 DART-FT) in the bottom canopy layers than in the top canopy layers. Table 2 shows the wood
 150 area density and the LAI for sun- and shade-adapted leaves (*cf.* Section III-1). We note that the
 151 concept of wood area density does not have an actual physical meaning linking with trunks and
 152 branches’ surface areas. It is derived from leaf off G-LiHT ALS data, and used to compensate
 153 the interception contribution induced by woody part. The presence of a local topography
 154 explains why the total ground area (*i.e.*, area based on DEM; Table 2) is larger than the scene
 155 area (*i.e.*, $100\text{ m} \times 100\text{ m}$). Leaf chlorophyll a+b and carotenoid contents ($\mu\text{g cm}^{-2}$) were
 156 derived from top of canopy leaf samples collected at SERC in July of 2017 (Campbell et al.,
 157 2018), and measured using established protocol described in (Campbell et al., 2007). Pigments
 158 were extracted in dimethyl sulfoxide, identified spectro-photometrically at 1-nm resolution

159 using a dual-beam spectrophotometer (Perkin-Elmer; Wellesley, MA, USA) and calculated
 160 using absorption coefficients and equations described by (Wellburn, 1994).

161 Biochemical and optical properties of leaves, woody elements and soil properties used in DART
 162 are listed in Table 3. The overall LAI of 3-D reconstruction has been validated against field
 163 litter-collection measurements in 2012 for various voxel dimensions from 0.5m to 5m.

164

165 Table 1. Study sites' nomenclature and description.

	Abbreviations	Description
Experimental status categories	C (Control)	No known management
	L (Logged)	Selective harvest (~ 50% of basal area)
Canopy development categories	M (Mature)	~125 years-old at time of harvesting
	I (Intermediate)	~70 years old at time of harvesting

166

167 Table 2. Wood area density, LAI (per sun-/shade-adapted leaves) and DEM-derived area for each site.

Parameter/Study site	CI1	CI2	CM1	CM2	LI1	LI2	LM1	LM2
Wood area density ($m^2 \cdot m^{-2}$)	0.792	0.863	0.939	0.991	0.665	0.435	0.827	0.615
Sun-adapted LAI ($m^2 \cdot m^{-2}$)	2.916	3.093	3.697	3.160	1.964	0.951	1.341	1.920
Shade-adapted LAI ($m^2 \cdot m^{-2}$)	2.601	2.847	2.996	3.174	3.181	2.810	3.419	3.559
Area based on DEM (m^2)	12450.7	14475.9	16535.3	11297.9	17628.8	15395.0	17576.3	20142.0

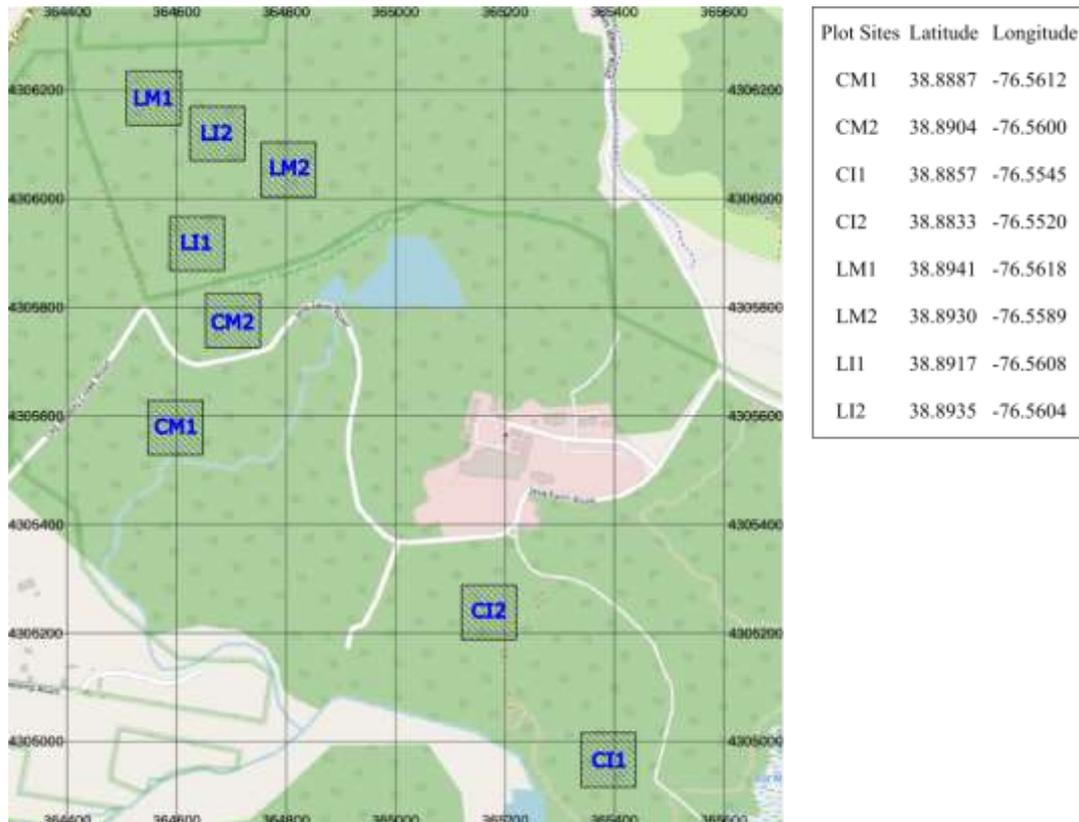
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169

Table 3. Biochemical and optical properties used in DART modeling of the study sites.

Parameter/Study site	CI1	CI2	CM1	CM2	LI1	LI2	LM1	LM2
Leaf chlorophyll a+b content ($\mu g. cm^{-2}$)	24.307	23.253	20.23	18.146	20.569	23.264	19.619	20.165
Leaf total carotenoid content ($\mu g. cm^{-2}$)	7.06	6.81	6.338	5.852	6.295	6.843	6.156	6.364
Leaf dry matter content ($g. cm^{-2}$)	0.012							
Leaf equivalent water thickness (cm)	0.009							
Leaf fluorescence quantum efficiency	PSI: 0.0053, PSII: shade-adapted: 0.0201, sun-adapted: 0.0154							
Wood optical property	Bark of <i>Populus tremuloides</i>							
Soil optical property	Loam-gravelly brown dark soil (Alfisol from the spectra library: http://speclib.jpl.nasa.gov/)							

170



171

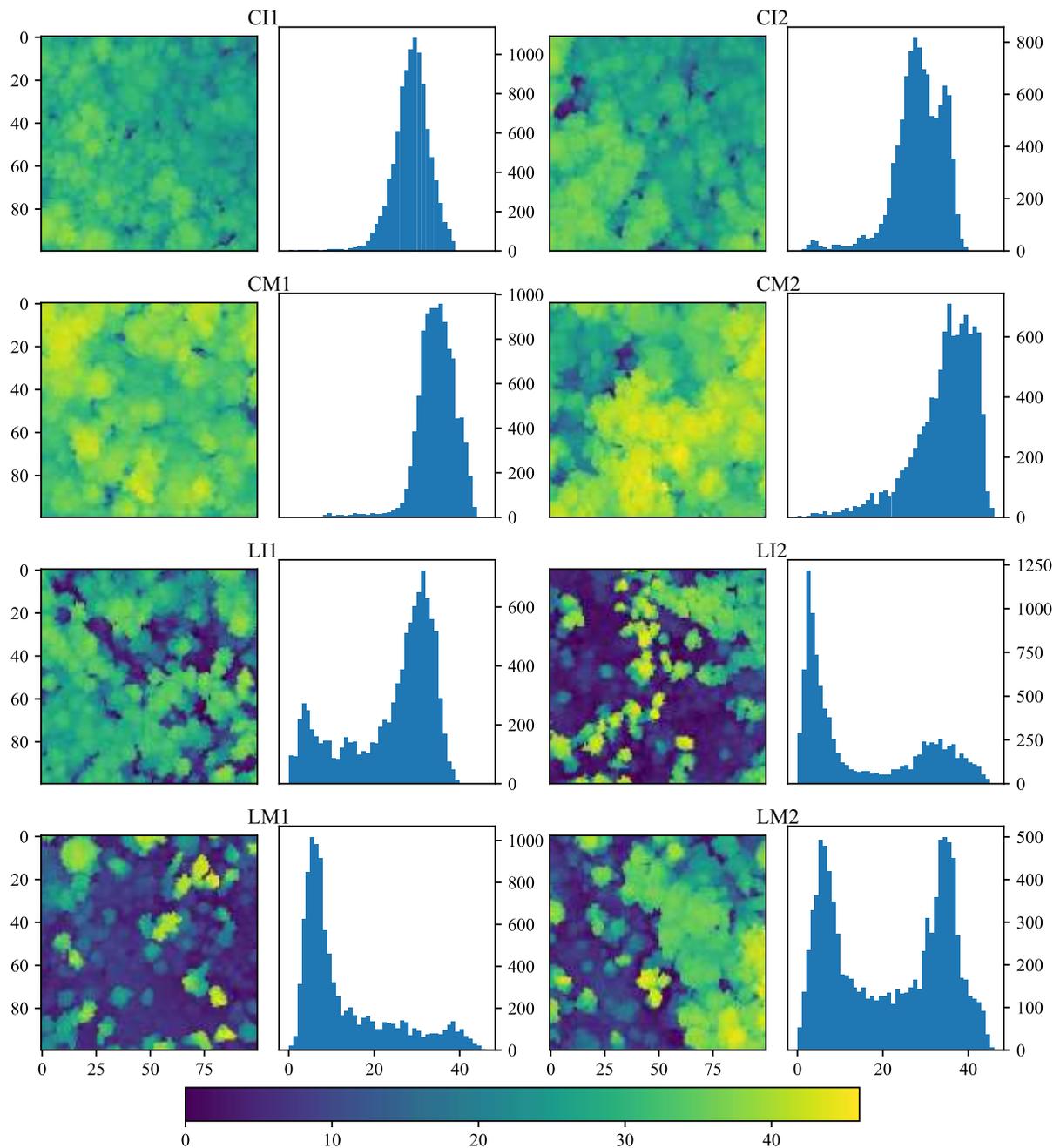
172 Figure 1. Locations of SERC forest study sites (Edgewater, MD, USA) and G-LiHT flight paths.

173

174 2.3. Creation of 3D forest abstractions from airborne LiDAR acquisitions

175 The 3D abstractions (mock-ups) of the eight forest sites were derived from 2012 multi-
 176 directional and multi-temporal acquisitions by an airborne discrete-return LiDAR scanner
 177 (Riegl's VQ480i), which is part of the Goddard's LiDAR, Hyperspectral and Thermal (G-LiHT)
 178 Airborne Imager (Cook et al., 2013). The LiDAR acquisitions were taken during two forest
 179 growth stages: i) the leaf-off stage (in March) and ii) the leaf-on stage (in June). Each
 180 constructed forest mock-up ($100m \times 100m$) corresponds to a 3D array of $1m$ -size voxels filled
 181 with a turbid medium. The leaf angle distribution varies with height following an ellipsoidal
 182 distribution generated by mean leaf incline angle from 10° at the lower canopy to 60° at the
 183 upper canopy. In this experiment, we assumed an overall leaf incline angle of 57.3° over the
 184 whole canopy, which may induce a slight underestimation of LAI at the upper canopy and over
 185 estimation at the lower canopy in scene construction. This assumption has minor influence since
 186 the change of incline angle is correlated with sun illumination, where majority of the sunlight
 187 is intercepted by the leaves with larger incline angle. Since the objective was to investigate

188 changes in the diurnal variation of canopy SIF radiance and leaf emissions on 15 June 2017
 189 between 7.00 and 19.00 (local time, with a time step of 1 h), the DART simulated solar zenith
 190 angles (SZA) and solar azimuth angles (SAA) were adjusted accordingly, with for example
 191 (SZA, SAA) = (76.85°, 109.51°) at 7.00, (15.62°, 5.8°) at 13.00, and (74.33°, 252.4°) at 19.00
 192 of the local time.



193

194

195

Figure 2. Maps and histograms of forest top-of-canopy height (m) for the eight forest study sites.

196 Table 4. Forest plot mean height and height standard deviation and number of pure bare ground pixels.

Plot	CI1	CI2	CM1	CM2	LI1	LI2	LM1	LM2
Mean Height (m)	28.65	28.34	34.54	34.33	23.80	15.19	13.31	21.75
Height standard deviation (m)	4.37	5.90	4.61	7.32	10.44	14.03	10.88	13.17
Number of pure bare ground pixels (out of 10 000)	2	1	2	4	89	258	8	48

197

198 **2.4. Preprocessing of modeled forest scenes**

199 Leaf biochemical and anatomical properties are adapted to the leaf exposure to sun direct and
200 scattered diffuse radiation (Givnish, 1988; Nobel, 1976). To assess 3D distribution of sun- and
201 shade-adapted foliage in each forest plot, we used DART-FT to compute hourly time series of
202 3D RB in the PAR domain from sunrise to sunset on 15 June 2012, with SZA and SAA as
203 specified in the section 2.3. The diurnal radiation intercepted by foliar elements in each turbid
204 voxel of the 3D plots computed by DART-FT was then used to classify the foliage turbid voxels
205 of each forest plot into sun- and shade-adapted foliage voxel groups. Sun- and shade-adapted leaf
206 classification methods based on thresholds on the intercepted radiation were developed for the
207 DART model for vegetation canopies simulated as facets (Malenovský et al., 2021). Here, in the
208 absence of information on the threshold definition, and for a vegetation canopy simulated as
209 turbid voxels, we chose to simply define classification decision threshold in such a way that the
210 numbers of sun-adapted voxels and shade-adapted voxels were equal. Subsequently, specific *fqe*
211 input values were assigned to the sun-adapted and shade-adapted cells (W. Liu et al., 2019)

212 Since the DART-FT mode was slow and too demanding for computer memory when simulating
213 SIF radiance of the forest plots represented by many voxels ($>10^5$) for 372 spectral bands (Table
214 5), we used the DART-Lux mode instead. As DART-Lux could at that time only simulate the
215 SIF signal of landscapes represented by geometrical facets, a “turbid-to-facet” conversion
216 procedure was designed to transform the forest turbid mock-ups (already classified into sun-
217 adapted and shade-adapted voxels) into forest 3D abstractions with leaf and woody elements
218 being represented with solid facets (cf. Appendix). DART-FT and DART-Lux give nearly
219 equivalent results in terms of canopy reflectance and SIF radiance (cf. Appendix). Small
220 differences may be observed due to the different strategies adopted by the two modes (*i.e.*,
221 discrete ordinates for DART-FT, Bi-directional Monte Carlo for DART-Lux), and also due to

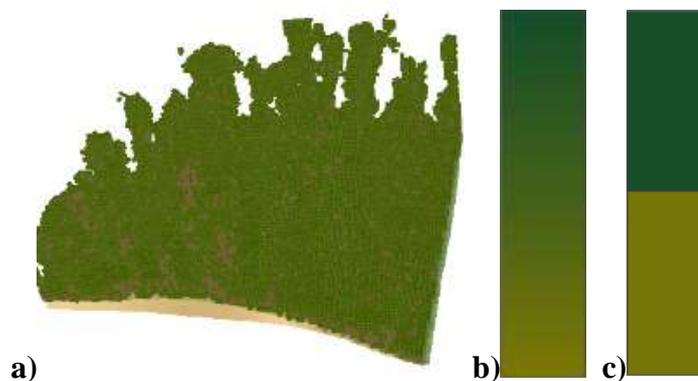
222 the approximation of turbid volumes by clouds of facets. These differences are supposed to be
 223 negligible compared to the differences caused by the canopy structure.

