



**HAL**  
open science

## UAV-based canopy textures assess changes in forest structure from long-term degradation

Clément Bourgoïn, Julie Betbeder, Pierre Couteron, Lilian Blanc, H  l  ne Dessard, Johan Oszwald, Renan Le Roux, Louis Reymondin, Lucas Mazzei, Plinio Sist, et al.

### ► To cite this version:

Cl  ment Bourgoïn, Julie Betbeder, Pierre Couteron, Lilian Blanc, H  l  ne Dessard, et al.. UAV-based canopy textures assess changes in forest structure from long-term degradation. *Ecological Indicators*, 2020, 115, pp.106386. 10.1016/j.ecolind.2020.106386 . hal-02566581

**HAL Id: hal-02566581**

**<https://hal.science/hal-02566581v1>**

Submitted on 7 May 2020

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destin  e au d  p  t et    la diffusion de documents scientifiques de niveau recherche, publi  s ou non,   manant des   tablissements d'enseignement et de recherche fran  ais ou   trangers, des laboratoires publics ou priv  s.

# 1 UAV-based canopy textures assess changes in forest structure from long-term degradation

2 Clément Bourgoïn<sup>1,2,3\*</sup>, Julie Betbeder<sup>1,2,4</sup>, Pierre Couteron<sup>5</sup>, Lilian Blanc<sup>1,2</sup>, Hélène Dessard<sup>1,2</sup>, Johan  
3 Oszwald<sup>6</sup>, Renan Le Roux<sup>1,2</sup>, Guillaume Cornu<sup>1,2</sup>, Louis Reymondin<sup>3</sup>, Lucas Mazzei<sup>7</sup>, Plinio Sist<sup>1,2</sup>, Peter  
4 Läderach<sup>3</sup> and Valéry Gond<sup>1,2</sup>

5 <sup>1</sup> CIRAD, Forêts et Sociétés, F-34398 Montpellier, France

6 <sup>2</sup> Forêts et Sociétés, Univ Montpellier, CIRAD, Montpellier, France.

7 <sup>3</sup> International Center for Tropical Agriculture (CIAT), Hanoi, Vietnam

8 <sup>4</sup> Ecosystems Modelling Unity, Forests, Biodiversity and Climate Change Program, Tropical Agricultural  
9 Research and Higher Education Center (CATIE), Turrialba, Cartago, Costa Rica

10 <sup>5</sup> UMR AMAP-IRD, Montpellier, France

11 <sup>6</sup> UMR CNRS LETG 6554, Laboratory of Geography and Remote Sensing COSTEL, Université de Rennes 2

12 <sup>7</sup> EMBRAPA Amazônia Oriental, Trav. Dr. Enéas Pinheiro, Bairro Marco, CEP, 66095-903 Belém, Pará, Brazil

13 \* Correspondance: Clément Bourgoïn, Campus International de Baillarguet, TA C-105/D

14 34398 Montpellier Cedex 5. E-mail : [bourgoin.clement2@gmail.com](mailto:bourgoin.clement2@gmail.com)

15

## 16 **Abstract:**

17 Degraded tropical forests dominate agricultural frontiers and their management is becoming an  
18 urgent priority. This calls for a better understanding of the different forest cover states and cost-  
19 efficient techniques to quantify the impact of degradation on forest structure. Canopy texture  
20 analyses based on Very High Spatial Resolution (VHSR) optical imagery provide proxies to assess forest  
21 structures but the mechanisms linking them with degradation have rarely been investigated. To  
22 address this gap, we used a lightweight Unmanned Aerial Vehicle (UAV) to map 739 ha of degraded  
23 forests and acquire both canopy VHSR images and height model. Thirty-three years of degradation  
24 history from Landsat archives allowed us to sample 40 plots in undisturbed, logged, over-logged and  
25 burned and regrowth forests in tropical forested landscapes (Paragominas, Pará, Brazil). Fourier  
26 (FOTO) and lacunarity textures were used to assess forest canopy structure and to build a typology

27 linking degradation history and current states. Texture metrics capture canopy grain, heterogeneity  
28 and openness gradients and correlate with forest structure variability ( $R^2 = 0.58$ ). Similar structures  
29 share common degradation history and can be discriminated on the basis of canopy texture alone  
30 (accuracy = 55%). Over-logging causes a lowering in forest height, which brings homogeneous textures  
31 and of finer grain. We identified the major changes in structures due to fire following logging which  
32 changes heterogeneous and intermediate grain into coarse textures. Our findings highlight the  
33 potential of canopy texture metrics to characterize degraded forests and thus be used as indicators  
34 for forest management and degradation mitigation. Inexpensive and agile UAV open promising  
35 perspectives at the interface between field inventory and satellite characterization of forest structure  
36 using texture metrics.

