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# 1 Accurate and fast simulation of remote sensing images at top 2 of atmosphere with DART-Lux

3  
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## 10 11 **Abstract**

12  
13 DART model is one of the most comprehensive and accurate radiative transfer (RT) models to  
14 simulate remotely sensed signals in the Earth-atmosphere system. Its standard RT modelling  
15 mode, called DART-FT, relies on the discrete ordinates method. Its recently developed Monte  
16 Carlo mode using an unbiased bidirectional path tracing method, called DART-Lux, increases  
17 hundredfold DART efficiency to simulate images. Since DART-Lux does not simulate yet  
18 atmospheric RT, a hybrid method has been designed to accurately and fast simulate remote  
19 sensing images at top of atmosphere (TOA). It couples the atmospheric RT modelling of  
20 DART-FT with the very efficient Earth surface RT modelling of DART-Lux. For that, a new  
21 sky light modelling, an innovative BRDF camera modelling and an adapted radiative coupling  
22 framework have been designed. The efficiency and accuracy of this hybrid method have been  
23 validated using DART-FT as a reference. Here, we present this validation for a realistic forest  
24 stand. Simulation time is reduced by a factor of 750 with a relative difference of solar plane

25 reflectance factor smaller than 1%. This hybrid method opens new perspectives for the use of  
26 3D modelling in remote sensing applications. It is already part of the DART version freely  
27 available for scientists (<https://dart.omp.eu>).

28

## 29 **Key words**

30

31 DART, Monte Carlo, Top of atmosphere, Radiative transfer, Image simulation

32

## 33 **1 Introduction**

34

35 Remotely sensed images at the top of atmosphere (TOA) are inevitably contaminated by the  
36 atmosphere due to scattering, absorption and emission of atmospheric constituents (*e.g.*, gases,  
37 aerosols) (Dave, 1980; Myneni and Asrar, 1994; Song et al., 2001; Ueno and Mukai, 1977).

38 Many approaches have been developed to remove or reduce atmospheric effects in TOA images,  
39 including empirical methods such as the line method and darkest pixel method (Chavez Jr, 1988;  
40 Conel et al., 1987; Crippen, 1987), radiative transfer (RT) modelling methods based on the  
41 physics of ray-matter interactions such as 6S (Vermote et al., 1997) and MODTRAN (Berk et  
42 al., 1987), and hybrid methods that combine empirical and RT modelling methods (Goetz et al.,  
43 1997).

44

45 In the absence of field data, modelling TOA radiance is of great interest to better understand  
46 radiation interactions in the Earth system and also to better use the remote sensing observations  
47 of the Earth surface (Gastellu-Etchegorry et al., 1996; Guanter et al., 2009; Kraska, 1996;  
48 Richtsmeier et al., 2001; White et al., 2004; Zahidi, 2019), because it takes into account the  
49 physical mechanisms in the coupled Earth-atmosphere system and the instrumental

50 characteristics that give rise to these TOA images. Most atmospheric RT models (*e.g.*,  
51 MODTRAN, 6S) used for atmospheric correction of remote sensing images simulate TOA  
52 radiance depending on a-priori knowledge of the Earth surface reflectance anisotropy. For that,  
53 they are usually coupled with Earth surface RT models such as DART and SAIL (Verhoef,  
54 1984). However, this coupling approach is usually approximate since it simplifies the 3D nature  
55 and topography of the Earth surface as a horizontal plane. In addition, most Earth surface RT  
56 models consider that downward atmospheric diffuse radiation is isotropic, which can be a large  
57 source of inaccuracy. DART does not make these simplifications because it simulates the Earth-  
58 Atmosphere radiative coupling with a 3D approach. It explains that it simulates high accuracy  
59 remote sensing images and it is efficient for remote sensing applications.

60

61 Based on its discrete ordinates method, called DART-FT, DART is able to simulate remote  
62 sensing images of arbitrary 3D urban and natural landscapes with atmosphere. Recently, DART  
63 efficiency to simulate BOA remote sensing images of large and complex landscapes has been  
64 greatly improved thanks to its newly developed Monte Carlo mode, called DART-Lux (Wang  
65 et al., 2021b). DART-Lux uses an unbiased and fast bidirectional path tracing method that  
66 improves DART efficiency by a hundredfold in terms of computer time and memory. However,  
67 it has not yet been adapted to simulate TOA images. This is due to two major difficulties: (1)  
68 Monte Carlo method needs a huge amount of samples to simulate accurate TOA spectrum; (2)  
69 Monte Carlo method can cause distortion of TOA spectrum, since all bands share a common  
70 path from source to detector while spectral properties usually lead to different path per band  
71 (Emde et al., 2011). On the other hand, DART-FT solves the radiative transfer equation per  
72 band with the discrete ordinates method (Grau and Gastellu-Etchegorry, 2013). Although the  
73 discrete ordinates method is less accurate than the exact monochromatic Monte Carlo method

74 due to its discretization approximation, it is much more efficient and does not cause distortion  
75 issues.

76

77 This paper presents a hybrid method that allows DART-Lux to simulate accurate and fast TOA  
78 images. It includes a new Monte Carlo modelling of sky lighting, an innovative BRF camera  
79 and a coupling framework for Monte Carlo Earth surface RT modelling and non-Monte Carlo  
80 atmospheric RT modelling. Its efficiency and accuracy are illustrated with a simulation of a  
81 realistic forest stand. The relationship between accuracy and simulation time is also discussed.

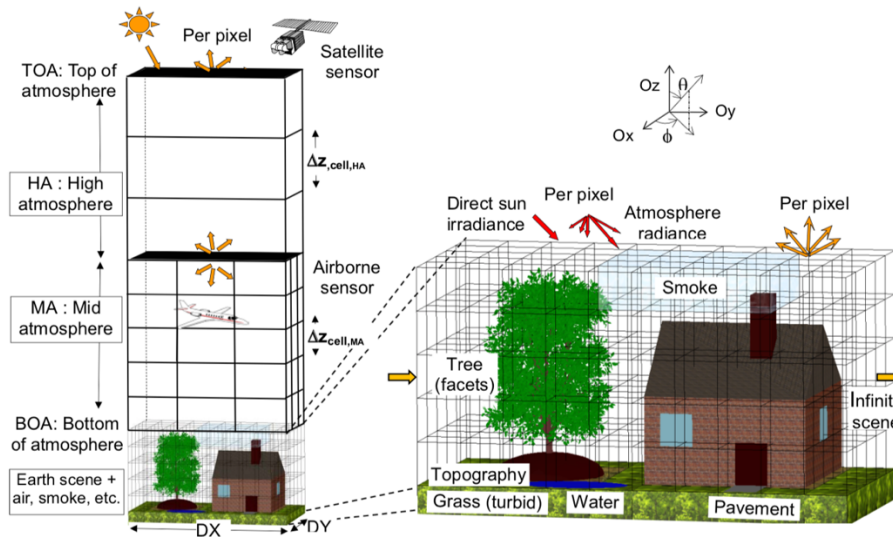
82

## 83 **2 Background and method**

84

85 DART is developed at CESBIO since 1992 (Figure 1). It is one of the most comprehensive and  
86 accurate 3D RT models in the optical remote sensing community (Gastellu-Etchegorry et al.,  
87 2017, 1996). It has been successfully validated against field measurements and through  
88 RADIATION Model Intercomparison (RAMI) (Grau and Gastellu-Etchegorry, 2013; Guillevic et  
89 al., 2003, 2013; Pinty et al., 2004, 2001; Wang and Gastellu-Etchegorry, 2020; Widlowski et  
90 al., 2015, 2013, 2007). Its standard mode, called DART-FT, simulates the bidirectional  
91 reflectance factor (BRF), directional brightness temperature (DBT) and remote sensing images  
92 of arbitrary 3D natural and urban landscapes, with topography and atmosphere, from visible to  
93 thermal infrared domain. Its newly developed Monte Carlo mode, called DART-Lux, increases  
94 hundredfold efficiency to simulate the RT in Earth surface. DART-Lux accuracy for simulating  
95 BOA images, fluorescence and LiDAR signals has already been validated by DART-FT.