224 **2.5. Simulated structural complexity**

225 Three structurally different forest abstractions were considered for this study (Figure 3):

- 226 1. 3D mock-ups: derived from airborne LiDAR data, with classified sun- and shade-adapted
 227 cells as explained in the two previous sections.
- 228 2. 1D mock-ups: horizontally homogenized 3D mock-ups having the same heights and vertical
 229 profiles of sun- and shade-adapted leaf area density and wood area density but missing the
 230 forest horizontal heterogeneity.
- 231 3. 0D mock-ups: horizontally and vertically homogenized mock-ups having the mean height
 232 of the original 3D canopies, shade-adapted leaves homogeneously distributed in the mock-
 233 up bottom half, sun-adapted leaves homogeneously distributed in the mock-up top half, and
 234 woody elements homogeneously distributed within the entire scene. Compared to 3D forest
 235 mock-ups, 0D mock-ups miss the forest horizontal and vertical heterogeneity, including the
 236 simplifying assumption that all sun-adapted leaves are located at the top and all the shade-
 237 adapted leaves are located at the bottom of the canopy.

238



239

240 Figure 3: The three types of scene abstractions: a) 3D, b) 1D, c) 0D (top: sun-adapted, bottom: shade-
 241 adapted leaves)

242

243 **2.6. Simulated SIF products**

244 SIF nadir images of a high spectral resolution, from 0.15 nm to 4 nm (Table 5), were simulated
 245 with DART-Lux. DART-FT was used to simulate the PAR and SIF radiative budget with a

246 lower spectral resolution ([400-640 nm] at 20 nm resolution, [640-850] at 10 nm resolution)
 247 and 40 discrete directions, in order to limit computational demands.

248

249 Table 5. The 372 spectral bands of DART-Lux simulations. They over-sample the O₂B (~687nm) and
 250 O₂A (~760nm) oxygen absorption bands, and under-sample the [400-640nm] band (no SIF emission)

Spectral interval (nm)	Spectral resolution (nm)	Number of spectral bands
400-640	4	60
640-641.5	1.5	1
641.5-686.5	1	45
686.5-694	0.15	50
694-694.5	0.5	1
694.5-759.5	1	65
759.5-770	0.15	70
770-770.5	0.5	1
770.5-848.5	1	78
848.5-850	1.5	1

251

252 The influence of the canopy 3D architectures on 3D SIF emissions was assessed by comparing
 253 the DART-FT RB fluxes (*i.e.*, intercepted, scattered, absorbed and emitted PAR and total SIF
 254 radiation) per voxel in the simulated 3D, 1D and 0D mock-ups. Here, the PAR absorbed by
 255 leaves (W.m⁻²) informs us on APAR_{green} (the 1st process). SIF_{emitted} (W.m⁻²) is the sum of PSI
 256 and PSII emissions by adaxial and abaxial sides of all leaves in the canopy. It depends on the
 257 directionality and intensity of the incident PAR relative to leaf orientation, and therefore on
 258 APAR_{green} and the local leaf physiology (*e.g.*, leaf sun and shade adaptations). SIF emission
 259 yield informs us on the 2nd process. It is defined as:

$$\text{SIF emission yield} = \frac{\text{SIF}_{\text{emitted}}}{\text{APAR}_{\text{green}}}. \quad (1)$$

260 Since satellite and airborne spectrometers only measure SIF radiation that exits a canopy, the
 261 3rd process is investigated through the so-called SIF escape factor_{hemi}:

$$\text{SIF escape factor}_{\text{hemi}} = \frac{\text{SIF}_{\text{exitance}}}{\text{SIF}_{\text{emitted}}} \quad (2)$$

262 where SIF_{exitance} is the total SIF radiation exiting the top of the canopy in all directions of the
 263 upper hemisphere. SIF escape factor $_{\text{hemi}}$ was computed for the chlorophyll fluorescence
 264 peaks located at 640 – 700 nm and 700 – 850 nm spectral regions.

265 SIF sensors generally measure from a unique viewing direction. Hence, the directional SIF
 266 nadir escape factor was also studied:

$$\text{SIF escape factor}_{\text{nadir}} = \frac{\pi \cdot SIF_{\text{nadir radiance}}}{SIF_{\text{emitted}}} \quad (3)$$

267 SIF escape factor $_{\text{nadir}}$ was also computed for the chlorophyll fluorescence peaks located at
 268 640 – 700 nm and 700 – 850 nm spectral regions.

269 Finally, the combination of the 2nd and the 3rd processes was in the case of a nadir observation
 270 evaluated with the SIF nadir yield (sr^{-1}) (van der Tol et al., 2019):

$$\text{SIF nadir yield} = \frac{SIF_{\text{nadir radiance}}}{APAR_{\text{green}}} \quad (4)$$

271 where $SIF_{\text{nadir radiance}}$ is a SIF flux ($\text{W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1}$), that is for example recorded by an optical
 272 remote sensing sensor in the nadir viewing direction.

273

274 2.7. Canopy structure error assessment

275 The impact of forest architecture on diurnal SIF emission and nadir observation was assessed
 276 as the relative errors made on SIF quantities that are simulated with mock-ups (*i.e.*, 1D, 0D)
 277 with simplified architecture, taking the quantities simulated with the 3D mock-ups as reference.

278 The influence of forest 3D structure on SIF observation was assessed by comparing the DART-
 279 Lux top-of-canopy (TOC) nadir SIF radiance L_v (PSI, PSII and total), of the 3D, 1D and 0D
 280 mock-ups of the eight forest sites simulated. Two types of relative errors were computed:

281 - Per spectral band for a specific time (*e.g.*, 12.00 local time), by computing the relative errors

282 $\epsilon_{SIF, L_v, iD-3D}(\lambda)$ where $i \in \{0, 1\}$:

$$\epsilon_{SIF, L_v, iD-3D}(\lambda) = 100\% \times \frac{SIF_{\text{radiance}, iD}(\lambda) - SIF_{\text{radiance}, 3D}(\lambda)}{SIF_{\text{radiance}, 3D}(\lambda)} \quad (5)$$

283

284 - Per hour from 7.00 to 19.00, by computing mean absolute relative errors (MARE) for the
 285 two 640 – 700 nm and 700 – 850 nm spectral regions:

$$MARE_{SIF,Lv,1D-3D}(t) = \frac{1}{\sum_i \Delta\lambda_i} \cdot \sum_i \frac{|SIF_{radiance,1D}(t, \lambda) - SIF_{radiance,3D}(t, \lambda)|}{SIF_{radiance,3D}(t, \lambda)} \cdot \Delta\lambda_i \quad (6)$$

286

287 Using 3D plots as reference, the influence of canopy architecture was also assessed for:

288 - Nadir reflectance ρ : relative errors $\varepsilon_{\rho,0D-3D}(\lambda)$ and $\varepsilon_{\rho,1D-3D}(\lambda)$ of 0D and 1D plots, as well as
 289 $MARE_{\rho,1D-3D}(t)$ of 1D plots.

290 - APAR_{green}: relative error $\varepsilon_{APAR,1D-3D}(t)$ of 1D plots.

291 - SIF emission yield: relative error $\varepsilon_{SIF.EY,1D-3D}(t)$ of 1D plots.

292 - SIF_{emitted}: relative error $\varepsilon_{SIF.em,1D-3D}(t)$ of 1D plots.

293 -SIF escape factor_{hemi} and SIF escape factor_{nadir}: relative errors $\varepsilon_{SIF.EF,1D-3D}(t)$ of 1D plots
 294 at 640 – 700 nm and 700 – 850 nm spectral regions.

295 - SIF nadir yield: relative errors $\varepsilon_{SIF.NY,1D-3D}(t)$ of 1D plots at 640 - 700 nm and 700 - 850 nm.

296 with relative error for a given quantity Q equal to $\varepsilon_{Q,1D-3D}(t) = 100\% \times \frac{Q_{1D}(t) - Q_{3D}(t)}{Q_{3D}(t)}$.

297 **2.8. Influence of canopy wood on SIF emission and measurements**

298 Although they do not intrinsically emit fluorescence, woody elements impact the RB and SIF
 299 observations through their interaction with PAR and SIF. They give rise to two major effects.

300 i) Shading effect: woody elements shade foliar elements, which lowers leaf irradiance and
 301 subsequently SIF emission. ii) Blocking effect: woody elements intercept the emitted SIF
 302 radiation, preventing it from escaping the canopy. These two effects are not independent, due
 303 to sky radiation and multiple scattering and re-absorption mechanisms in the canopy. For
 304 example, the same woody element can shade a leaf element and block its SIF radiation.

305

306 DART simulations were used to quantify the influence of woody elements on SIF observation,
 307 and to separate the shading and blocking effects of woody elements for the CM1 and LM2 sites.
 308 For that, theoretical “no wood” (NW) scenes were constructed by removing cells corresponding
 309 to woody elements from the original “with wood” 3D mock-ups (W). It allowed us to compare

310 the DART-Lux top-of-canopy (TOC) nadir SIF radiance (PSI, PSII and total) of the (W) and
 311 (NW) abstractions, and to compute two types of relative error:

312 - Per spectral band for a specific time (*e.g.*, 12.00 local time):

$$\varepsilon_{SIF,Lv,NW-W}(\lambda) = 100\% \times \frac{SIF_{radiance,NW}(\lambda) - SIF_{radiance,W}(\lambda)}{SIF_{radiance,W}(\lambda)} \quad (7)$$

313 - Per hour from 7.00 to 19.00, by computing mean absolute relative errors for the 640 – 700
 314 nm and 700 – 850 nm spectral regions:

$$MARE_{SIF,Lv,NW-W}(t) = \frac{1}{\sum_i \Delta\lambda_i} \cdot \sum_i \frac{|SIF_{radiance,NW}(t, \lambda) - SIF_{radiance,W}(t, \lambda)|}{SIF_{radiance,W}(t, \lambda)} \cdot \Delta\lambda_i \quad (8)$$

315 Using W plots as reference, the influence of woody elements was assessed for:

316 - APAR_{green} (shading effect): relative error $\varepsilon_{APAR,NW-W}(t)$ NW.

317 - SIF nadir escape factor SIF_{nadir EF} (blocking effect): relative error $\varepsilon_{SIF,NEF,NW-W}(t)$ of NW
 318 plots, where:

$$SIF_{nadir EF} = \frac{\pi \cdot SIF_{nadir radiance}}{SIF_{emitted}} \quad (9)$$

319 With the relative error for a given quantity Q equal to:

$$\varepsilon_{Q,NW-W}(t) = 100\% \times \frac{Q_{NW}(t) - Q_W(t)}{Q_W(t)} \quad (10)$$

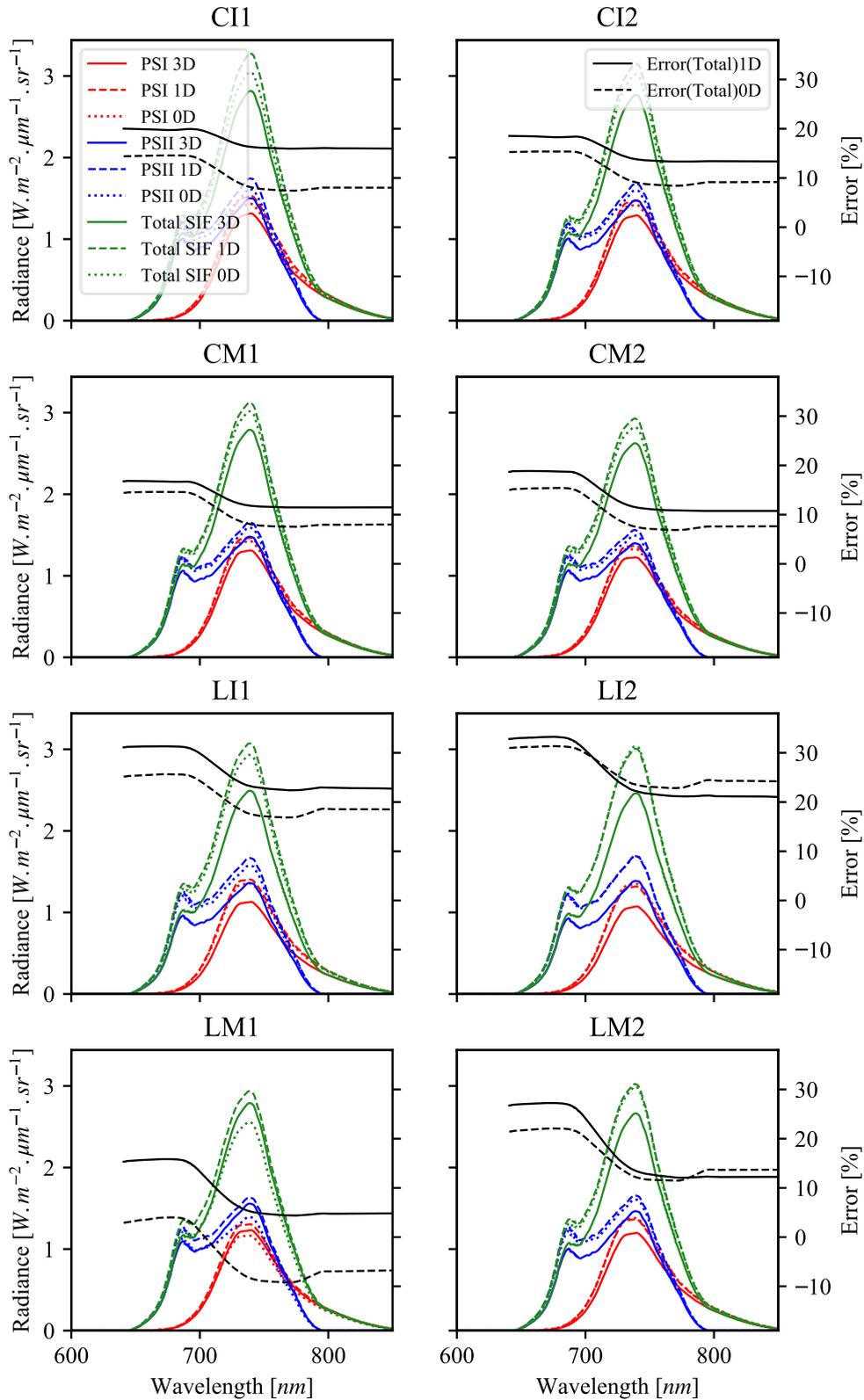
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321 **3. Results**

322 **3.1. General influence of forest abstractions on SIF nadir observations**

323 Figure 4 shows the PSI, PSII and total SIF nadir radiance of the 8 forest plots simulated with
 324 3D, 1D and 0D mock-ups at 12.00 (SZA = 21.050°, SAA = 47.256°). $\varepsilon_{SIF,Lv,0D-3D}(\lambda)$ and
 325 $\varepsilon_{SIF,Lv,1D-3D}(\lambda)$ quantify the relative errors associated with the 0D and 1D forest plots. For all
 326 plots, the 1D mock-ups give the largest nadir total SIF, PSI and PSII radiance. $\varepsilon_{SIF,Lv,1D-3D}$
 327 illustrates the influence of the forest horizontal heterogeneity on radiation propagation in forest,
 328 since the canopy horizontal heterogeneity is the only difference between 3D and 1D mock-ups.
 329 These larger values of 1D SIF radiance can be explained by the fact that the top layers of 1D

330 plots intercept more radiation than the top layers of 3D plots (i.e., clumping effect), which gives
331 rise to larger SIF emission by canopy layers that tend to contribute most to the canopy SIF
332 radiance. Also, the ground is more visible in 3D plots than 1D plots, whereas the ground has no
333 SIF emission. The order of magnitude of the difference between the radiance of 1D and 3D
334 mockups is similar for all investigated forest sites.