37 **Highlights:**

- 38 • We assessed canopy texture – structure relations along forest degradation gradients
- 39 • Canopy textures capture 58% of degradation-induced variability of canopy structure
- 40 • Degradation generates specific canopy textures linked with logging and fire history
- 41 • Texture metrics can be used to evaluate the state of degraded forests

42

43

44 **Keywords:** Canopy structure, Forest degradation, Remote Sensing, Texture, Tropical forest,

45 Unmanned Aerial Vehicle.

46

## 47 **1. Introduction**

48 Forest degradation is a threat (Potapov et al., 2017) to the provision of ecosystem services by tropical  
49 forests. Degradation causes loss of biodiversity through habitat disturbance and fragmentation  
50 (Barlow et al., 2016; Broadbent et al., 2008), erosion of hydrological and soil properties, the reduction  
51 of non-timber forest resources (Lewis et al., 2015; Thompson et al., 2009), and currently accounts for  
52 68.9% of overall carbon losses from tropical forests (Baccini et al., 2017).

53 The accumulation of forest disturbances such as selective logging and understory fires affects the  
54 states of the forest by destroying the canopy and the internal structure without triggering any changes  
55 in land use (Ghazoul and Chazdon, 2017; Putz and Redford, 2010). Degraded forests are therefore the  
56 consequence of complex degradation and recovery processes, which creates a gradient of varying  
57 structures within the forest landscape (Chazdon et al., 2016; Malhi et al., 2014).

58 Measuring the current forest structure and its degree of degradation are crucial for effective but  
59 sustainable management of degraded forests to guarantee the conservation, management and  
60 betterment of their ecological values (Goldstein, 2014).

61 However, the identification, characterization and measurement of forest degradation remains a  
62 scientific challenge, in particular in the remote sensing community (Frolking et al., 2009; Herold et al.,  
63 2011; Hirschmugl et al., 2017; Mitchell et al., 2017). Among the wide range of remote sensing  
64 approaches, optical time series of medium resolution Landsat images have been used to derive forest  
65 states indicators and to reconstruct forest degradation history through the detection and  
66 quantification of disturbances within the canopy (Asner et al., 2009; Bullock et al., 2018; DeVries et  
67 al., 2015; Souza et al., 2013). These approaches are steps towards degradation monitoring and  
68 informing Reducing Emissions from Deforestation and Degradation (REDD+) systems (Goetz et al.,  
69 2014) but do not provide quantitative information on the forest structure which is directly related to  
70 carbon stocks. Airborne Light Detection and Ranging (A-LiDAR) is the most successful technique to  
71 retrieve three-dimensional forest structural parameters and estimate aboveground biomass (AGB)

72 stocks (Asner et al., 2012; Longo et al., 2016; Rappaport et al., 2018) but the data are often costly to  
73 acquire and to replicate both in space and over time (Silva et al., 2017).