96



97

98

Figure 1. DART-FT 3D discrete mock-up. Landscape elements are made of triangles, and/or fluid and turbid medium in a cell array. In DART-Lux, the simulation of landscapes is similar to that of DART-FT without using a cell array.

99

100

101

## 102 2.1 Earth-atmosphere radiative coupling

103

104 DART-FT simulates sequentially the atmospheric RT and Earth surface RT and couples them.

105 Its RT modelling relies on the discrete ordinates method that iteratively tracks rays along finite

106 discrete directions. Figure 2 illustrates the 5 major steps of DART RT modelling in the coupled

107 Earth-atmosphere system in order to simulate TOA images (Grau and Gastellu-Etchegorry,

108 2013; Wang et al., 2020):

109 (1) Sun illumination followed by atmosphere scattering and thermal emission.

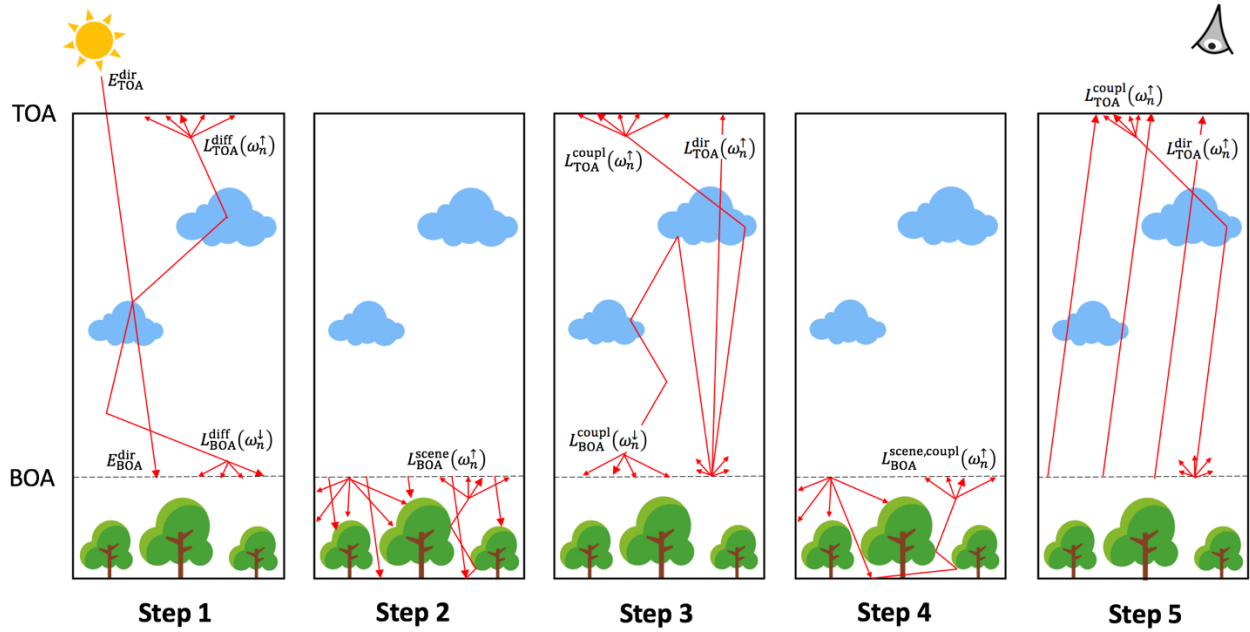
110 (2) Earth surface RT.

111 (3) Earth-atmosphere radiative coupling.

112 (4) Earth surface RT of atmosphere backscattered radiation.

113 (5) Transfer of BOA upward radiation to TOA.

114



115

116 Figure 2. Major steps to model RT in the Earth-atmosphere system. Step 1: Sun illumination, thermal  
 117 emission and atmosphere scattering. Step 2: Earth surface RT, including scene scattering and  
 118 emission. Step 3: Earth-atmosphere radiative coupling. Step 4: Earth surface RT of atmosphere  
 119 backscattered radiation. Step 5: Transfer of BOA upward radiation to TOA.

120

## 121 2.2 Hybrid method for simulating TOA images

122

123 DART-Lux models the Earth surface RT using the Monte Carlo based bidirectional path tracing  
 124 method (Veach, 1997; Veach and Guibas, 1995a, 1995b). This method simulates the remote  
 125 sensing signals by sampling a group of paths between the light source and the detector and  
 126 evaluates the contribution of these path samples. It can increase DART efficiency by a  
 127 hundredfold to simulate remote sensing images of complex 3D landscapes (Wang et al., 2021b).  
 128 However, this new Monte Carlo modelling is not yet adapted to simulate the atmospheric RT.  
 129 Since DART-FT simulates efficiently the atmospheric RT, a hybrid method is proposed to  
 130 simulate TOA images that takes advantage of fast DART-Lux Earth surfaces RT modelling and  
 131 fast DART-FT atmospheric RT modelling.

132

133 The three following sections present the details of the hybrid method:

134 - A new Monte Carlo modelling of the anisotropic sky lighting.

135 - An innovative BRDF camera modelling to capture directional radiation exiting the Earth surface.

136 - A framework to couple Monte Carlo Earth surface RT and non-Monte Carlo Atmospheric RT.

137

### 138 2.2.1 Anisotropic sky lighting

139

140 Figure 3 illustrates the sky lighting. The Monte Carlo method models the sky lighting by

141 sampling a random direction  $\omega_0$  and a start vertex  $p_0$  on the virtual disk that is the projection

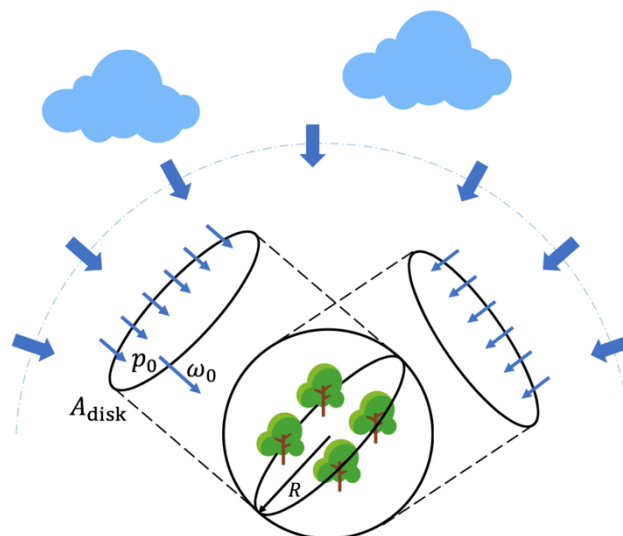
142 of the scene sphere along  $\omega_0$  (Figure 3). Most Monte Carlo RT models consider sky light to be

143 isotropic (e.g., (Qi et al., 2019)) or compute the sky light with empirical equations (e.g., (Pharr

144 et al., 2016)). With the aim of better precision, we designed a new method to accurately model

145 the anisotropic sky light. This method uses the DART-FT computed BOA diffuse radiance.