335

336

337

338

Figure 4. PSI, PSII and total SIF nadir radiance of the eight sites simulated with 3D, 1D and 0D abstractions, at 12.00 local time ($SZA = 21.050^\circ$, $SAA = 47.256^\circ$).

339 SIF radiance values of 0D and 1D forest mock-ups differ due to differences in the leaf and wood
 340 vertical distributions, which vary greatly among the sites (except for LI2 and LM2). In general,
 341 nadir SIF radiance relative differences $\varepsilon_{SIF,L_v,0D-1D}(\lambda)$ between 0D and 1D plots are much
 342 smaller than $\varepsilon_{SIF,L_v,1D-3D}(\lambda)$ between 1D and 3D plots, except for LM1. It means that forest
 343 horizontal heterogeneity has a larger influence on SIF radiance than forest vertical
 344 heterogeneity. SIF radiance was always smaller for 0D mock-ups than for 1D mockups. This is
 345 mostly explained by the homogenized vertical distribution of both foliar and woody elements
 346 in the 0D abstractions compared to 1D abstractions. For example, in CI1, CI2, CM1 and CM2,
 347 leaf density is higher in upper canopy layers (Figure 14), foliar homogenization increases the
 348 density of foliar elements in the canopy bottom layers, which increases the canopy shading and
 349 blocking effects. For LI2, the situation is different because leaf density is highest in the lower
 350 canopy layers. Therefore, foliar homogenization increases leaf density in the canopy upper
 351 layers, which decreases the canopy shading and blocking effects. These trends are also
 352 influenced by the vertical distribution of woody elements.

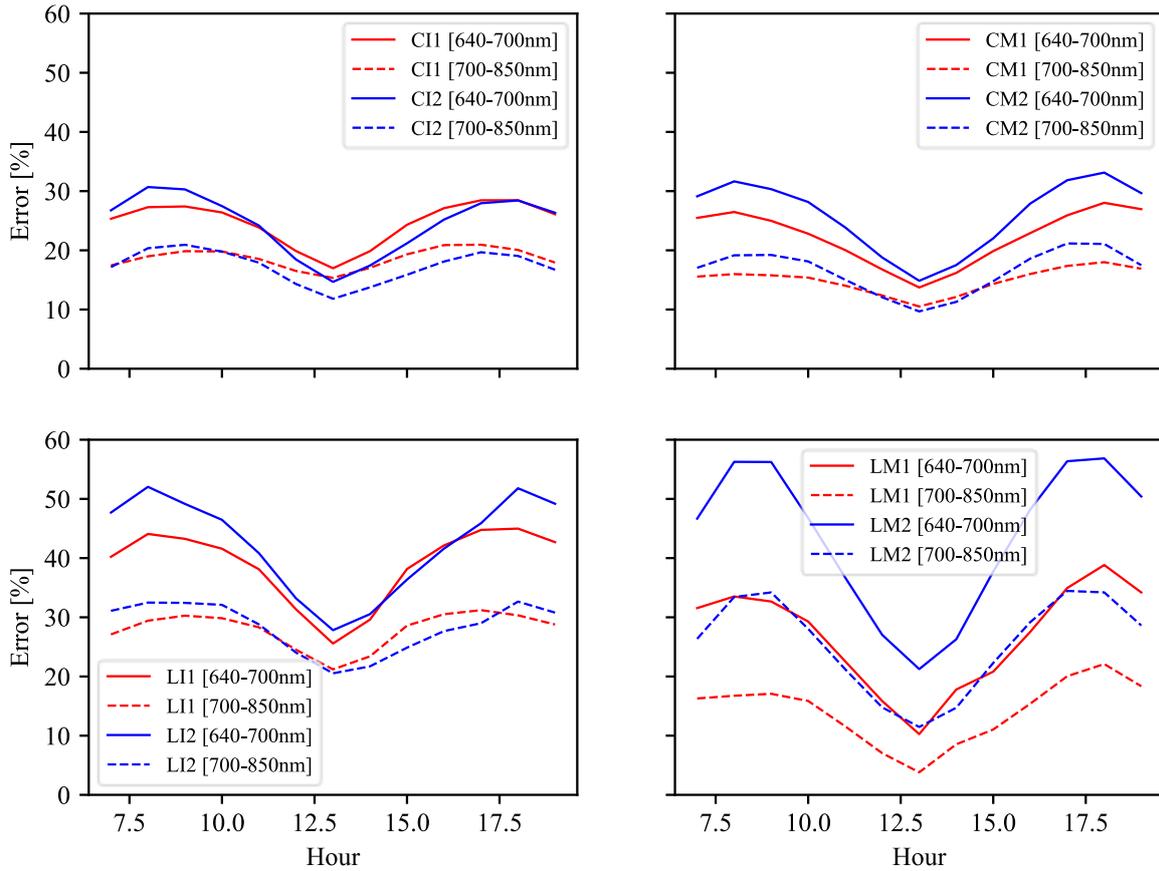
353 The relative difference $\varepsilon_{SIF,L_v,0D-3D}(\lambda)$ between the radiance of 0D and 3D mock-ups is driven
 354 by horizontal and vertical heterogeneity. The inequality $\varepsilon_{SIF,L_v,0D-3D}(\lambda) < \varepsilon_{SIF,L_v,1D-3D}(\lambda)$
 355 indicates that vertical and horizontal heterogeneities have an opposite effect on canopy SIF
 356 radiance in our simulations. While the horizontal heterogeneity tends to decrease canopy SIF
 357 nadir radiance, the vertical heterogeneity tends to increase it. LM1 is an exception. Its 0D SIF
 358 radiance is lower than its 3D SIF radiance in the NIR domain. It means that its vertical
 359 heterogeneity imposes a larger influence on SIF nadir radiance than its horizontal heterogeneity,
 360 which is consistent with the fact that LM1 is the only plot where the density of woody and foliar
 361 elements is very dense in the lower canopy layers.

362

363 Figure 5 shows the diurnal evolution of $MARE_{SIF,L_v,1D-3D}(t)$ (*i.e.*, relative error of total nadir
 364 SIF radiance of 1D plots compared to 3D plots) at 640 - 700 nm and 700 - 850 nm. This quantity
 365 is mostly influenced by the forest horizontal heterogeneity. It appears symmetrically distributed
 366 between the morning and the afternoon hours, with a dip appearing always at local noon. It is
 367 the largest around 8.00 and 18.00, reaching up to 55%, and the smallest at 13.00 (local solar
 368 noon), with values between 10% and 20%. It is usually larger at 640 - 700 nm than at 700 - 850
 369 nm, where shading effects are dampened by prevailing multiple scattering events. This diurnal
 370 variation can be explained by the shadow effects associated with changing solar zenith angle

371 and associated variability in the proportions of direct sun and diffuse atmospheric radiation. In
 372 the early morning, it starts increasing because shadow effects are increasing due to the increase
 373 of the direct sun proportion in total irradiance. Later in the morning, it starts decreasing because
 374 shadow effects decrease due to the decrease of solar zenith angle, reaching a minimum at solar
 375 noon. A symmetrical behavior starts in the second half of the day.

376



377

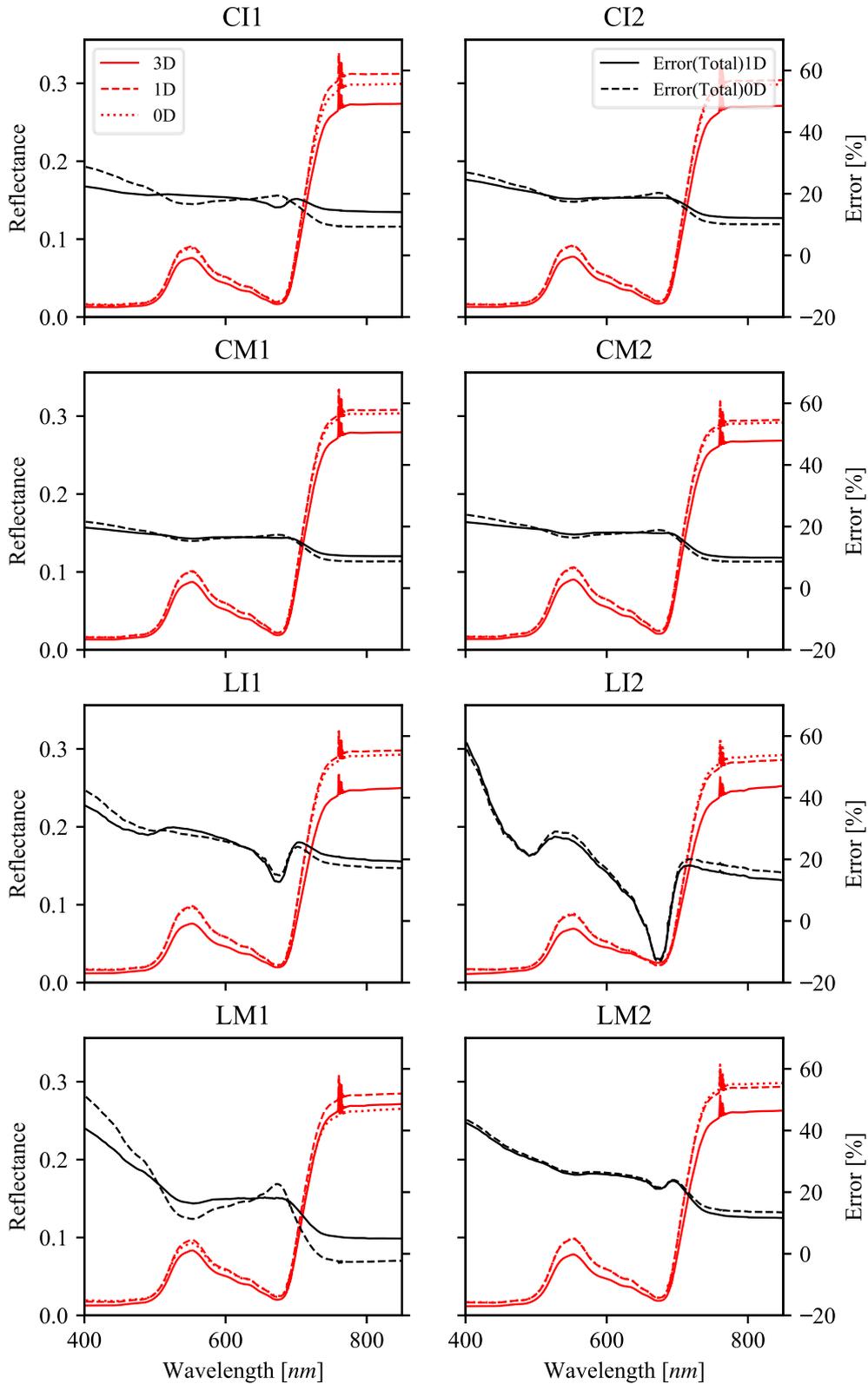
378 Figure 5. Diurnal evolution of the total nadir SIF radiance relative error $MARE_{SIF,L,1D-3D}(t)$
 379 between 1D and 3D mock-ups at 640 – 700 nm and 700 – 850 nm.

380 Figure 6 shows the canopy nadir reflectance of the 8 forest plots simulated with 3D, 1D and 0D
 381 mock-ups at 12.00 (SZA = 21.050°, SAA = 47.256°). $\epsilon_{\rho,0D-3D}(\lambda)$ and $\epsilon_{\rho,1D-3D}(\lambda)$ quantify
 382 the of 0D and 1D abstractions compared to 3D abstraction. All curves have the expected local
 383 spectral peak around the O₂-A absorption band at 760nm. As for the SIF radiance (Figure 4),
 384 the total reflectance of 3D plots is the smallest compared to the 1D and 0D plots, except for
 385 LM1 where the 0D plot has a slightly lower reflectance than the 3D plot above 700nm.

386 Therefore, as for SIF radiance, the horizontal heterogeneity tends to decrease the nadir
387 reflectance.

388 The influence of the vertical heterogeneity of the plots on their reflectance is not as clear as for
389 SIF radiance. By contrast to the relative errors on the SIF radiance, the relative errors on the
390 total reflectance of the 1D and 0D forest plots are similar. This stresses two points. 1) As for
391 SIF, the forest vertical heterogeneity plays a lesser role than the forest horizontal heterogeneity.
392 2) The vertical heterogeneity plays a larger role for canopy SIF radiance than for canopy
393 radiance that contains radiance due to the scattering of solar radiation. Also, these relative errors
394 tend to higher for wavelengths under 700nm. Indeed, the 1D and 0D abstractions of the forest
395 cover neglect the shadow effects due to direct and diffuse radiation and canopy structure.
396 Multiple scattering being smaller at wavelengths lower than 700nm, shadowing effects are
397 larger in these wavelengths. The diurnal evolutions of the relative error $MARE_{\rho,1D-3D}(t)$ in
398 nadir reflectance of 1D plots at 640-700 nm and 700-850 nm (Figure 7) have shapes and orders
399 of magnitude similar to those of SIF radiance $MARE_{SIF,L,1D-3D}$ (Figure 5), except for LI2 at
400 640 - 700nm, where the relative error is higher for SIF radiance.