74 In addition to the spectral properties of optical remote sensing, Very High Spatial Resolution (VHSR)  
75 sensors (images with less than 5m/pixel) also acquire information on the distribution of dominant tree  
76 crowns that define the forest canopy and also canopy gaps, thereby providing important indirect  
77 indicators of forest three-dimensional structure (Meyer et al., 2018). The spatial distribution of trees,  
78 the shapes and dimensions of their crowns and the characteristics of the inter-crown gaps interact to  
79 define the forest canopy grain and can be assessed through canopy texture analysis (Couteron et al.,  
80 2005). Several studies have demonstrated the potential of texture methods to characterize VHSR  
81 canopy images (Couteron et al., 2005; Frazer et al., 2005). Among them, the FOurier-based Textural  
82 Ordination (FOTO) method has been used in a variety of tropical forests to characterize gradients of  
83 canopy grain, heterogeneity and crown size distribution (Barbier et al., 2010; Bastin et al., 2014;  
84 Couteron et al., 2005; Ploton et al., 2012; Singh et al., 2014). Case studies have shown that FOTO  
85 indices can correlate with forest structural parameters along gradients of natural variation (Couteron  
86 et al. 2005) of degradation (Ploton et al. 2012; Singh et al. 2014) or in landscapes mixing both (Bastin  
87 et al. 2014 ; Pargal et al. 2017). Lacunarity analysis, another textural approach, also captures spatial  
88 heterogeneity of forest canopies and additionally provides a quantitative measure of canopy  
89 'gapiness' that correlates with canopy cover and gap fraction (Frazer et al., 2005; Malhi and Román-  
90 Cuesta, 2008; Ploton et al., 2017). However, the possible links between canopy texture and forest  
91 structure parameters are context dependent (Ploton et al. 2017), and relationships have to be verified  
92 and calibrated using reference data from either field plots or airborne canopy altimetry, and such data  
93 are not available in many tropical landscapes or regions. Moreover, one cannot expect the variety of  
94 stand structures generated by degradation processes to display unequivocal relationships with canopy  
95 texture variables (Rappaport et al., 2018). For instance, severe degradation may result in coarse  
96 texture (e.g. because of big gaps) as well as fine-grained aspects owing to small crowns in regenerating  
97 patches. In this sense, there is a lack in understanding and quantifying the consequences of forest

98 degradation on canopy texture. Using unmanned aerial vehicles (UAV), the aim of this paper is to  
99 demonstrate that texture information can efficiently characterize degraded forest types. Unmanned  
100 aerial vehicles are thus a new promising tool to acquire altimetry data and very high resolution images  
101 of the canopy (Koh and Wich, 2012; Zhang et al., 2016).

102 Here, we used very high resolution UAV images to sample a broad range of degraded and intact forests  
103 conditions in an old deforestation pioneer front of the Brazilian Amazon. For each forest site, we  
104 combined degradation history from Landsat time series with UAV data including canopy elevation and  
105 grey-level images. Our large-area and diverse UAV coverage addressed two questions: (1) How do  
106 canopy textures correlate with forest structure parameters within a large range of degraded forest  
107 types? (2) How do disturbance type and frequency contribute to variability in texture metrics through  
108 heterogeneity, coarseness and openness canopy gradients?

109 In so doing, our study aims to pave the way for interpreting canopy texture in VHSR satellite images  
110 from agile UAV-based ground truthing and consequently help decision makers improve the  
111 management of degraded forests.