146 Note that it can use BOA diffuse radiance computed by other atmospheric RT models.



147

148 Figure 3. Sky lighting. The Earth scene is in a sphere of radius  $R$ . It is illuminated by the light from

149 the sky dome.



150

151 DART-FT tracks radiations along  $N_\Omega$  predefined discrete directions  $\omega_n(\Delta\omega_n)$  with  $n \in$   
 152  $[1, N_\Omega]$  (Yin et al., 2013). The computed sky light is stored per discrete downward direction per  
 153 band  $L_{\text{BOA}}^{\text{diff}}(\omega_n^\downarrow, \lambda)$ . In order to adapt to Monte Carlo method such as DART-Lux that samples  
 154 arbitrary sky light direction, we designed a 2D distribution sampler. We first resample  
 155  $L_{\text{BOA}}^{\text{diff}}(\omega_n^\downarrow, \lambda)$  from discrete directions to directions with equal angle step (angle steps  $\Delta\theta$  and  
 156  $\Delta\varphi$ , angle numbers:  $N_\theta = \frac{\pi/2}{\Delta\theta}$  and  $N_\varphi = \frac{2\pi}{\Delta\varphi}$ ) (Figure 4). It results that pixel  $(i, j)$  on the  
 157 hemisphere stores  $L(\omega_{i,j}, \lambda) = L_{\text{BOA}}^{\text{diff}}(\omega_n^\downarrow, \lambda)$  if  $\omega_{i,j} \in \Delta\omega_n$ . Below, the wavelength term  $\lambda$  is  
 158 omitted for compactness.

159

160 Then, a direction is sampled with the probability density function (PDF)  $p(\omega) = \frac{p(\theta, \varphi)}{\sin \theta}$  where  
 161  $p(\theta, \varphi)$  is constructed by Eq. (1).  $p(\theta, \varphi)$  and radiance  $\bar{L}(\omega_{i,j})$  are constant in  $\Delta\omega_{i,j}$ .  $\bar{L}(\omega_{i,j})$   
 162 is the mean radiance of all spectral bands along  $\omega_{i,j}$ . It is only used to compute the PDF.

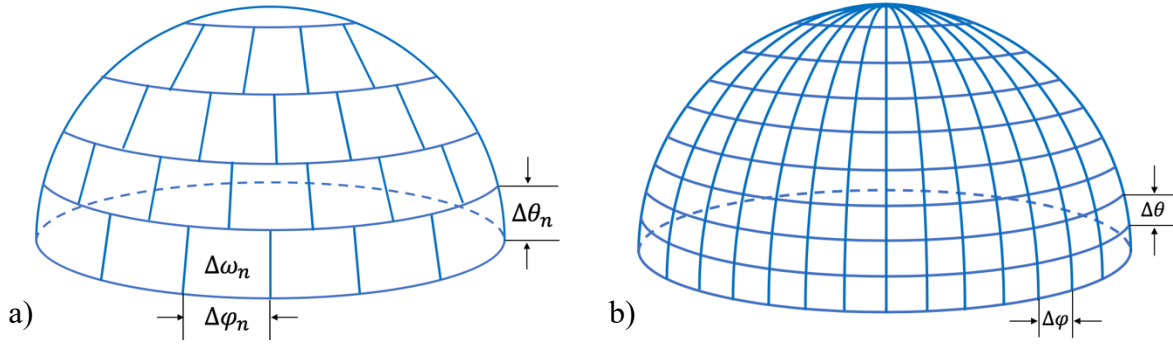
163

$$p(\theta, \varphi) = \frac{\int_{\Delta\omega_{i,j}} \bar{L}(\omega) \cdot \cos \theta \cdot \sin \theta \cdot d\theta \cdot d\varphi / (\Delta\theta \cdot \Delta\varphi)}{\int_{2\pi} \int_{\pi/2} \bar{L}(\omega) \cdot \cos \theta \cdot \sin \theta \cdot d\theta \cdot d\varphi} = \frac{\bar{L}(\omega_{i,j}) \cdot \sin(2\theta_i) \cdot \frac{\sin \Delta\theta}{\Delta\theta}}{\sum_{i'=1}^{N_\theta} \sum_{j'=1}^{N_\varphi} \bar{L}(\omega_{i',j'}) \cdot \sin(2\theta_{i'}) \cdot \sin \Delta\theta \cdot \Delta\varphi} \quad (1)$$

164 with

$$\begin{cases} p(\theta) = \int_{2\pi} p(\theta, \varphi) d\varphi = \sum_{j=1}^{N_\varphi} p(\theta, \varphi) \cdot \Delta\varphi \\ p(\varphi|\theta) = \frac{p(\theta, \varphi)}{p(\theta)} \end{cases} \quad (2)$$

165



166 Figure 4. Radiance resampling from discrete directions to equal angle step directions. a) DART-FT  
 167 discrete directions with solid angle  $\Delta\omega_n$  ( $\Delta\theta_n, \Delta\varphi_n$ ). b) Resampled equal angle step directions  
 168 on the hemisphere with constant  $\Delta\theta$  and  $\Delta\varphi$  for each solid angle.

169

### 170 2.2.2 BRF camera and anisotropic upward fluxes

171

172 To couple Earth surface RT with atmospheric RT, one must compute the anisotropic upward  
 173 radiance from the Earth surface. Most Monte Carlo models compute the directional fluxes by  
 174 repeatedly simulating directional images, which is very inefficient. In order to avoid this  
 175 inefficient approach, we designed and implemented an innovative “BRF camera” in DART-  
 176 Lux. This BRF camera simulates directional upward fluxes in a single run. It has infinite radius  
 177 to capture the upward radiance from the Earth scene. The conceptual hemispherical sensor is  
 178 shown in Figure 5.b. It has  $N_\theta \cdot N_\varphi$  pixels, with  $N_\theta = \frac{\pi/2}{\Delta\theta}$  and  $N_\varphi = \frac{2\pi}{\Delta\varphi}$ .  $\Delta\theta$  and  $\Delta\varphi$  are  
 179 respectively the step of zenith and azimuth angles. It corresponds to  $N_\theta \cdot N_\varphi$  orthographic  
 180 cameras (Figure 5.a) placed around the 3D scene. The average radiance captured by each  
 181 orthographic camera is stored in the corresponding pixel.