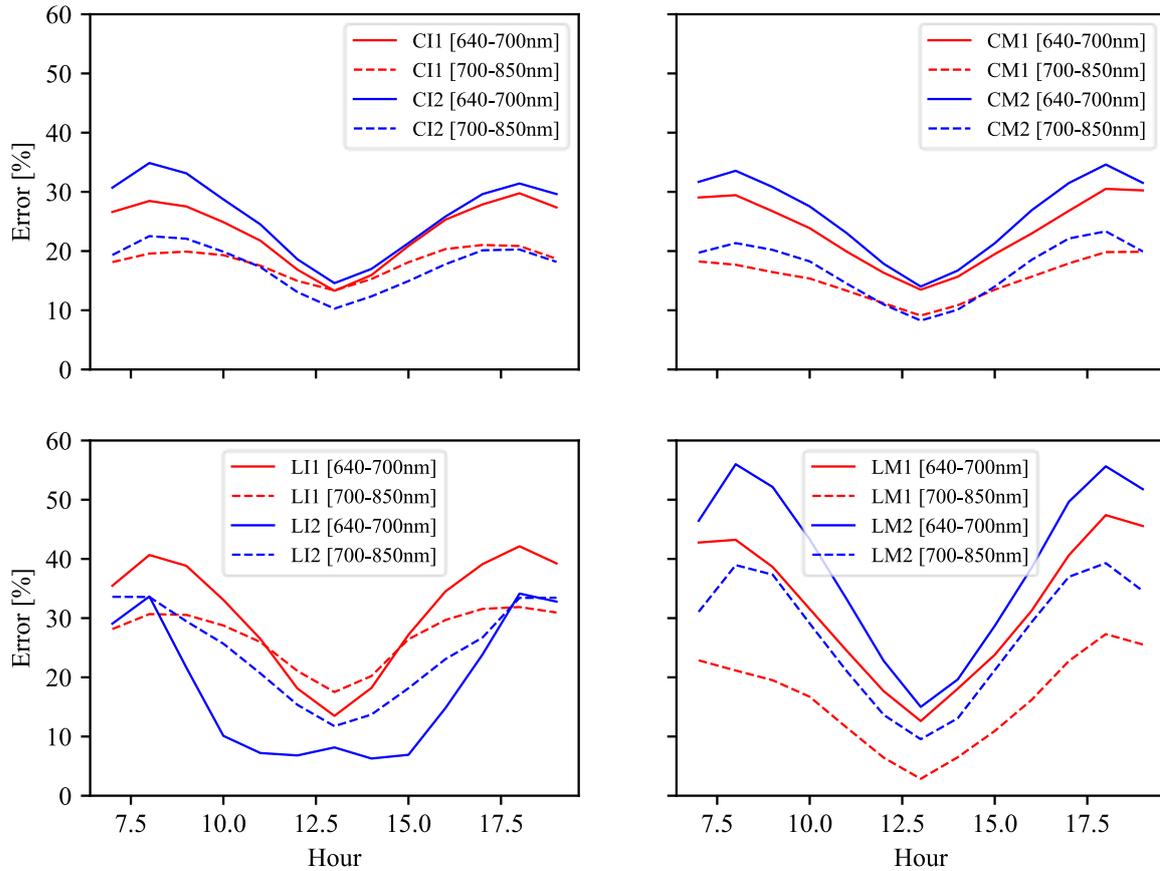
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404
405

Figure 6: Canopy nadir reflectance of the eight study sites simulated with 3D, 1D and 0D mock-ups, at 12.00 local time (SZA = 21.050°, SAA = 47.256°). $\epsilon_{\rho,1D-3D}(\lambda)$

406

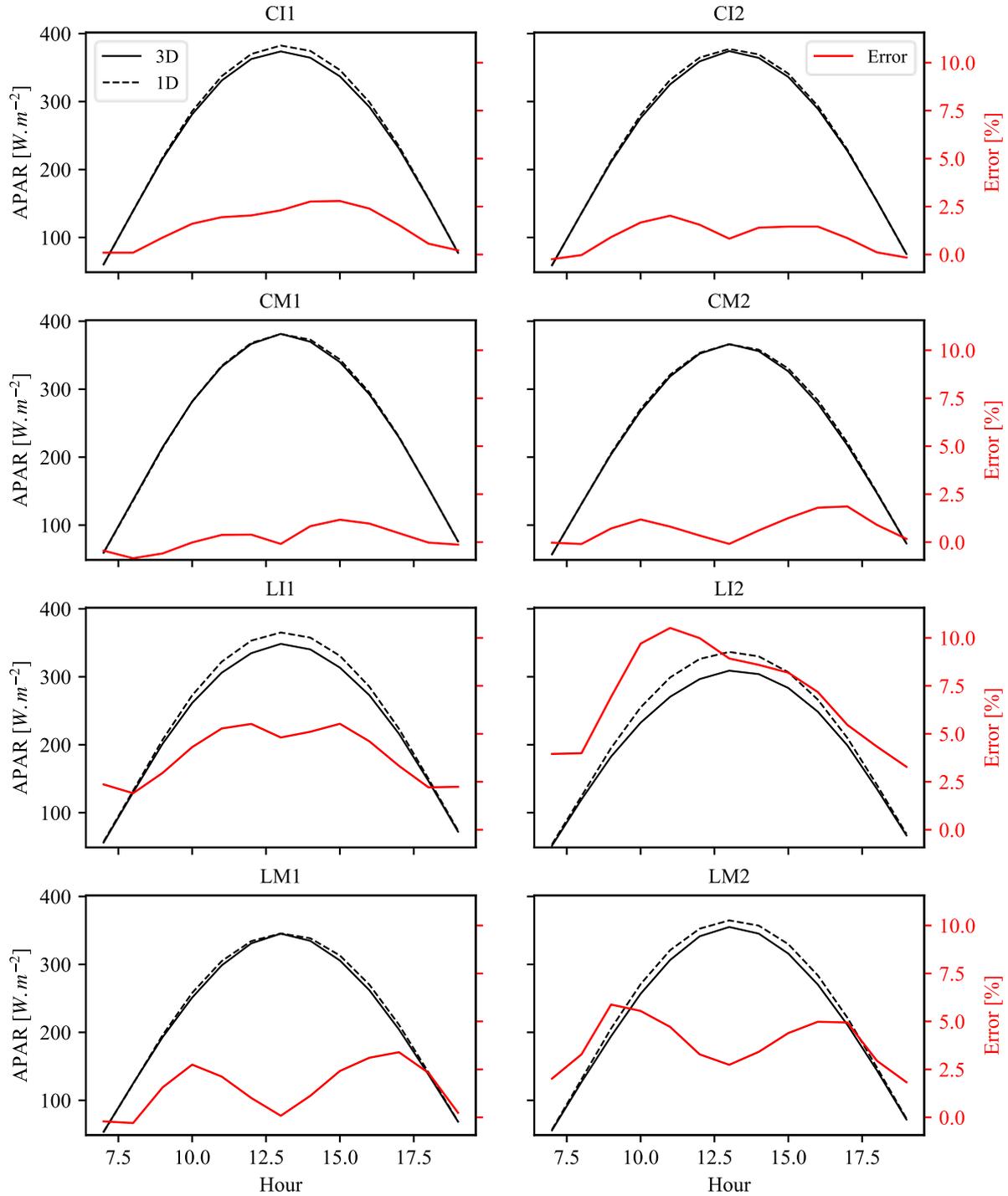


407

408 Figure 7: Diurnal evolution of canopy nadir reflectance relative error $MARE_{\rho,1D-3D}$ at 640-700 nm
 409 and 700-850 nm due to differences in horizontal heterogeneity in 1D and 3D mock-ups.
 410

411 3.2. Impact of forest 3D structure on $APAR_{green}$ (1st process)

412 Figure 8 shows the diurnal PAR absorbed by green leaves ($APAR_{green}$) in the eight 3D and 1D
 413 forest mock-ups, and their associated relative error $\varepsilon_{APAR,1D-3D}(t)$. The 3D mock-ups have
 414 smaller $APAR_{green}$ than the 1D mock-ups. This is consistent with the larger reflectance of 1D
 415 mock-ups compared to the 3D mock-ups, due to the horizontal heterogeneity of the forest plots.
 416 $\varepsilon_{APAR,1D-3D}(t)$ is usually smaller than 5%, with a maximum of 10% for LI2 before noon. It is
 417 smaller than the relative difference of nadir SIF radiance between 3D and 1D forest abstractions
 418 (Figure 5). This indicates that even though the $APAR_{green}$ diurnal changes play an important
 419 role, they are not the only cause responsible for the relative difference in the nadir SIF radiance.
 420



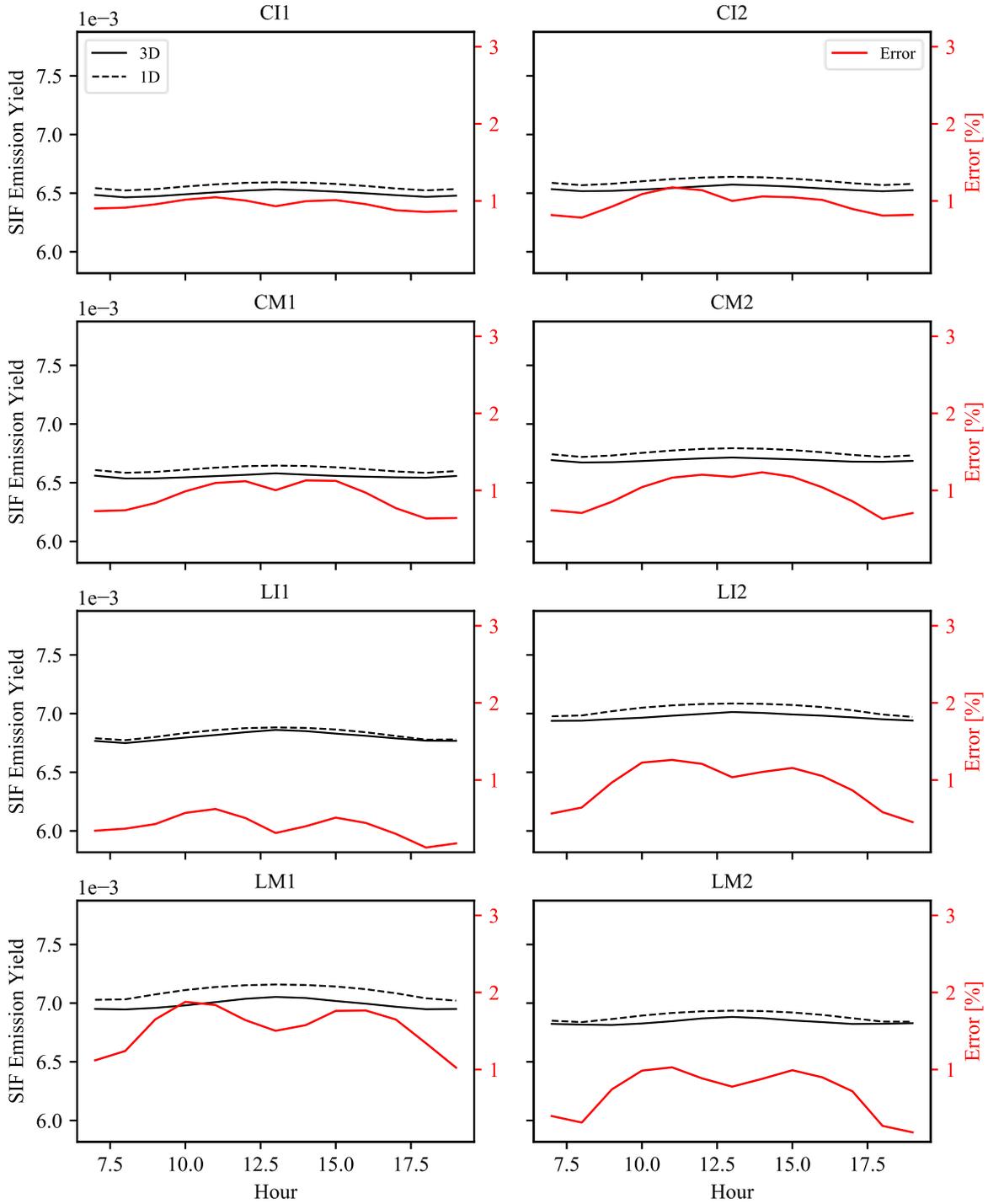
421

422 Figure 8. Diurnal PAR absorbed by green leaves ($APAR_{green}$) in 3D and 1D forest abstractions of the
 423 eight study sites, and their associated relative error $\varepsilon_{APAR,1D-3D}(t)$ triggered by changes in
 424 horizontal heterogeneity of the forest abstractions.
 425

426

3.3. Impact of forest 3D structure on leaf SIF emission yield (2nd process)

427 Figure 9 shows the diurnal total SIF emission yield for 3D and 1D mock-ups and the associated
428 diurnal relative error $\varepsilon_{SIF.EY,1D-3D}(t)$ due to horizontal heterogeneity differences. Relative
429 errors are similar and small for all plots. They reveal that in our simulations the impact of forest
430 3D architecture on SIF emission yield in our simulations is of a less importance. The almost
431 constant diurnal response due to our modeling assumption of constant leaf SIF properties
432 throughout the day.
433



434

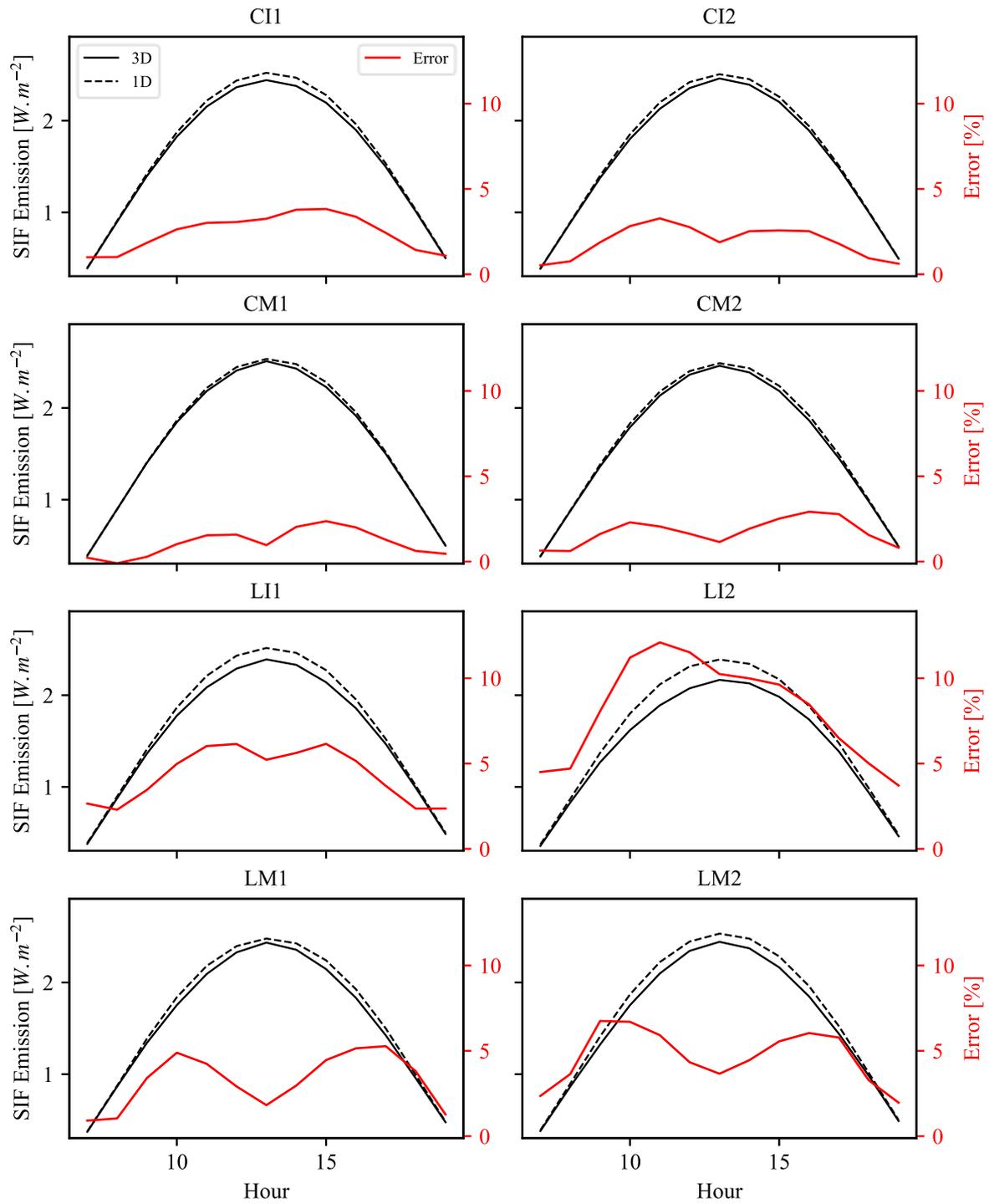
435 Figure 9. Diurnal SIF emission yield of the 3D and 1D forest mock-ups and relative
 436 errors $\varepsilon_{SIF.EY,1D-3D}(t)$
 437

438 Since SIF emission yield in our simulations is hardly affected by the forest 3D architecture, the
 439 diurnal behavior of the DART-FT simulated leaf SIF emission (Figure 10) is understandably
 440 very similar to that of $APAR_{green}$ (Figure 8). The relative error $\varepsilon_{SIF.em,1D-3D}(t)$ computed

441 between the 3D and 1D forest abstractions (Figure 10) gathers the combined errors related to
442 both the 1st and the 2nd processes, without being a simple addition of their relative errors.