112

113

114

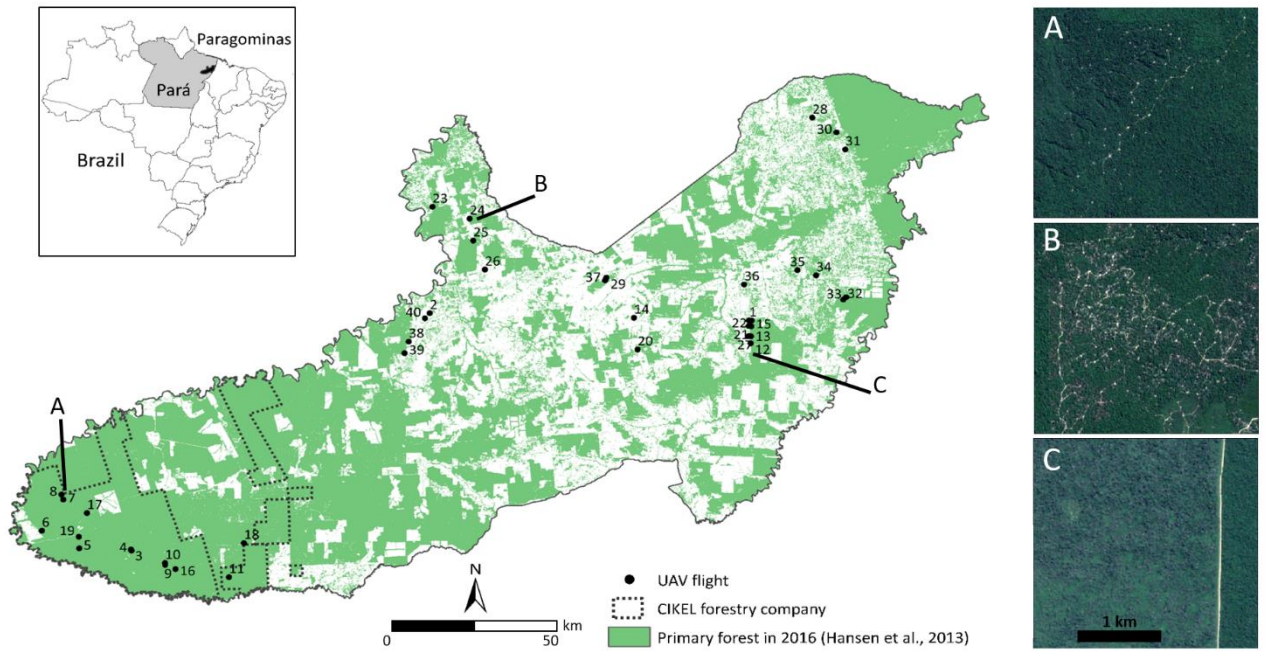
115

116

## 117 **2. Materials and Methods**

### 118 2.1. Study area

119 The study was carried out in the municipality of Paragominas, located in the northeastern part of the  
120 State of Pará, Brazil, and covered an area of 19,342 km<sup>2</sup> (Fig. 1). The municipality experienced different  
121 colonization processes since its foundation in 1965, which led to significant deforestation with  
122 conversion of land to pasture for cattle ranching and forest degradation through overexploitation of  
123 timber. Deforestation was accentuated by the grain agro-industry in the 2000s, dominated by  
124 intensive soybean and maize cultivation mainly in the center of the municipality (Piketty et al., 2015).  
125 We demonstrated in previous studies that the history and processes of colonization spatially differ  
126 within Paragominas (Laurent et al., 2017). This led to a mosaic of forests in very different cover states  
127 within heterogeneous landscape mosaics dominated by different land uses (Bourgoin et al., 2018;  
128 Mercier et al., 2019). In this region, forest management plans with selective logging have rarely been  
129 adopted except in CIKEL Brasil Verde Madeiras Ltda forestry company (Mazzei et al., 2010). Forest  
130 suffered from two major anthropogenic disturbances. Unplanned logging with over-logging intensity  
131 is marked by repeated frequencies over time. Fire alters deeply the understory and generate high  
132 mortality rates for canopy trees (Fig. 1)(Hasan et al., 2019; Tritsch et al., 2016).



133

134 *Figure 1: Location of the study site, Paragominas municipality, in Pará state in the Brazilian Amazon. Distribution of the 40*  
 135 *forest plots covered using UAV. Illustrations of selective logging (A), over-logging (B) and fire (C) from Google Earth® 2017*

136 2.2. Data collection

137 2.2.1. UAV surveys and processing

138 Forty forest sites were selected in various forested landscapes to cover a large variation of disturbance  
 139 types (Fig.1). Using visual interpretation from Google Earth® VHSR images validated by in-situ UAV  
 140 observations, we distinguished between sites that experienced disturbances such as logging and fire  
 141 and intact sites with no human-induced disturbance. We also used the management plan of the Cikel  
 142 forestry company (Fig.1) that provides spatial information on undisturbed and selectively logged  
 143 forests at different dates over the last 20 years.

144 We used a DJI mavic pro UAV carrying its original RGB camera of 12.71 megapixel resolution (DJI,  
 145 Shenzhen, China). The acquisition plan was designed with Pix4D Capture software (Pix4D, Lausanne,  
 146 Switzerland). We used a single grid with 80% of front and side overlap between images and a constant  
 147 flight altitude of 300 meters above ground level. The objective was to maximize the overlap between  
 148 each image and the total surface area mapped. As a result, the average surface mapped in each forest  
 149 plot was 24 ha (~600 by 400 meters) at 10 centimeters spatial resolution (Appendix C) for a total of



150 739 ha. In order to generate a high quality canopy height model, each flight was constrained by several  
151 conditions:

- 152 i) Flat terrain was selected with imaged areas that overlapped with roads or agricultural fields  
153 to allow us to retrieve the ground elevation during the preprocessing step;
- 154 ii) Acquisition in the morning (9 to 11 am) and afternoon (3 to 5 pm) was preferred to avoid  
155 zenithal effects (halo and low image contrast);
- 156 iii) Either cloud free or totally cloudy sky conditions were necessary to avoid cloud shadows;
- 157 iv) Absence of wind to low wind conditions were needed to generate crisp images of the forest  
158 canopy.