182

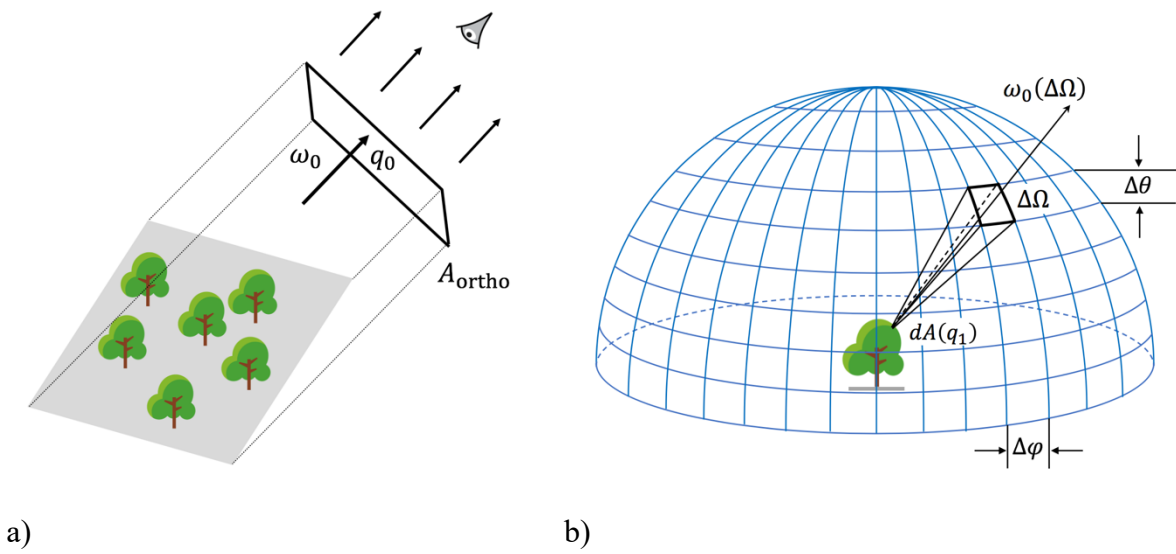
183 This BRF camera modelling was adapted to the Monte Carlo models of interest (i.e., backward,  
 184 forward, bi-directional path tracing). For that, a viewing direction is sampled with directional

185 PDF  $p(\omega_0)$  (Eq. (3)) and a depart point is uniformly sampled on the scene ortho-projected  
 186 surface  $A_{\text{ortho}}(\omega_0)$  along the viewing direction  $\omega_0$ .

187

$$p(\omega_0) = \frac{p(\theta, \varphi)}{\sin \theta}, \text{ with } \begin{cases} p(\theta) = \frac{1}{\pi/2} \\ p(\varphi|\theta) = \frac{1}{2\pi} \end{cases} \quad (3)$$

188



189

190 Figure 5. a) Radiation exits the Earth scene along direction  $\omega_0$  reaches a virtual orthographic plane  
 191  $A_{\text{ortho}}(\omega_0)$  (detector) that is the projection of the scene along the viewing direction  $\omega_0$ . b)  
 192 BRF camera. The hemispheric sensor of the camera has infinite radius from the Earth scene.  
 193 Any radiation along viewing direction  $\omega_0(\Delta\Omega)$  is captured by a pixel on the hemisphere.

194

195 After the Earth surface RT modelling, the image of BRF camera that maps the upward  
 196 directional radiance is created (Figure 6). In a latter step, this radiance map is used to compute  
 197 the radiance and BRF for any viewing direction. Pixel  $(i, j)$  gives the radiance  $L(\omega_{i,j})$  for

198 direction  $\omega_{i,j}$  on the hemisphere (Figure 4.b), which allows one to compute the upward  
 199 radiance  $L_{\text{BOA}}^{\text{scene}}(\omega_n^\uparrow)$  along any discrete direction  $\omega_n$ :

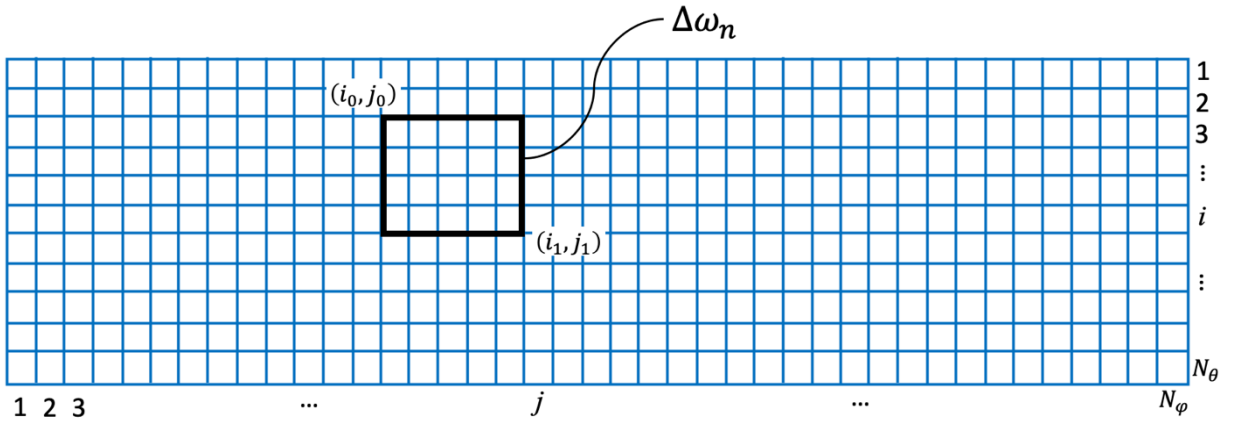
200

$$L_{\text{BOA}}^{\text{scene}}(\omega_n^\uparrow) = \frac{\int_{\Delta\omega_n} L(\omega) \cdot \cos\theta \cdot \sin\theta \, d\theta d\varphi}{\int_{\Delta\omega_n} \cos\theta \cdot \sin\theta \, d\theta d\varphi} = \frac{\sum_{i=i_0}^{i_1} \sum_{j=j_0}^{j_1} L(\omega_{i,j}) \cdot \sin(2\theta_i) \cdot \sin\Delta\theta \cdot \Delta\varphi}{\cos\theta_n^c \cdot \Delta\omega_n} \quad (4)$$

201

202 where solid angle  $\Delta\omega_n$  covers pixel region from line  $i_0$  to  $i_1$  and from column  $j_0$  to  $j_1$ . The

203 effective zenith angle  $\theta_n^c$  of direction  $\omega_n$  verifies:  $\cos\theta_n^c \cdot \Delta\omega_n = \int_{\Delta\omega_n} \cos\theta \cdot \sin\theta \, d\theta d\varphi$ .



204

205 Figure 6. Radiance map simulated by the BRF camera. It has  $N_\theta$  lines and  $N_\varphi$  columns. The value of  
 206 pixel  $(i, j)$  is the scene radiance along direction  $\omega_{i,j}$ . The black rectangle outlines the region  
 207 of a solid angle  $\Delta\omega_n$  of discrete direction  $\omega_n$ .  $\theta_i$  and  $\varphi_j$  represent the zenith and azimuth  
 208 angle at centre of pixel  $(i, j)$  respectively.