443 Figure 11 plots the vertical profiles of LAI, and SIF emission in 3D and 1D plots. The LAI of
444 a layer i located between $[i m, (i + 1) m]$ is the total foliar area of this layer divided by the
445 scene area. It shows that the overestimation of the SIF emission in 1D plots compared to 3D
446 plots mainly occurs in the canopy top layers, *i.e.*, $SIF_{\text{emitted},1D} > SIF_{\text{emitted},3D}$ in these layers.
447 Also, SIF emission is underestimated in the lower layers of 1D plots. Indeed, in 3D forest mock-
448 ups, the forest horizontal heterogeneity leads to better illumination of the lower layers.

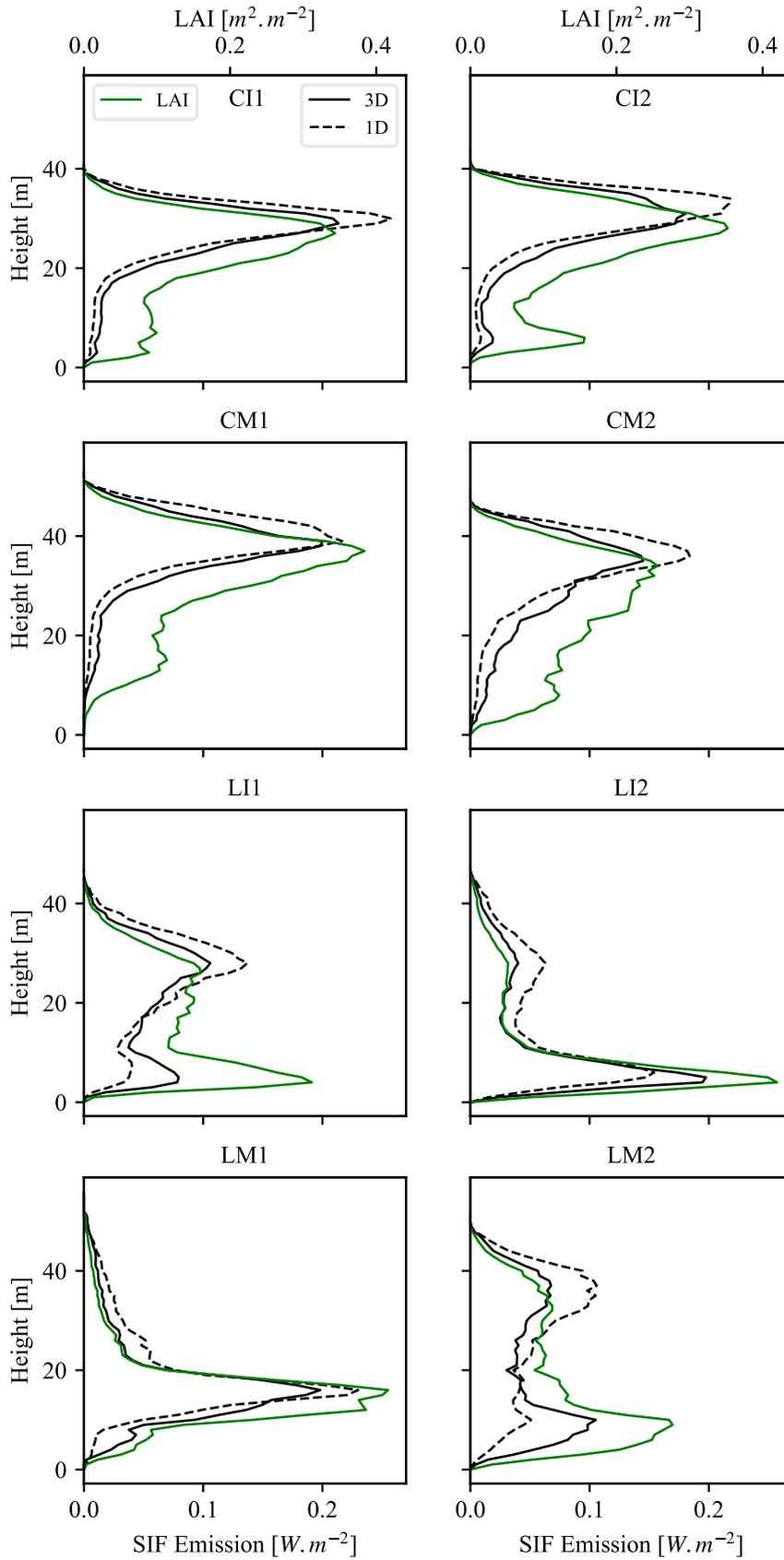
449



450

451 Figure 10. Diurnal leaf SIF emissions for the 3D and 1D forest abstractions and their associated relative
 452 errors $\varepsilon_{SIF.em,1D-3D}(t)$.
 453

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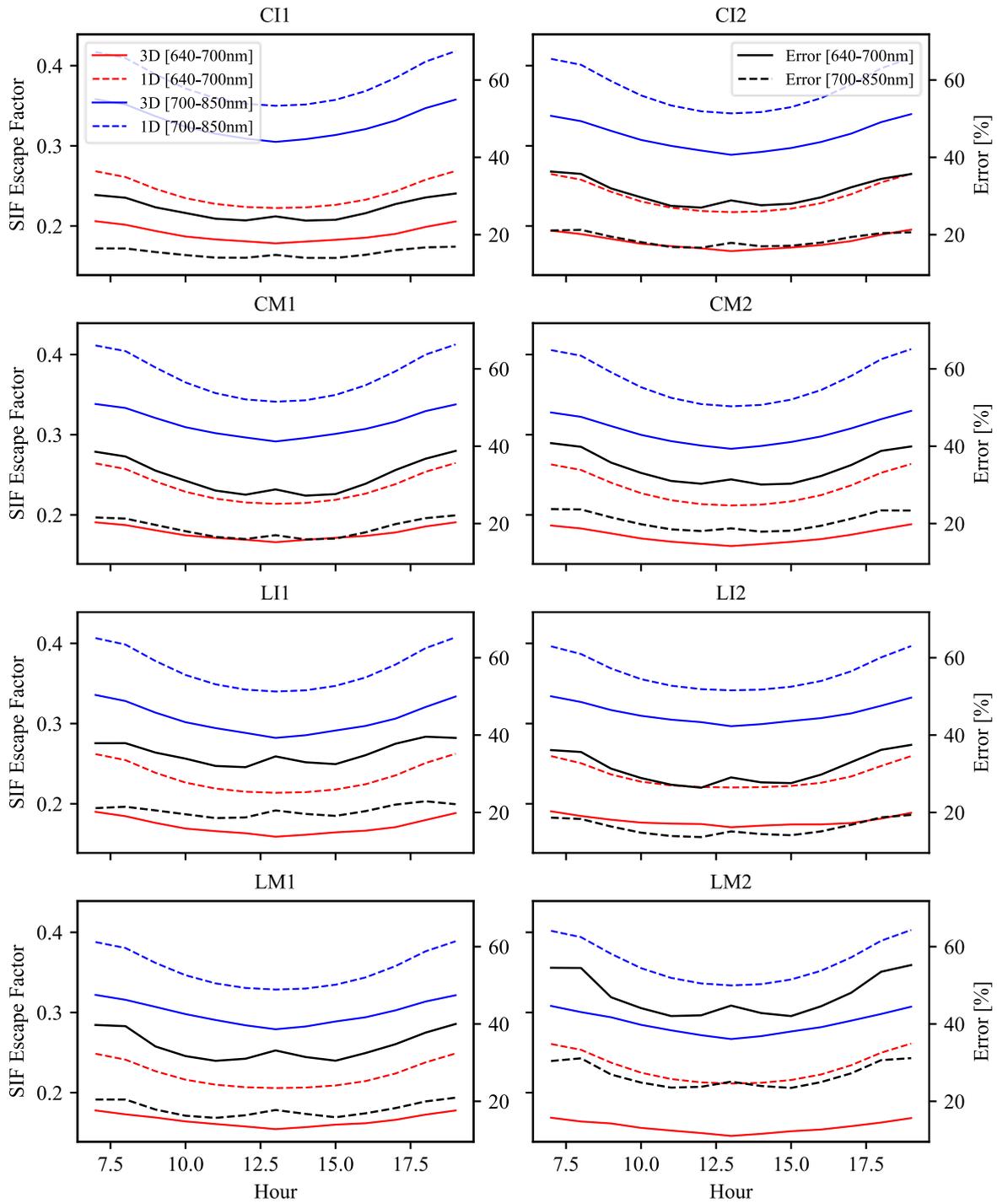
456

Figure 11. Vertical profiles of LAI and leaf SIF emission at 12.00 (local time).

457 **3.4. Impact of forest 3D structure on SIF escape factor (3rd process)**

458 Figure 12 and Figure 13 show the diurnal SIF escape factor_{hemi} and SIF escape factor_{nadir} of 3D
 459 and 1D plots at 640 - 700 nm and 700 nm - 850 nm, and their relative errors $\varepsilon_{SIF.EF,1D-3D}(t)$
 460 and $\varepsilon_{SIF.EFnadir,1D-3D}(t)$ are larger (*e.g.*, > 50% for LM2) than for APAR_{green} (Figure 8) and
 461 leaf SIF emission (Figure 10). Therefore, the 3rd process is more affected by forest 3D structure
 462 than the first two processes. The SIF escape factor is systematically overestimated in 1D plots.
 463 It is larger at 700 nm - 850 nm than at 640 - 700 nm, due to more important multiple scattering
 464 mechanisms, which results in lower relative errors at 700 nm - 850 nm than at 640 - 700 nm.

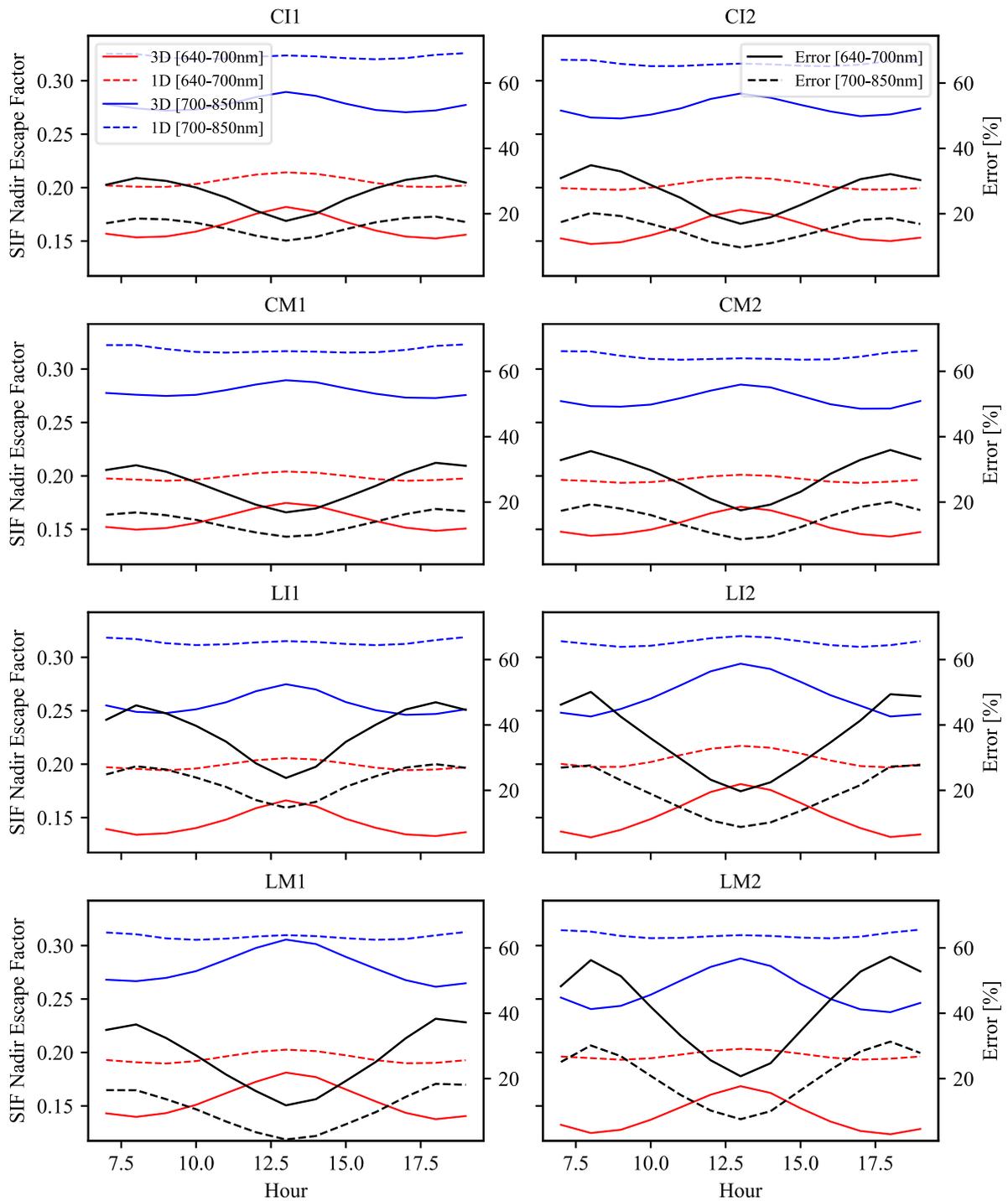
465 The SIF photons that cannot escape the canopy are absorbed by the canopy elements (*i.e.*, leaves,
 466 woody elements, ground). The overestimation of the SIF escape factor of 1D plots compared
 467 to 3D plots is also reflected by a higher absorption of SIF photons in 3D plots (Table 6, Table
 468 7). We can note that the ground absorption is greatly underestimated in 1D forest abstractions.
 469 Again, this is explained by the forest horizontal heterogeneity.



470

471 Figure 12. Diurnal SIF escape factor_{hemi} of the 3D and 1D plots and their associated relative errors.

472



473

474 Figure 13: Diurnal SIF escape factor_{nadir} of the 3D and 1D plots and their associated relative errors.

475

476 Figure 14 shows the vertical profiles of LAI, woody elements (defined similarly as the vertical
 477 profile of LAI), and SIF absorption in 3D and 1D plots. The vertical profiles of SIF absorption

478 show that in 1D forest abstractions, absorption is overestimated in the top layers and
 479 underestimated in the bottom layers as for the leaf SIF emission profiles (Figure 11).

480

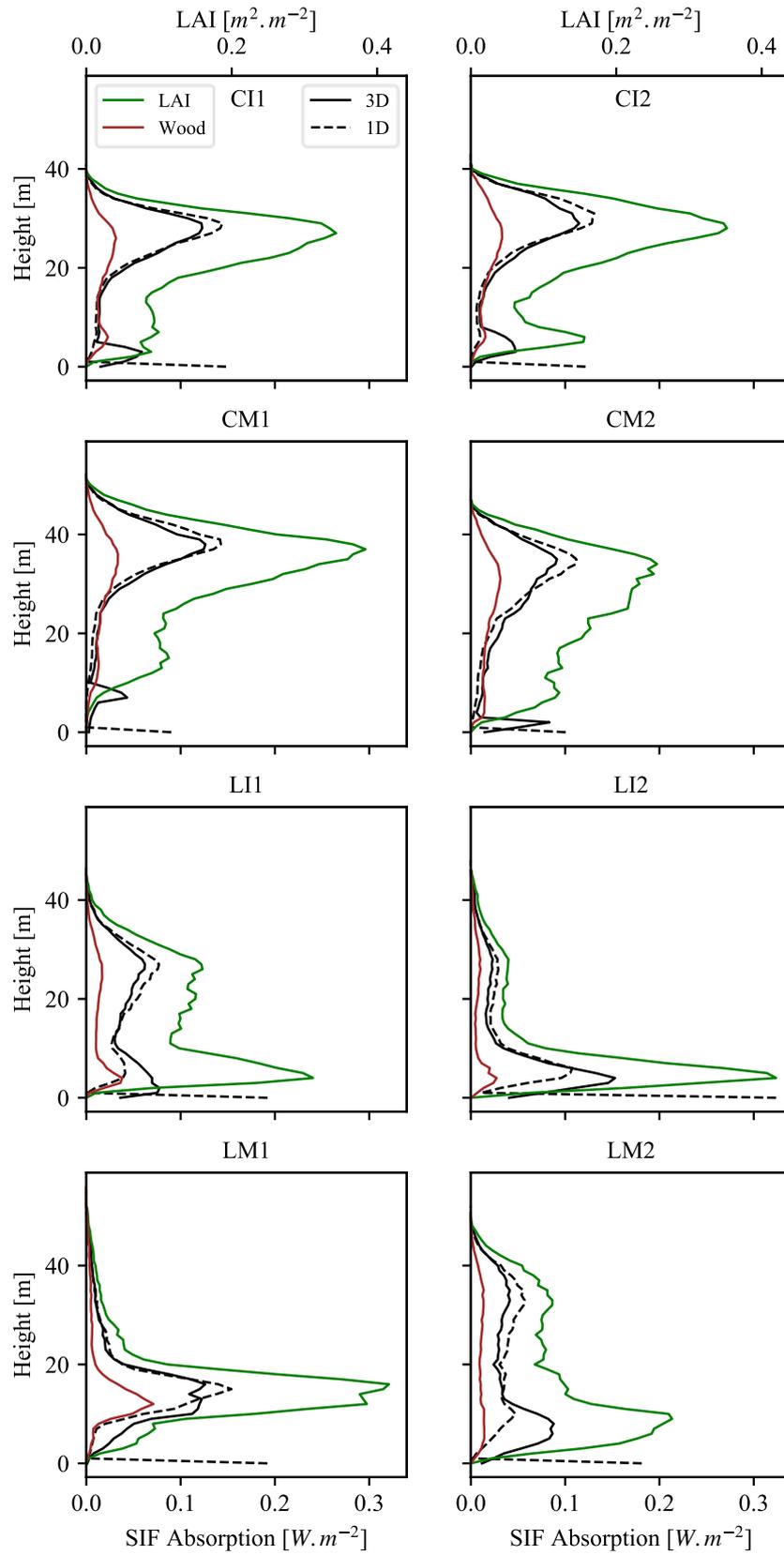
481 Table 6. SIF absorption by the ground and vegetation (leaves and wood) (640-700nm) at 12pm

Plot	CI1	CI2	CM1	CM2	LI1	LI2	LM1	LM2
Fraction of emitted SIF absorbed by "Ground" (3D)	0,0310	0,0290	0,0230	0,0272	0,0463	0,0704	0,0486	0,0449
Fraction of emitted SIF absorbed by "Ground" (1D)	0,0216	0,0180	0,0130	0,0160	0,0301	0,0584	0,0329	0,0274
Relative difference (%)	-30,28	-38,19	-43,40	-41,38	-35,14	-17,12	-32,44	-38,97
Fraction of emitted SIF absorbed by "Leaves + Wood" (3D)	0,7765	0,7838	0,7903	0,7912	0,7757	0,7352	0,7636	0,7843
Fraction of emitted SIF absorbed by "Leaves + Wood" (1D)	0,7512	0,7545	0,7616	0,7613	0,7461	0,7073	0,7462	0,7492
Relative difference (%)	-3,26	-3,74	-3,63	-3,78	-3,81	-3,79	-2,28	-4,47
Absorption fraction (3D)	0,8075	0,8129	0,8133	0,8184	0,8220	0,8056	0,8123	0,8291
Absorption fraction (1D)	0,7728	0,7725	0,7746	0,7772	0,7762	0,7657	0,7791	0,7766
Relative difference (%)	-4,30	-4,97	-4,76	-5,03	-5,57	-4,95	-4,09	-6,34

482

483 Table 7. SIF absorption by the ground and vegetation (leaves and wood) (700-850nm) at 12pm.

Plot	CI1	CI2	CM1	CM2	LI1	LI2	LM1	LM2
Fraction of emitted SIF absorbed by "Ground" (3D)	0,0905	0,0842	0,0683	0,0768	0,1249	0,1741	0,1282	0,1249
Fraction of emitted SIF absorbed by "Ground" (1D)	0,0716	0,0593	0,0440	0,0502	0,0941	0,1640	0,0952	0,0887
Relative difference (%)	-20,96	-29,52	-35,50	-34,62	-24,68	-5,78	-25,71	-28,95
Fraction of emitted SIF absorbed by "Leaves + Wood" (3D)	0,6194	0,6369	0,6543	0,6600	0,6062	0,5265	0,5897	0,6185
Fraction of emitted SIF absorbed by "Leaves + Wood" (1D)	0,6133	0,6257	0,6453	0,6482	0,5991	0,5098	0,6037	0,6057
Relative difference (%)	-0,98	-1,77	-1,39	-1,79	-1,16	-3,19	2,38	-2,08
Absorption fraction (3D)	0,7099	0,7211	0,7226	0,7369	0,7311	0,7006	0,7179	0,7434
Absorption fraction (1D)	0,6849	0,6850	0,6893	0,6985	0,6932	0,6738	0,6989	0,6944
Relative difference (%)	-3,53	-5,01	-4,61	-5,21	-5,18	-3,83	-2,64	-6,59



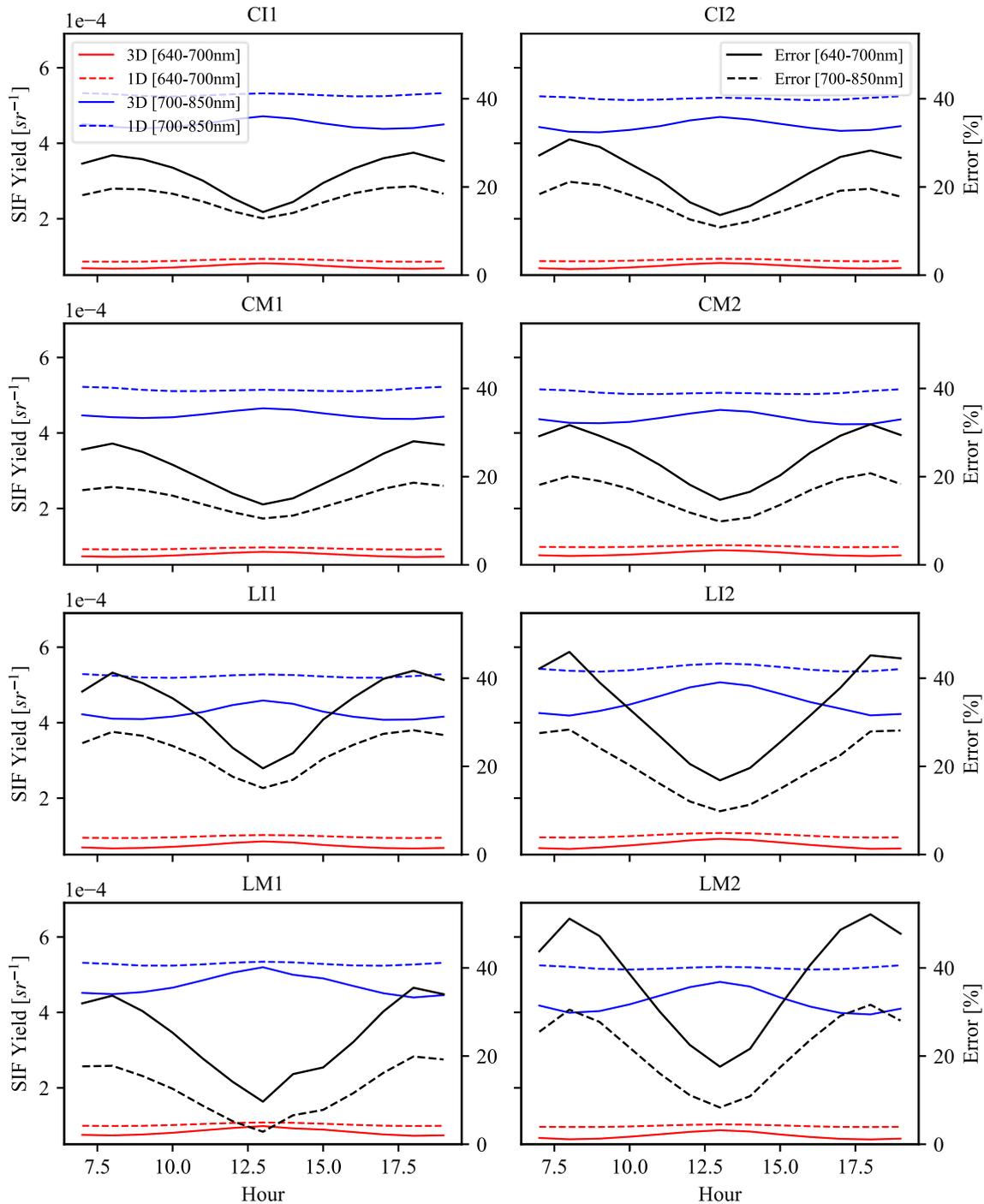
484

485 Figure 14. Vertical profiles of LAI, woody elements and SIF absorption in 3D and 1D forest
 486 abstractions, at 12.00 (local time).

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489

3.5. Impact of forest 3D structure on SIF nadir yield (2nd and 3rd processes)

490 Figure 15 shows diurnal values of SIF nadir yield for 3D and 1D forest plots and their relative
491 error $\varepsilon_{SIF.NY,1D-3D}(t)$. SIF nadir yield informs on the potential of nadir viewing remote sensing
492 instruments to observe leaf SIF emission. The diurnal evolution of $\varepsilon_{SIF.NY,1D-3D}$ is similar to
493 the diurnal evolution of total nadir SIF radiance relative error $MARE_{SIF,L_v,1D-3D}$ (Figure 5):
494 larger errors occur in early morning around 8:00 and late afternoon around 18:00, with minimal
495 errors at noon. SIF yield of 1D plots is always overestimated. Also, errors are larger at 640 nm
496 - 700 nm than at 700 - 850 nm. This is due to the lower impact of multiple scattering at 640 -
497 700 nm than at 700 - 850 nm and therefore the larger impact of shadowing effects at 640 - 700
498 nm.



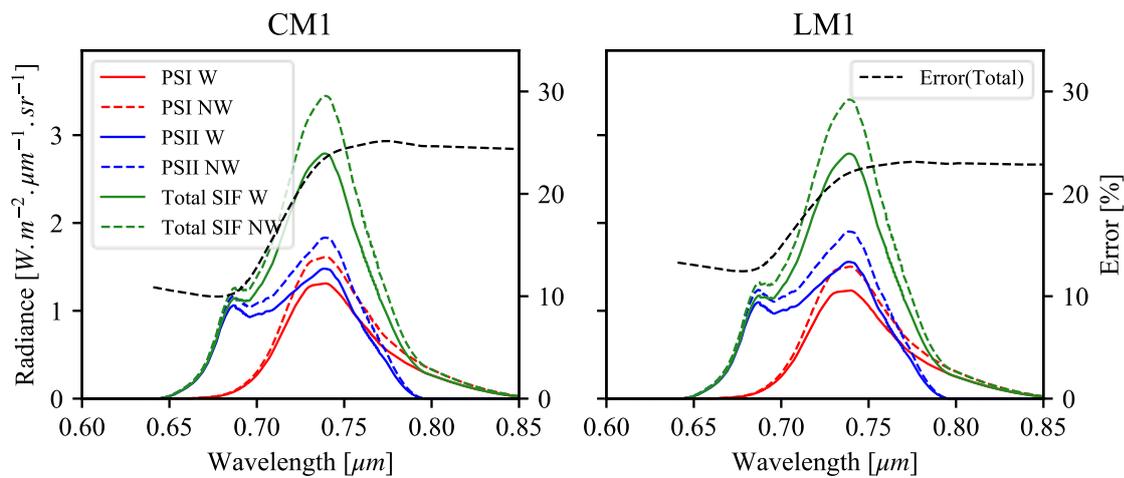
499
500 Figure 15. Diurnal SIF nadir yield of 3D and 1D plots and relative errors at 640 - 700 nm and 700 - 850 nm.

501 **3.6. Influence of woody elements**

502 Figure 16 illustrates the impact of woody elements (*i.e.*, branches and trunks) on the canopy
503 SIF signal. It shows PSI, PSII and total SIF nadir spectral radiance at 12.00 of local time for
504 CM1 and LM1 3D plots simulated with (W) and without (NW) woody elements, and also the

505 associated relative errors $\varepsilon_{SIF,L,NW-W}(\lambda)$ for the total SIF nadir radiance. SIF radiance is
 506 significantly higher if wood is neglected in DART simulations, especially in the near-infrared
 507 domain. $\varepsilon_{SIF,Lv,NW-W}(\lambda)$ is larger ($\approx 25\%$) at wavelengths above 750nm, and smaller at
 508 wavelengths smaller than 680nm. This is explained by the fact that there is more multiple
 509 scattering at these wavelengths, which in turn increases the probability of interception of SIF
 510 radiation by woody elements.