209

### 210 2.2.3 Radiative coupling framework

211

212 In the hybrid method, the DART-FT atmospheric RT modelling realizes the steps 1, 3 and 5 of  
 213 the five major radiative steps (Figure 2), while the DART-Lux Earth surface RT modelling

214 realizes steps 2 and 4, plus an additional step 6. Steps 1 to 5 give spatially averaged radiance  
 215 values conversely to step 6 that gives images. These steps are detailed below.

216

217 1) DART-FT atmospheric RT modelling. TOA direct irradiance  $E_{\text{TOA}}^{\text{dir}}$  leads to diffuse  
 218 radiance  $L_{\text{TOA}}^{\text{diff}}(\omega_n^\uparrow)$  per upward direction  $\omega_n^\uparrow$ , BOA direct irradiance  $E_{\text{BOA}}^{\text{dir}}$ , BOA diffuse  
 219 irradiance  $E_{\text{BOA}}^{\text{diff}}$  and BOA diffuse radiance  $L_{\text{BOA}}^{\text{diff}}(\omega_n^\downarrow)$  per downward direction  $\omega_n^\downarrow$ .

220

221 2) DART-Lux Earth surface RT modelling. It uses two light sources: sunlight with direct  
 222 irradiance  $E_{\text{BOA}}^{\text{dir}}$  and anisotropic sky light with BOA diffuse radiance  $L_{\text{BOA}}^{\text{diff}}(\omega_n^\downarrow)$ . This step  
 223 gives the upward scene radiance  $L_{\text{BOA}}^{\text{scene}}(\omega_n^\uparrow)$  per upward direction  $\omega_n^\uparrow$  using Eq. (4).

224

225 3) DART-FT atmospheric RT modelling. It computes the transfer functions  $\text{TF}_{\text{BA-BA}}$  (*i.e.*,  
 226 BOA downward radiance  $L_{\text{BOA}}^{\text{coupl}}(\omega_n^\downarrow)$  contributed by BOA upward radiance  $L_{\text{BOA}}^{\text{scene}}(\omega_n^\uparrow)$ )  
 227 and  $\text{TF}_{\text{BA-TOA}}$  (*i.e.*, TOA radiance  $L_{\text{TOA}}^{\text{coupl}}(\omega_n^\uparrow)$  contributed by BOA upward radiance  
 228  $L_{\text{BOA}}^{\text{scene}}(\omega_n^\uparrow)$ ). Then,  $L_{\text{BOA}}^{\text{coupl}}(\omega_n^\downarrow)$  is extrapolated to infinite coupling order radiance  
 229  $L_{\text{BOA}}^{\text{coupl}(\infty)}(\omega_n^\downarrow)$  using the Earth scene albedo  $\rho$  and atmosphere backscattering albedo  $s$  (Eq.  
 230 (5)). The backscattered irradiance  $E_{\text{BOA}}^{\text{coupl}(\infty)}$  is computed using  $L_{\text{BOA}}^{\text{coupl}(\infty)}(\omega_n^\downarrow)$ :

231

$$L_{\text{BOA}}^{\text{coupl}(\infty)}(\omega_n^\downarrow) = \frac{1}{1 - \rho \cdot s} \cdot L_{\text{BOA}}^{\text{coupl}}(\omega_n^\downarrow) \tag{5}$$

$$E_{\text{BOA}}^{\text{coupl}(\infty)} = \sum_{\omega_n^\downarrow} L_{\text{BOA}}^{\text{coupl}(\infty)}(\omega_n^\downarrow) \cdot \cos \theta_n^c \cdot \Delta\omega_n$$

232

233 with

234

$$\rho = \frac{\sum_{\omega_n^\uparrow} L_{\text{BOA}}^{\text{scene}}(\omega_n^\uparrow) \cdot \cos \theta_n^c \cdot \Delta\omega_n}{E_{\text{BOA}}^{\text{dir}} + E_{\text{BOA}}^{\text{diff}}} \quad (6)$$

$$s = \frac{\sum_{\omega_n^\downarrow} L_{\text{BOA}}^{\text{coupl}}(\omega_n^\downarrow) \cdot \cos \theta_n^c \cdot \Delta\omega_n}{\sum_{\omega_n^\uparrow} L_{\text{BOA}}^{\text{scene}}(\omega_n^\uparrow) \cdot \cos \theta_n^c \cdot \Delta\omega_n}$$

235

236 4) DART-Lux surface RT modelling. It uses a single light source: the extrapolated anisotropic

237 sky light with radiance  $L_{\text{BOA}}^{\text{coupl}(\infty)}(\omega_n^\downarrow)$ . It computes the scene radiance per upward direction

238  $\omega_n^\uparrow$  using Eq. (4), which added to  $L_{\text{BOA}}^{\text{scene}}(\omega_n^\uparrow)$  gives  $L_{\text{BOA}}^{\text{scene,coupl}}(\omega_n^\uparrow)$ .

239

240 5)  $\text{TF}_{\text{BA-TOA}}$  is applied to compute direct transmitted radiance  $L_{\text{TOA}}^{\text{dir}}(\omega_n^\uparrow)$  and scattered

241 radiance  $L_{\text{TOA}}^{\text{coupl}}(\omega_n^\uparrow)$  per upward direction using  $L_{\text{BOA}}^{\text{scene,coupl}}(\omega_n^\uparrow)$ .

242

243 6) DART-Lux Earth surface RT modelling. It uses two light sources: sunlight with irradiance

244  $E_{\text{BOA}}^{\text{dir}}$  and anisotropic sky light with BOA diffuse radiance  $L_{\text{BOA}}^{\text{diff}}(\omega_n^\downarrow) + L_{\text{BOA}}^{\text{coupl}(\infty)}(\omega_n^\downarrow)$ . It

245 gives BOA upward radiance images  $L_{\text{BOA}}(i, j, \omega_n^\uparrow)$ . TOA radiance images are computed as:

246

$$L_{\text{TOA}}(i, j, \omega_n^\uparrow) = L_{\text{BOA}}(i, j, \omega_n^\uparrow) \cdot \frac{L_{\text{TOA}}^{\text{dir}}(\omega_n^\uparrow)}{L_{\text{BOA}}^{\text{scene,coupl}}(\omega_n^\uparrow)} + L_{\text{TOA}}^{\text{diff}}(\omega_n^\uparrow) + L_{\text{TOA}}^{\text{coupl}}(\omega_n^\uparrow) \quad (7)$$

247

248 Reflectance images can be also computed:

249

$$\rho_{\text{BOA}}(i, j, \omega_n^\uparrow) = \frac{L_{\text{BOA}}(i, j, \omega_n^\uparrow)}{E_{\text{BOA}}^{\text{dir}} + E_{\text{BOA}}^{\text{diff}} + E_{\text{BOA}}^{\text{coupl}(\infty)}}, \quad \rho_{\text{TOA}}(i, j, \omega_n^\uparrow) = \frac{L_{\text{TOA}}(i, j, \omega_n^\uparrow)}{E_{\text{TOA}}^{\text{dir}}} \quad (8)$$

250

251 **3 Results and discussion**

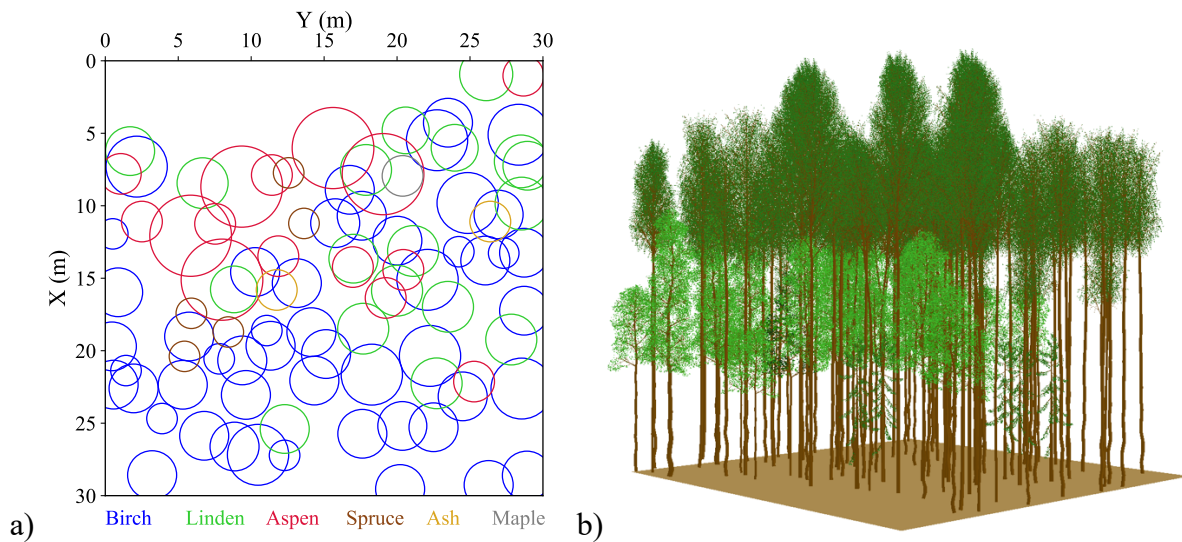
252

253 **3.1 Validation with realistic forest stand**

254

255 The accuracy and efficiency of the presented hybrid method (hereinafter, it is referred by  
256 DART-Lux) are assessed by comparing its results with those of DART-FT for a 30 m × 30 m  
257 plot of Järvelja Birch forest (summer) from RAMI experiment ([https://rami-](https://rami-benchmark.jrc.ec.europa.eu)  
258 [benchmark.jrc.ec.europa.eu](https://rami-benchmark.jrc.ec.europa.eu); (Widłowski et al., 2015)) (Figure 7). This plot contains 91 trees  
259 including 50 birch trees, 18 linden trees, 15 aspen trees, 5 spruce trees, and 3 ash and maple  
260 trees (Figure 7). We did not consider the full 100 m × 100 m birch forest that contains more  
261 than 550 million of facets because it would have required too much RAM and computation time  
262 for DART-FT.

263



264

265 Figure 7. The 30 m × 30 m plot of Järvelja birch forest. a) Spatial distribution of tree species. b)  
266 DART 3D mock-up.

267

268 Table 1. Optical properties of ground and tree species for four spectral band.  $\rho$  is the reflectance and  
 269  $\tau$  is the transmittance.  
 270

<b>3D object</b>	<b>Optical properties</b>	<b>B</b>	<b>G</b>	<b>R</b>	<b>NIR</b>
Birch	$\rho_{\text{leaf}}$	0.045	0.104	0.039	0.474
	$\tau_{\text{leaf}}$	0.000	0.110	0.012	0.483
	$\rho_{\text{branch}}$	0.072	0.094	0.101	0.464
	$\rho_{\text{trunk}}$	0.355	0.410	0.436	0.539
Linden	$\rho_{\text{leaf}}$	0.045	0.073	0.035	0.442
	$\tau_{\text{leaf}}$	0.000	0.074	0.004	0.462
	$\rho_{\text{branch}}$	0.125	0.167	0.206	0.363
	$\rho_{\text{trunk}}$	0.125	0.167	0.206	0.363
Aspen	$\rho_{\text{leaf}}$	0.045	0.078	0.036	0.436
	$\tau_{\text{leaf}}$	0.000	0.107	0.009	0.517
	$\rho_{\text{branch}}$	0.111	0.107	0.118	0.266
	$\rho_{\text{trunk}}$	0.169	0.189	0.215	0.441
Spruce	$\rho_{\text{leaf}}$	0.045	0.077	0.036	0.447
	$\tau_{\text{leaf}}$	0.000	0.044	0.002	0.369
	$\rho_{\text{branch}}$	0.117	0.141	0.155	0.363
	$\rho_{\text{trunk}}$	0.117	0.141	0.155	0.363
Ash	$\rho_{\text{leaf}}$	0.045	0.098	0.038	0.516
	$\tau_{\text{leaf}}$	0.000	0.046	0.002	0.379
	$\rho_{\text{branch}}$	0.125	0.167	0.206	0.363
	$\rho_{\text{trunk}}$	0.125	0.167	0.206	0.363
Maple	$\rho_{\text{leaf}}$	0.046	0.123	0.042	0.465
	$\tau_{\text{leaf}}$	0.001	0.155	0.025	0.025



	$\rho_{\text{branch}}$	0.125	0.167	0.206	0.363
	$\rho_{\text{trunk}}$	0.125	0.167	0.206	0.363
Ground	$\rho_{\text{background}}$	0.019	0.058	0.032	0.329

271

272 DART-FT and DART-Lux simulations are conducted with direct sun illumination ( $\theta_{\text{sun}} =$

273  $36.6^\circ$ ,  $\varphi_{\text{sun}} = 270.69^\circ$ ), THKUR TOA irradiance spectra (Berk et al., 2008), a 0.125 m spatial

274 resolution and 4 spectral bands (blue:  $0.44 \mu\text{m}$ , green:  $0.55 \mu\text{m}$ , red:  $0.66 \mu\text{m}$ , NIR:  $0.87 \mu\text{m}$ ),

275 with 6 scattering orders at most. The atmosphere model is mid-latitude summer (Anderson et

276 al., 1986) and the aerosol model is rural (Shettle and Fenn, 1979). Specific optical properties

277 were assigned per tree species (Table 1). Here, DART-Lux is run with 800 samples per pixel

278 and DART-FT is run with 62500 illumination rays per pixel, and 1000 discrete directions.