511

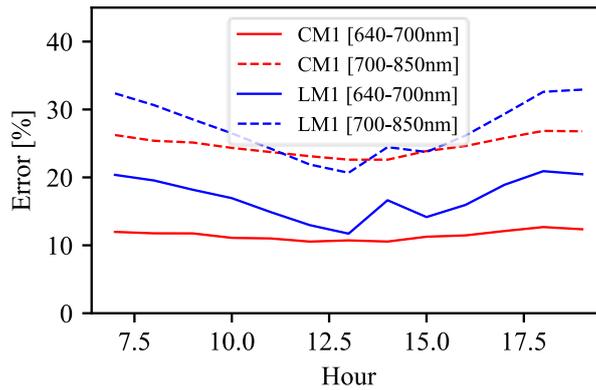


512

513 Figure 16. PSI, PSII and total SIF nadir spectral radiance and error $\varepsilon_{SIF,Lv,NW-W}(\lambda)$ of 3D CM1 and
 514 LM1 plots simulated with (W) and without (NW) woody elements at 12.00 (local time)

515 The diurnal relative error of the SIF total nadir radiance for CM1 and LM1 3D plots simulated
 516 without woody elements, compared to presence of woody elements, varies over the course of
 517 the day (Figure 17). It is lowest at solar noon for LM1 and relatively stable for CM1. The time
 518 variability for LM1 is explained by the fact that its leaf and wood densities are in the canopy
 519 upper layers, which increases the influence of horizontal heterogeneity, and consequently the
 520 occurrence of smaller errors at noon. Conversely, for CM1, the leaf and wood densities are
 521 larger at lower tree heights, which leads to smaller horizontal heterogeneity effects, including
 522 smaller shadow effects.

523

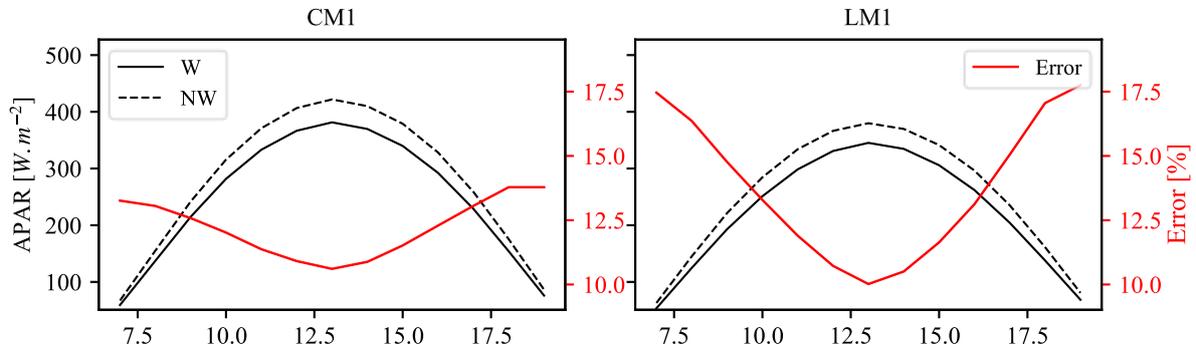


524

525 Figure 17. Diurnal relative error of total nadir SIF radiance $MARE_{SIF,L_v,NW-W}(t)$ of the CM1 and
 526 LM1 3D forest plots simulated without woody elements. 640 – 700 nm and 700 – 850 nm.

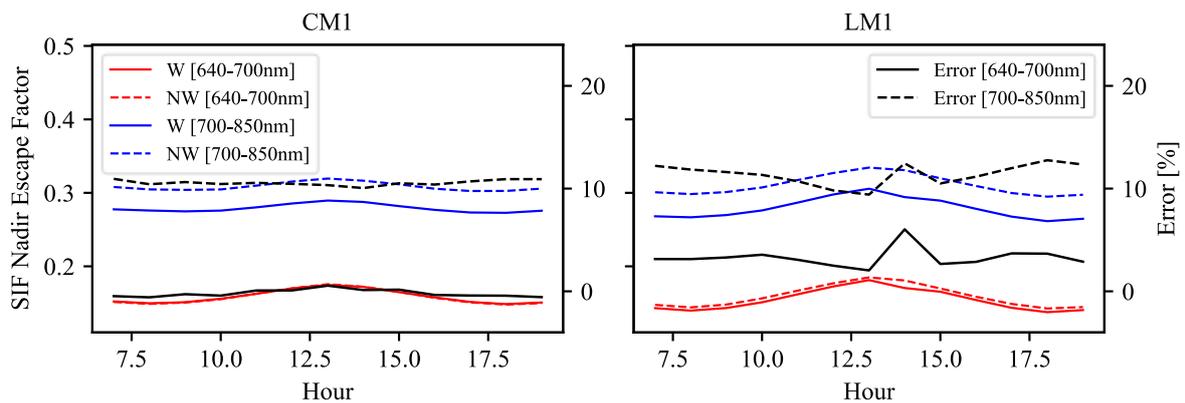
527 The influence of woody elements on the remotely sensed SIF signal can be split into shading
 528 and blocking effects. These effects are not independent. The shading effect corresponds to the
 529 shading of leaves by woody elements during the direct sun and atmosphere illumination of the
 530 forest scene. It limits the absorption of PAR by chlorophylls and consequently decreases leaf
 531 SIF emission (*i.e.*, 1st process). The blocking effect corresponds to the interception (*i.e.*,
 532 absorption and scattering) by woody elements of SIF radiation from its leaf emission to the exit
 533 of the forest canopy along the viewing direction of the remote sensing sensor. Figure 18
 534 illustrates the magnitude of the shading effect. It shows the DART simulated diurnal
 535 $APAR_{green}(t)$ and the associated relative error $\varepsilon_{APAR,NW-W}(t)$, for the CM1 and LM1 3D plots
 536 with and without woody elements. $APAR_{green}$ is always larger for the plots without wood, as
 537 expected. The relative error associated to the shading effect greatly varies over the selected day.
 538 It is minimal at solar midday, when trunks and branches are blocking the least amount of direct
 539 solar radiation, and largest in early morning and late afternoon when trunks and branches are
 540 blocking a larger part of direct PAR. Figure 19 illustrates the blocking effect. It shows the
 541 diurnal SIF nadir escape factor at [400nm-700nm] and [700nm-850nm] for the CM1 and LM1
 542 3D plots simulated with (W) and without (NW) woody elements, and the associated relative
 543 error $\varepsilon_{SIF.NEF,NW-W}(t)$. This relative error is nearly constant over the day, conversely to the
 544 relative error on the canopy $APAR_{green}$. Indeed, as a first approximation $SIF_{nadir EF}$
 545 corresponds to a quantity that is relatively constant: the sum of the canopy "direct – direct" and
 546 "diffuse – direct" transmittance (Vermeire et al., 1997) weighted by a normalized vertical
 547 distribution of leaf SIF emitted radiation. The "diffuse – direct" transmittance is much smaller
 548 at [640-700nm] than at [700nm-850nm] because vegetation absorbs much more at [640-700nm]
 549 than at [700nm-850nm]. Since the blocking effect of wood is more pronounced for oblique

550 directions, it has a higher impact on the "diffuse – direct" than on the "direct – direct"
 551 transmittance. This explains that $\varepsilon_{SIF,NEF,NW-W}(t)$ is smaller at [640-700nm] than at [700nm-
 552 850nm].



553

554 Figure 18. Diurnal $APAR_{green}$ of CM1 and LM1 3D forest plots with (Wood) and without (No Wood)
 555 woody elements and their associated relative errors $\varepsilon_{APAR,NW-W}(t)$.



556

557 Figure 19. Diurnal SIF nadir escape factor over [640nm-700nm] and [700nm-850nm] of CM1 and LM1
 558 3D plots simulated with (W) and without (NW) woody elements and associated relative error
 559 $\varepsilon_{SIF,NEF,NW-W}(t)$.

560

561

4. Discussion

562

4.1. 3D structure of the forest study sites

563 The comparison of DART simulated SIF and non SIF radiometric quantities of 1D and 3D
 564 abstractions of the studied forest plots highlights the influence of the forest architecture, and
 565 especially the forest horizontal heterogeneity, on these quantities: $APAR_{green}$ ($\varepsilon_{APAR,1D-3D}(t)$:
 566 Figure 8), SIF emitted ($\varepsilon_{SIF.em,1D-3D}(t)$: Figure 10), SIF_{nadir yield} ($\varepsilon_{SIF.NY,1D-3D}(t)$: Figure
 567 15), canopy SIF exitance and escape factor ($\varepsilon_{SIF.EF,1D-3D}(t)$: Figure 12), SIF nadir yield
 568 ($\varepsilon_{SIF.NY,1D-3D}(t)$: Figure 15) and reflectance (Figure 6). Braghieri et al. (2021) found that the

569 SIF modeling was improved by introducing a clumping index (Nilson, 1971; Pinty et al., 2006)
 570 to replicate the behavior of structurally complex 3D canopies in the 1D model CliMA-Land
 571 (based on the mSCOPE model (Yang et al., 2017)). In this study, simulating the SIF signal
 572 while neglecting the forest horizontal heterogeneity can lead to very large relative errors,
 573 especially for logged “L” forest sites where they can reach 60%. For example, the error on SIF
 574 radiance $MARE_{SIF,Lv,1D-3D}(t)$ is higher for the logged “L” forest sites (Figure 5). This is
 575 consistent with the fact that these forest sites have a higher horizontal heterogeneity, with a
 576 higher canopy height variability and a higher number of pure bare ground pixels, as shown in
 577 Table 4 and in the height maps (Figure 2). Generally, the horizontal heterogeneity tends to
 578 decrease the SIF signal that escapes the forest canopy. The vertical heterogeneity appeared to
 579 have an opposite effect in most cases. These points are further discussed below.

580

581 **4.2. Effect of 3D architecture on the three processes driving SIF generation**

582 Several sensitivity analysis studies based on radiative transfer modeling were carried out to
 583 assess the impact of some structural parameters on the SIF such as leaf density, leaf angular
 584 distribution and fractional vegetation cover (Tong et al., 2021; Zeng et al., 2020), the
 585 contribution of understory (Hornero et al., 2021), clumping and woody elements impacts
 586 (Malenovsky et al., 2021). In this study, we assessed the impact of canopy heterogeneity on SIF
 587 and processes driving its generation. High relative errors in nadir SIF radiance were observed
 588 for the 8 forest plots due to neglecting the 3D forest architecture, in particular, the horizontal
 589 heterogeneity. Errors were maximal in the hours of the day with lowest PAR having the larger
 590 shading effects. They were higher than 50% in the most heterogeneous plots (LI2 and LM2)
 591 and at [640-700nm] where shading effects are higher due to the lower importance of multiple
 592 scattering in the canopy. The errors in the canopy SIF radiance where forest horizontal
 593 architecture was neglected (*i.e.*, 1D forest plots) can be explained by two processes that drive
 594 the SIF signal generation.

595 1) $APAR_{green}$ is overestimated if the forest horizontal architecture is neglected. It leads to an
 596 overestimation of the SIF emitted by leaves. This overestimation of SIF emission mainly
 597 occurs in the upper canopy layers. This is mainly due to the fact that in the forest 1D
 598 abstractions, the leaves of the top layers are homogeneously distributed, whereas in actual
 599 3D forests, they can be greatly clumped at two levels: they are grouped within distinct tree

600 crowns, and also, they tend to be clumped within each tree crown. Combined, these effects
 601 result in upper layers of 1D plots that are more efficiently illuminated than in 3D plots,
 602 which explains higher SIF emission in 1D plots than in 3D plots. However, in the bottom
 603 layers, the SIF emission of 1D plots is underestimated. Indeed, the roughness of the actual
 604 canopy causes a better penetration of light to the bottom layers of the 3D plots, compared
 605 to the associated 1D plots, where the top layers of the canopy shade more efficiently the
 606 light. This is illustrated by Figure 11: the profile of SIF emission is similar to the profile of
 607 LAI with a higher $\frac{\text{SIF}_{\text{emitted}}}{\text{LAI}}$ value in the top layers. This means that the SIF emission per leaf
 608 area unit is higher for the top layers because leaves in the top layers are able to capture
 609 more light than the leaves in the bottom layers.

610 2) The emitted SIF radiation has a higher ability to escape from the canopy in the 1D
 611 abstractions of the forest plots both for the upward nadir direction (*cf.* SIF yield in Figure
 612 15), and for the upper hemisphere (*cf.*, SIF escape factor_{hemi} in Figure 12). It corresponds
 613 to an underestimation of the total absorption fraction of SIF in all 1D abstractions of the 8
 614 forest plots (Table 6, Table 7). This underestimation of SIF absorption is rather large for
 615 the ground, and larger for [640-700nm] (*i.e.*, between -17 and -43% for [640-700nm],
 616 between -5% and -35% for [700-850nm]) and rather small for "Leaf + Wood" (*i.e.*, between
 617 -2 and -4% for [640-700nm], between -1 and -3% for [700-850nm]). LM1 has a slightly
 618 different behavior: in its 1D abstraction, the absorption of "Leaf + Wood" is slightly
 619 overestimated for [700-850nm] (*i.e.*, around 2%). Part of the underestimation of SIF
 620 absorption by the ground for 1D plots is due to the smaller area of the ground in the 1D
 621 plot compared to the 3D plot where topography is simulated (Table 2).

622 The vertical profiles of SIF emission (Figure 11) and absorption (Figure 14) of the 1D plots
 623 show that emission and absorption are both overestimated in the top layers and underestimated
 624 in the bottom layers. A main particularity for the absorption profile is the influence of the
 625 ground. It shows sharp peaks at 0 m height for 1D simulations. For the 3D abstractions of the
 626 forest plots, the height of the ground is variable. Therefore, ground absorption peaks appear in
 627 the bottom for the "C" plots. These peaks are not visible in "L" plots, because of important
 628 absorption of the leaves and woody elements in the bottom part of the canopies.

629

630 **4.3. Influence of 3D architecture on the canopy reflectance.**

631 As a first approximation, SIF emission can be considered as the reflection of radiation at a
 632 different wavelength from that of the incident radiation. Therefore, it makes sense to find
 633 similar errors for SIF radiance $MARE_{SIF,L_v,1D-3D}(t)$ and canopy reflectance $MARE_{\rho,1D-3D}(t)$.
 634 However, SIF has some particularities that may differ from reflectance. Indeed, the SIF
 635 emission only comes from leaf elements. Other components of the canopy (*i.e.*, woody elements
 636 and ground) do not emit SIF radiation, even though they contribute indirectly by scattering SIF
 637 radiation emitted by foliar elements. On the other hand, all elements of the canopy can
 638 contribute directly to the canopy radiance. Since bare ground does not directly contribute to the
 639 SIF radiance of forest plots, pure bare ground pixels have SIF radiance values close to zero. A
 640 nadir viewing sensor cannot see the bare ground in 1D plots, conversely to 3D plots. Hence,
 641 $MARE_{SIF,L_v,1D-3D}$ tends to be larger than $MARE_{\rho,1D-3D}$ because for canopy reflectance, pure
 642 bare ground pixels and vegetation pixels have values of the same order of magnitude. This
 643 explains that for LI2, the SIF radiance errors (Figure 5) are notably larger than the reflectance
 644 errors (Figure 7). Indeed, compared to the other sites (cf. Table 4), the LI2 site has the
 645 particularity to have the largest surface of ground without vegetation cover. Therefore, its
 646 $MARE_{SIF,L_v,1D-3D}$ tends to be large, especially if the ground reflectance is high. Multiple
 647 scattering explains that SIF radiance errors are larger in 640 – 700nm than in 700-850nm
 648 domain. Indeed, in the 700 – 850nm, the shadowing effects due to the canopy structure are
 649 attenuated by the important multiple scattering in this spectral domain. It is also the case for
 650 canopy reflectance in most cases expect for LI1 (in the middle of the day) and LI2 (Figure 7).
 651 This is because we only consider the 640 – 700nm spectral region and not all the 400 – 700nm
 652 for the comparison with SIF. Indeed, In Figure 6, we see that for these plots, $\varepsilon_{\rho,1D-3D}(\lambda)$ has a
 653 local minimum around 680nm, and even a sign change for LI2.