279 DART-FT and DART-Lux BOA colour composite images are shown in Figure 8.a, d. The

280 associated scatter plot of BOA pixel reflectance (Figure 9.a) gives R-squared  $> 0.92$  and bias  $\approx$

281  $0.01$ . Densities of scatter points are shown by colours in order to stress that most points are on

282 the diagonal. TOA colour composite images are shown in Figure 8.b, e. The associated scatter

283 plot of TOA pixel reflectance (Figure 9.b) gives R-squared  $\approx 0.92$  and bias  $\approx 0.01$ . Scatter points

284 outside the diagonal are mainly due to DART-Lux Monte Carlo noises and to DART-FT

285 discretization. By averaging the image resolution from 0.125 m to 1.0 m, which more or less

286 compensates these effects, scatter plots become more linear, with R-square  $> 0.998$  and bias  $\approx$

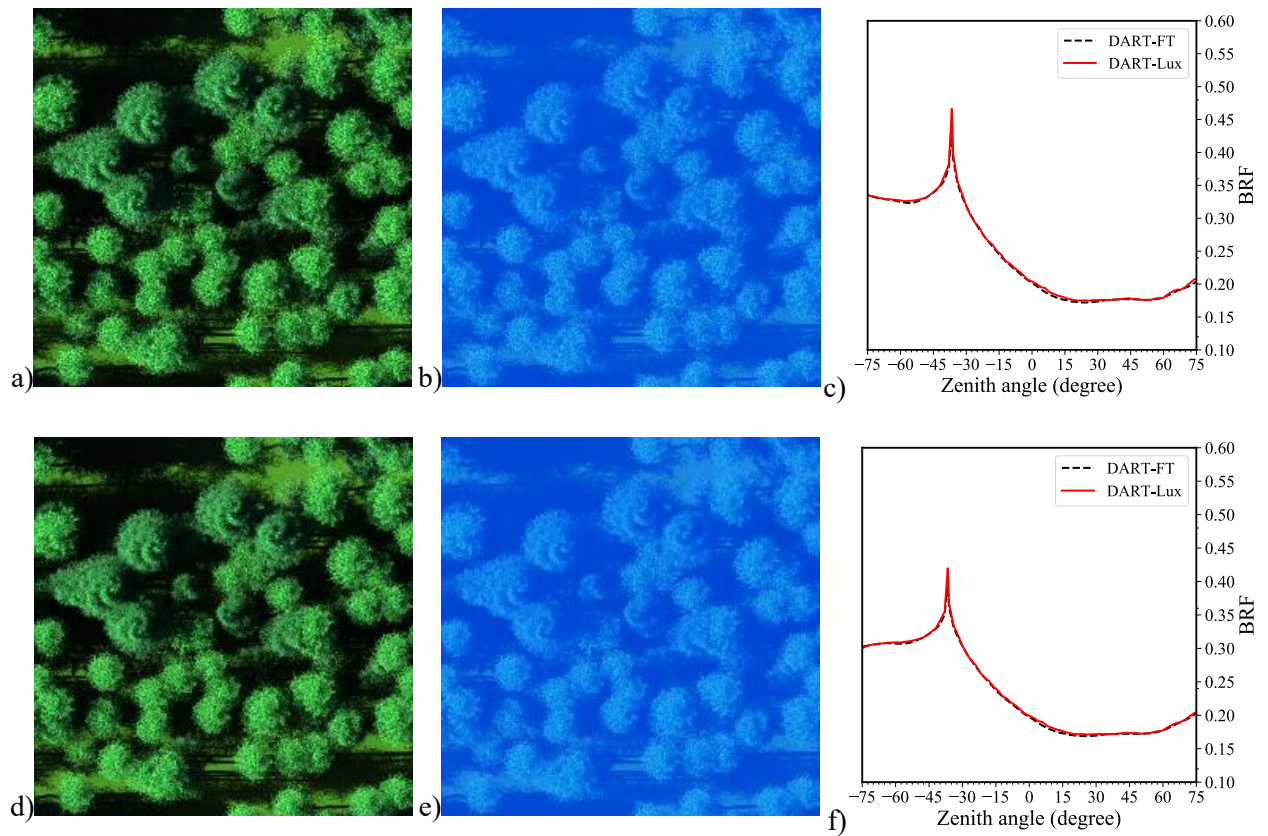
287  $0.0002$  (Figure 9.c). We also assessed the BRF accuracy in the solar plane by computing the

288 average absolute relative "DART-Lux - DART-FT" BRF difference

289 
$$\bar{\varepsilon} = \frac{1}{N_{\theta_v}} \cdot \sum_{\theta_v} \frac{|\rho_{\text{DART-Lux}}(\theta_v) - \rho_{\text{DART-FT}}(\theta_v)|}{\rho_{\text{DART-FT}}(\theta_v)} \cdot 100\%$$
 with  $N_{\theta_v}$  viewing directions in the solar plane

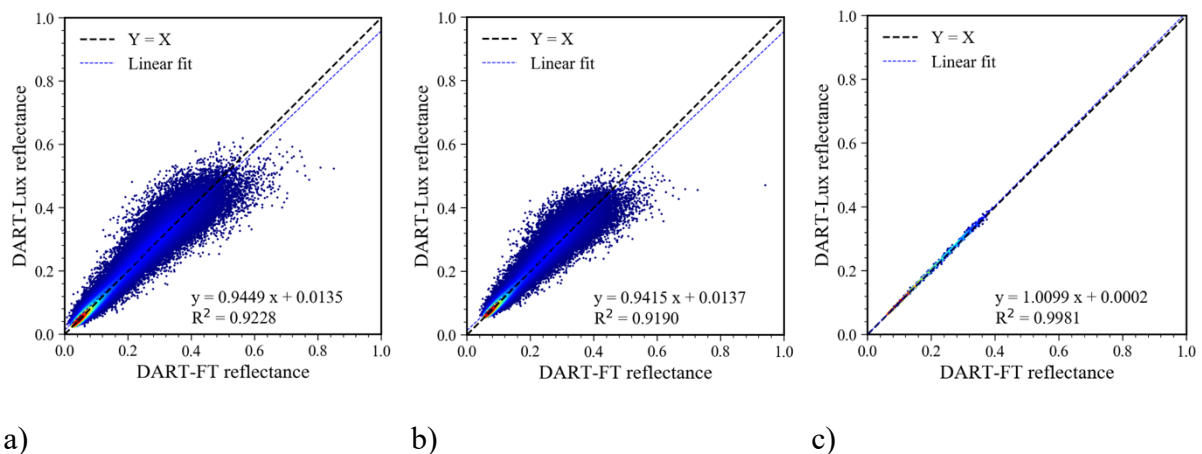
290 with zenith angle step  $\Delta\theta_v = 2^\circ$ . Here,  $\bar{\varepsilon}$  is 1.0% at BOA level and 0.8% at TOA level.

291



292 Figure 8. Nadir colour composite images of the forest plot shown in Figure 7. DART-FT BOA (a) and  
 293 TOA (b) images. DART-Lux BOA (d) and TOA (e) images. DART-FT and DART-Lux BOA  
 294 (c) and TOA (f) BRFs at NIR band in the solar plane, with 2° zenith angle step.

295



296 Figure 9. Pixelwise comparison of DART-FT and DART-Lux nadir images at NIR band. a) BOA.  
 297 0.125 m resolution. b) TOA. 0.125 m resolution. c) TOA. 1.0 m resolution.