654

655 **4.4. Influence of woody elements**

656 Although woody elements do not generate SIF emission, their interaction with the
 657 photosynthetically active light and with SIF radiation emitted by leaves can highly impact the
 658 SIF signal, as shown in (Malenovský et al., 2021). We studied their influence on the SIF signal
 659 by comparing the SIF signal of forest plots that was simulated without and with woody elements.
 660 For that, we removed the woody elements from the 3D abstractions of the CM1 and LM1 plots.
 661 It appeared that the plots without woody elements had a higher simulated SIF radiance,

662 especially in the 700-850 nm spectral domain where multiple scattering is highly influenced by
 663 the presence of woody elements. The influence of woody elements is smaller in the 640 – 700
 664 nm spectral domain. The shading effect of woody elements on SIF emission leads to a lower
 665 $fAPAR_{green}$ (Figure 18) and therefore triggering less SIF emission. It was shown to be more
 666 important than the blocking effect of woody elements (Figure 19), especially for oblique solar
 667 directions and at 640-700 nm.

668

669 **5. Concluding remarks**

670 This study investigated the potential effect of the forest 3D architecture on diurnal nadir SIF
 671 RS observations and SIF emissions inside the canopy. We studied the following three processes
 672 responsible for modulation of the canopy SIF signal: i) the attenuation of incident PAR in the
 673 canopy, ii) the leaf SIF emission efficiency, and iii) the attenuation of the SIF between its place
 674 of emission and its observation above the canopy. The potential impact of woody elements on
 675 the SIF signal of forest stands was also investigated. Eight study sites, located within the
 676 temperate deciduous forest in the Smithsonian Environmental Research Center, were modeled
 677 using the DART-FT and DART-Lux radiative transfer modes and the effects of their forest
 678 architecture were assessed by comparing SIF quantities of the sites simulated as 3D, 1D and
 679 0D scenes.

680 Although several general trends common to all sites were clearly identified, some results
 681 were of the site-specific nature due to structural differences in canopy horizontal and vertical
 682 heterogeneity. Results revealed that the horizontal heterogeneity of forests had a larger
 683 influence than the canopy vertical heterogeneity. Therefore, for a correct modeling of remotely
 684 sensed SIF signals of spatially heterogeneous canopies, one must consider the full 3D
 685 architecture of forests and not only their vertical heterogeneity as being assumed in 1D RTMs.

686 Studying the propagation of SIF radiation within the canopy through quantitative
 687 parameters, such as the SIF escape factor and the nadir SIF yield, is essential for linking the
 688 SIF RS observation to the canopy foliage SIF emission. Three key indicators were able to
 689 explain most of the differences between the nadir SIF signal of canopies simulated as 3D and
 690 1D landscapes. The SIF escape factor (ϵ_{1D-3D} up to 40%) was shown to be the most indicative
 691 parameter, followed by the attenuation of incident PAR and consequently reduction of
 692 $fAPAR_{green}$ (ϵ_{1D-3D} less than 5%), and the SIF emission yield (ϵ_{1D-3D} less than 2%) induced
 693 by different f_{qe} values assigned to the sun- and shade-adapted leaves. Our results indicated that

694 the influence of forest architecture on SIF escape factor and nadir SIF yield values (ϵ up to 40%)
695 varies in time, with differences in forest stand structure and per spectral domain, with ϵ being
696 always greater for the wavelength range of 640 – 700 nm than for the range of 700 – 850 nm.

697 The presence of woody elements inside DART-simulated forest scenes appeared to have
698 a relatively large influence on the canopy SIF radiance through the two effects: i) a shading of
699 photosynthetically active foliage and ii) a blocking (obstruction) of SIF radiation. The relative
700 error associated with the neglect of wood existence ranged between 10% and 35%,
701 depending on analyzed spectral domain and forest site, where the relative errors for the shading
702 effect were ranging between 10 and 20%, and for the blocking effect between 0 and 10%.

703 Although this work underlines the usefulness of 3D RTMs for investigating physical
704 bases linking RS SIF observations with SIF emitted inside a forest canopy, there are several
705 modeling aspects that should be reconsidered and improved in the follow-up work. For example,
706 leaf SIF emission properties were assumed to be constant throughout the day, *i.e.*, the actual
707 modulation of SIF emission by local environmental conditions (*e.g.*, leaf temperature, air
708 humidity, etc.) was not considered. Remediation of this strong assumption requires inclusion of
709 a full canopy energy balance in the DART modeling scheme, that would allow to account for
710 crucial environmental parameters of radiative (*i.e.*, visible, near infrared and thermal infrared
711 radiation budgets) as well as non-radiative processes (*e.g.*, photosynthesis). This is currently
712 possible only by coupling DART with a 1D energy budget model like SCOPE. The development
713 of a 3D energy balance modeling, based on DART radiation budget computations, is on the list
714 of our future works. Three major DART-Lux modeling works, partly completed, will also be very
715 helpful for rapid simulations of SIF over larger landscapes: SIF and thermal emission of
716 vegetation simulated as turbid medium, and 3D radiative budget, including SIF emission.

717

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 727 providing leaf biochemical properties measured for the selected SERC forest species and her
 728 contribution to the improvement of the manuscript.

729

730 **Appendix 1: Conversion of turbid voxels into triangles clouds.**

731 Each turbid cell of a forest mock-ups is converted to a linear combination of a few 3D objects
 732 (i.e., made of facets) among N cell objects whose LAI is LAI_n , with $n \in [1 N]$. Accuracy on the
 733 simulated LAI is 10^{-2} with $N = 16$ with LAI_n equal to 0.01, 0.02, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 1, 1.5,
 734 2, 2.5, 3, 3.5, 4, and 4.5. The area of a facet in each cell object is $5 \cdot 10^{-5} \text{ m}^2$ if $LAI_n \leq 2$, and 10^{-4}
 735 m^2 if $LAI_n > 2$.

736

737 The algorithm of the conversion method is based on the value of LAI_{cell} of the turbid cell to
 738 convert:

739 * Scene $LAI_{cell} < 1$: the turbid cell is replaced by two 3D cell objects at most:

740 - 1st cell object (i.e., cell object with the larger LAI): it can be only enlarged. Its enlargement
 741 is 5% at most. If it should be 5% to get the exact LAI of the turbid cell, then a 2nd cell is
 742 introduced.

743 - 2nd cell object: it can be enlarged or shrunk.

744 * Scene $LAI_{cell} > 1$: the turbid cell is replaced by three cell objects cells at most:

745 - 1st cell object: it cannot be scaled. If precision $< 10^{-2}$, then a 2nd cell is used.

746 - 2nd cell object: it can be only enlarged, by 5% at most. A 3rd cell is used if a larger
 747 enlargement is needed.

748 - 3rd cell object: it can be enlarged or shrunk.

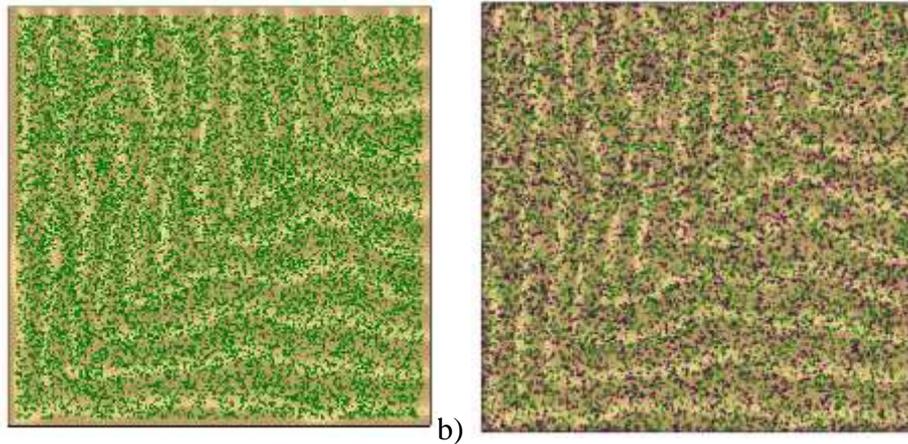
749 Examples of replacement of a turbid cell (LAI_{cell}) by up to 3 3D cell objects:

750 - $LAI_{cell} = 0.92$ (Figure 20). Replacing it by a cell object of $LAI = 1$, (i.e., shrinking it by a factor
 751 0.96) would create 2 cm wide empty spaces at the cell borders. Therefore, it was instead replaced
 752 by a cell object of $LAI = 0.5$ and a cell object of $LAI = 0.4$ enlarged by a factor 1.025. (i.e., 0.92
 753 $\approx 0.5 + 0.4 \times 1.025^2$).

754 - $LAI_{cell} = 0.23 (\approx 0.2 + 0.02 \times 1.2247^2) \Rightarrow$ 2 cell objects: $LAI_n = 0.2$, $LAI_n = 0.02$ scaled by 1.2247

755 - $LAI_{cell} = 0.48 (\approx 0.4 + 0.1 \times 0.8944^2) \Rightarrow$ 2 cell objects: $LAI_n = 0.4$, $LAI_n = 0.1$ shrunk by 0.8944

- 756 - $LAI_{cell} = 0.93 (\approx 0.5 + 0.4 \times 1.0368^2) \Rightarrow$ 2 cell objects: $LAI_n=0.5$, $LAI_n=0.4$ scaled by 1.0368
 757 - $LAI_{cell} = 0.64 (\approx 0.5 + 0.1 + 0.05 \times 0.8944) \Rightarrow$ 3 cell objects: $LAI_n=0.5$, $LAI_n=0.1$, $LAI_n=0.05$
 758 shrunk by 0.8944.
 759
 760



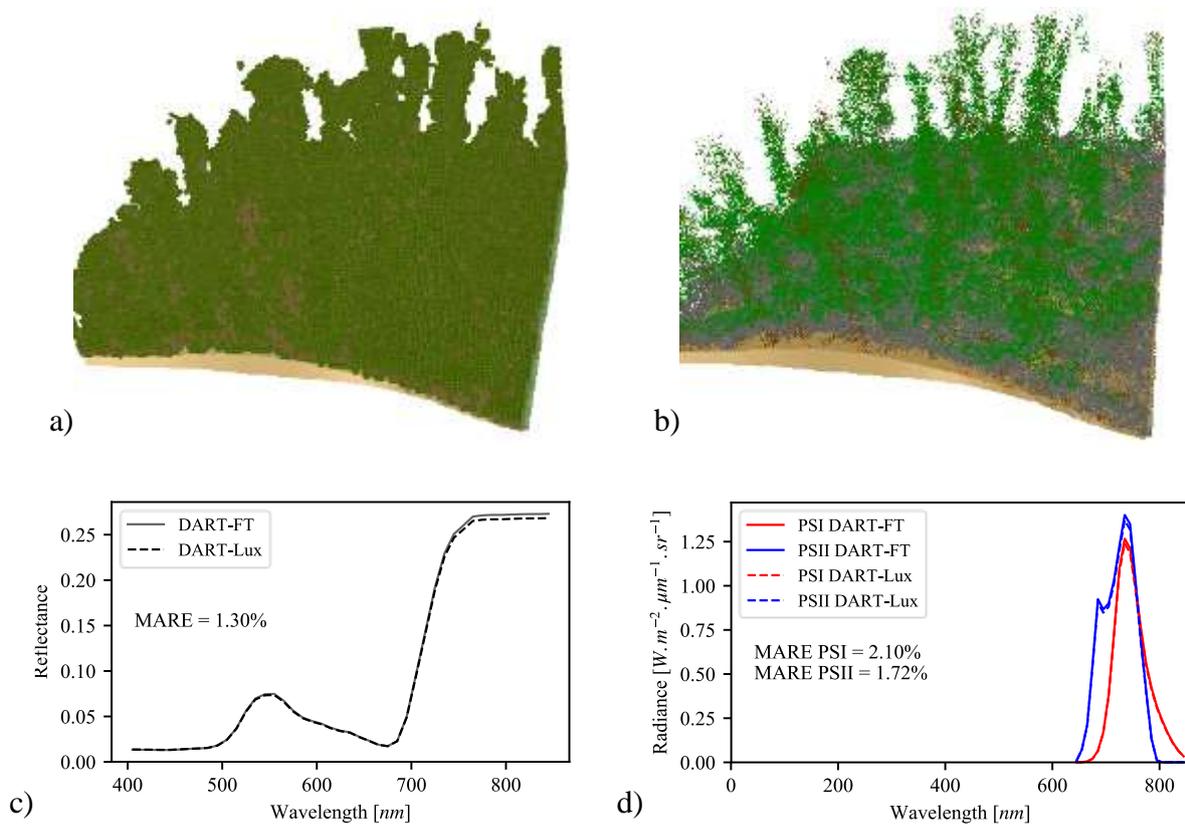
761 a) b)
 762 Figure 20. Top view of a turbid cell of $LAI = 0.92$ simulated with N cell objects. a) $N=1$: cell
 763 object of $LAI = 1$ is shrunk by a factor 0.96, resulting in empty space along the borders of the
 764 cell. b) $N=2$: 3D object of $LAI = 0.5$ (green) + 3D object of $LAI = 0.4$ enlarged by a factor
 765 1.025 (purple).
 766

767 This conversion method ensures that the mock-up is represented by a finite number of 3D objects
 768 (i.e., $16 \times 3 = 48$). It also avoids the appearance of holes due to shrinking the 3D objects, and large
 769 exceeding of voxel limits due to the enlargement of 3D objects. $M=3$ samples of each cell object
 770 are randomly used to introduce a random variability in the mock-ups. Also, a random rotation of
 771 0° , 90° , 180° or 270° relative to the vertical axis ensures more randomness of the simulated cell.
 772

773 **Appendix 2: Equivalence between DART-FT and DART-Lux simulations**

774 Our work combines DART-FT simulations of radiative budget and DART-Lux simulations of
 775 scene radiance / reflectance. Therefore, the consistency of these two DART modes is an essential
 776 point. Relative differences of DART-FT and DART-Lux can be as small as 10^{-5} depending on
 777 their modeling parameters of each mode. For example, the number of discrete directions for
 778 DART-FT, and the number of samples per pixel for DART-Lux. Here, this similarity is illustrated

779 through the comparison of the reflectance and SIF radiance of LM1, using model parameters hat
 780 were used in our work. Figure 21 indicates that MARE is equal to 1.3% for scene reflectance,
 781 2.1% for PSI radiance, and 1.72% for PSII radiance.



782
 783 Figure 21: Comparison of DART-FT (turbid voxels) and DART-Lux (turbid voxels transformed to
 784 triangles) for a 10m x 10m subscene of CI1. a) LM1 turbid mock-up. b) LM1 triangles cloud
 785 mock-up (after conversion). Green: sun-adapted leaves, Grey: shade-adapted leaves, Brown:
 786 woody elements. c) DART-FT and DART-Lux scene reflectance. d) Scene PSI and PSII
 787 radiance simulated by DART-FT and DART-Lux.

788

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