298

299 Therefore, DART-Lux and DART-FT give similar results but DART-Lux has two major  
300 advantages: much smaller computer time and RAM. In this simulation, DART-FT takes 86.35  
301 hours and 305.5 Gb RAM on a server (Intel Xeon E5-2687W @ 3.1 GHz, 40 cores) for steps 2  
302 and 4 in Figure 2 whereas DART-Lux takes only 2.3 minutes and 1.2 Gb RAM to simulate the  
303 spectral nadir image or the spectral radiance map (*i.e.*, steps 2, 4 and 6 take a total of 6.9  
304 minutes). Compared to DART-FT, DART-Lux computer time is reduced by a factor of 750 and  
305 the required RAM is reduced by a factor of 255. Since the atmospheric RT modelling for  
306 stratified 1D atmosphere in steps 1, 3 and 5 takes much less time than the Earth surface RT  
307 modelling in steps 2 and 4, the hybrid method greatly accelerates the simulation of TOA images.

308

### 309 **3.2 Discussion**

310

311 Monte Carlo method is usually the most precise RT method since no approximations are applied.  
312 It gives exact results after running a sufficient long time. However, we have to balance the  
313 computation time and the accuracy in practical applications. Based on the simulation of the  
314 forest stand (Figure 7) in step 2, we did a sensitivity study about the time cost and the accuracy  
315 using DART-Lux. The time cost is quantified by the samples/pixel since time increases linearly  
316 with this ratio. Accuracy is quantified by two variables: image mean reflectance difference  
317  $\epsilon_{\text{mean}}$  and root-mean-square-error (RMSE)  $\epsilon_{\text{pixel}}$  of all pixel reflectance by comparing with a  
318 reference simulation with 2000 samples/pixel. Table 2 summarizes results. It illustrates three  
319 major points: 1)  $\epsilon_{\text{mean}}$  and  $\epsilon_{\text{pixel}}$  decrease nearly exponentially with the increase of  
320 samples/pixel. 2) The image mean reflectance converges much faster than image pixel  
321 reflectance. 3) The low reflectance band (G) converges much faster than high reflectance band  
322 (NIR). It indicates that the DART-Lux simulation time can be optimised according to the  
323 application and accuracy requirements. For example, with the above-mentioned computer and

324 configuration and RMSE accuracy 0.05 of the NIR band pixel reflectance, DART-Lux takes  
 325 5.25 minutes and 3.3 Gb RAM to simulate nadir BOA and TOA images of the 100 m  $\times$  100 m  
 326 RAMI forest stand (Figure 10).

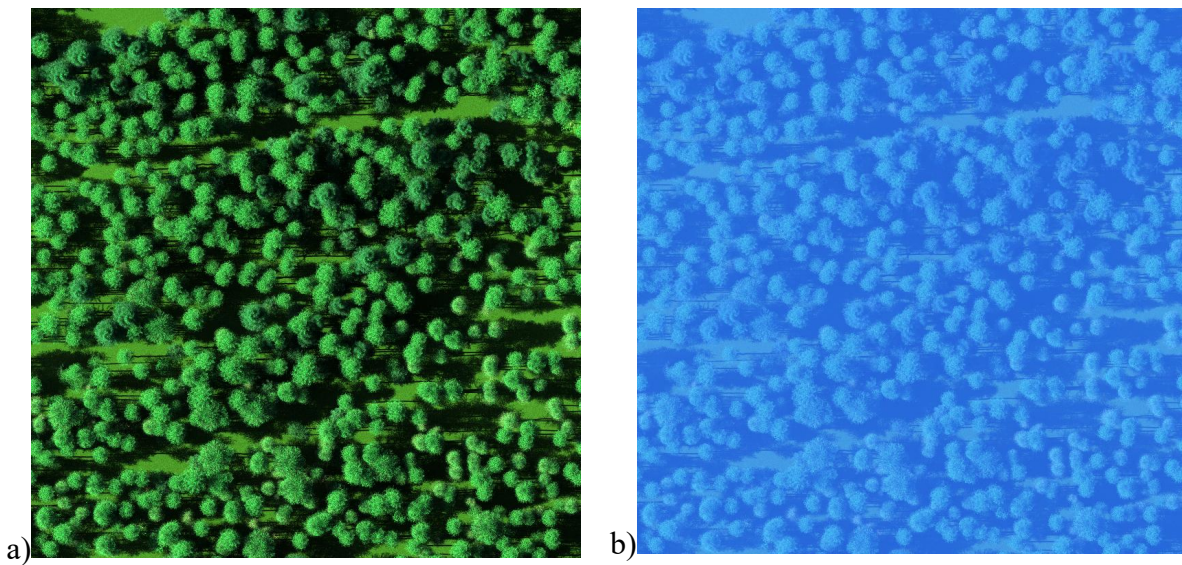
327

328 Table 2. Mean reflectance error  $\epsilon_{\text{mean}}$  and RMSE of image pixel reflectance  $\epsilon_{\text{pixel}}$  for different  
 329 samples/pixel ratios and for G and NIR bands. The reference image is simulated with 2000  
 330 samples/pixel.

331

<b>Samples/pixel</b>		<b>10</b>	<b>25</b>	<b>50</b>	<b>100</b>	<b>200</b>	<b>400</b>	<b>800</b>
<b>G</b>	$\epsilon_{\text{mean}}$	5.8e-5	1.2e-5	1.6e-5	1.1e-5	6.1e-6	2.3e-6	4.9e-6
	$\epsilon_{\text{pixel}}$	0.011	0.007	0.005	0.004	0.003	0.002	0.0015
<b>NIR</b>	$\epsilon_{\text{mean}}$	1.2e-4	3.5e-4	4.1e-5	4.1e-5	2.4e-5	1.8e-5	5.5e-6
	$\epsilon_{\text{pixel}}$	0.094	0.061	0.043	0.031	0.022	0.017	0.013

332



333

334 Figure 10. DART-Lux BOA (a) and TOA (b) colour composite nadir images of the 100 m  $\times$  100 m  
 335 Järvelja birch forest stand.

336

#### 337 **4 Concluding remarks**

338

339 This paper proposes a new Monte Carlo sky lighting modelling, an innovative BRF camera  
340 modelling and a coupling framework in order to (1) couple Monte Carlo Earth surface RT  
341 modelling with non-Monte Carlo atmospheric RT modelling and to (2) accurate and fast  
342 simulate TOA images. The efficiency of this hybrid method is illustrated here with a realistic  
343 forest stand, using DART-FT as a reference. Compared to DART-FT, DART-Lux decreased  
344 computer time by a factor of 750 and the need of RAM by a factor of 255. Also, the average  
345 absolute relative difference of solar plane BRF profile is 0.8% at TOA. The pixelwise  
346 reflectance comparison of TOA image shows good agreement with R-squared  $\approx 0.92$  and bias  
347  $\approx 0.01$  at 0.125m resolution, and R-squared  $> 0.998$  and bias  $\approx 0.0002$  at 1m resolution. A  
348 sensitivity study of accuracy in function of simulation time shows that pixel RMSE decreases  
349 nearly exponentially with simulation time. It stresses that DART-Lux offers the advantage to  
350 set computation time as a function of the expected accuracy. This accurate and fast hybrid  
351 method opens new perspectives for DART model applications. Readers are referred to DART  
352 user manual  
353 ([https://dart.omp.eu/Public/documentation/contenu/documentation/DART\\_User\\_Manual.pdf](https://dart.omp.eu/Public/documentation/contenu/documentation/DART_User_Manual.pdf))  
354 for more details about DART-Lux simulation preparation.

355

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357

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361

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