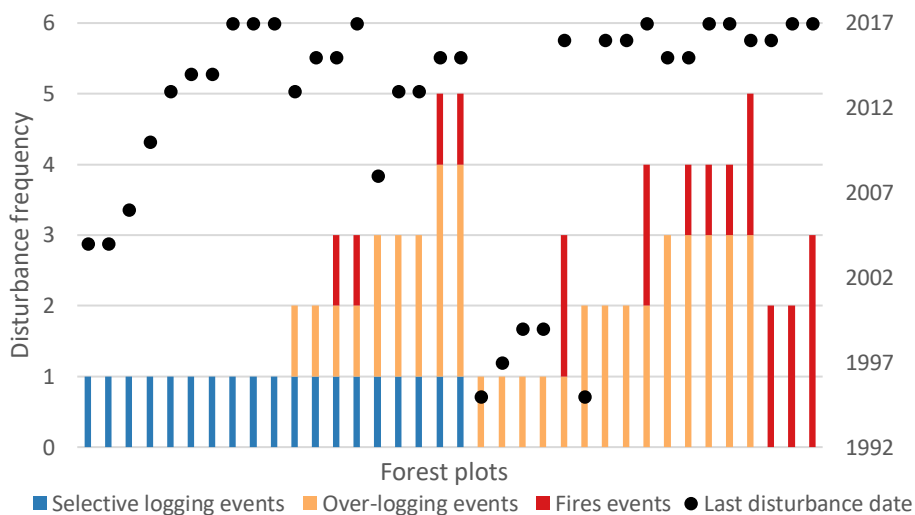
159 Raw image data were processed to the highest density point cloud using structure from motion (SfM)  
160 followed by densification using multi-view stereo algorithms in the Pix4D software (Alonzo et al., 2018;  
161 Westoby et al., 2012). Final point cloud densities were  $\sim 27$  pts.m<sup>-3</sup> depending on the availability of  
162 viable tie points, and some other acquisition parameters (Table 1). Using the georectified point clouds,  
163 we corrected the raw images to generate RGB mosaics, which were then converted into single-band  
164 panchromatic grey level mosaics. Digital Surface Models (DSM) of the canopy (i.e. the top of the  
165 forest's surface) at 0.10 m resolution were directly computed from the point cloud. We extracted the  
166 average ground elevation data in non-forest areas (e.g. roads, agricultural fields or canopy gaps) from  
167 the DSMs and derived canopy height models for each forest plot.

168

#### 169 2.2.2. Landsat time series to detect forest disturbances and reconstruct degradation history

170 We acquired Landsat data from 1984 to 2017 (Appendix A) to detect forest disturbances along time  
171 and reconstruct degradation history for each forest site. The images at Level 1 (Tier 1 product) were  
172 pre-processed to surface reflectance by the algorithm developed by the NASA Goddard Space Flight  
173 Center (<http://earthexplorer.usgs.gov/>). We computed the Normalized Difference Moisture Index

174 (NDMI) from the Short-Wave InfraRed (SWIR) and Near InfraRed (NIR) bands as follows (Gao, 1996):  
 175  $NDMI = NIR - SWIR / NIR + SWIR$   
 176 This index previously used to monitor forest degradation (DeVries et al., 2015) allowed us to identify  
 177 disturbance type and frequency (selective logging, over-logging and fire) at forest plot scale, using  
 178 photointerpretation (Appendix B). The disturbance type was identified based on its spatial extent and  
 179 shape and on the low NDMI values. Selective logging is marked by regular and spaced logging roads  
 180 (Fig.1A), over-logging is marked by irregular logging roads (Fig. 1B) and fire presents open canopy  
 181 structure and low values of NDMI (Silva et al., 2018; Tritsch et al., 2016). We also recorded the date of  
 182 the most recent disturbance (Appendix C) which has a significant influence on the current forest  
 183 structure (Rappaport et al., 2018). Figure 2 shows the diversity of forest degradation history of our  
 184 sampling such as selectively logged forests, over-logged forests and over-logged and burned forests.

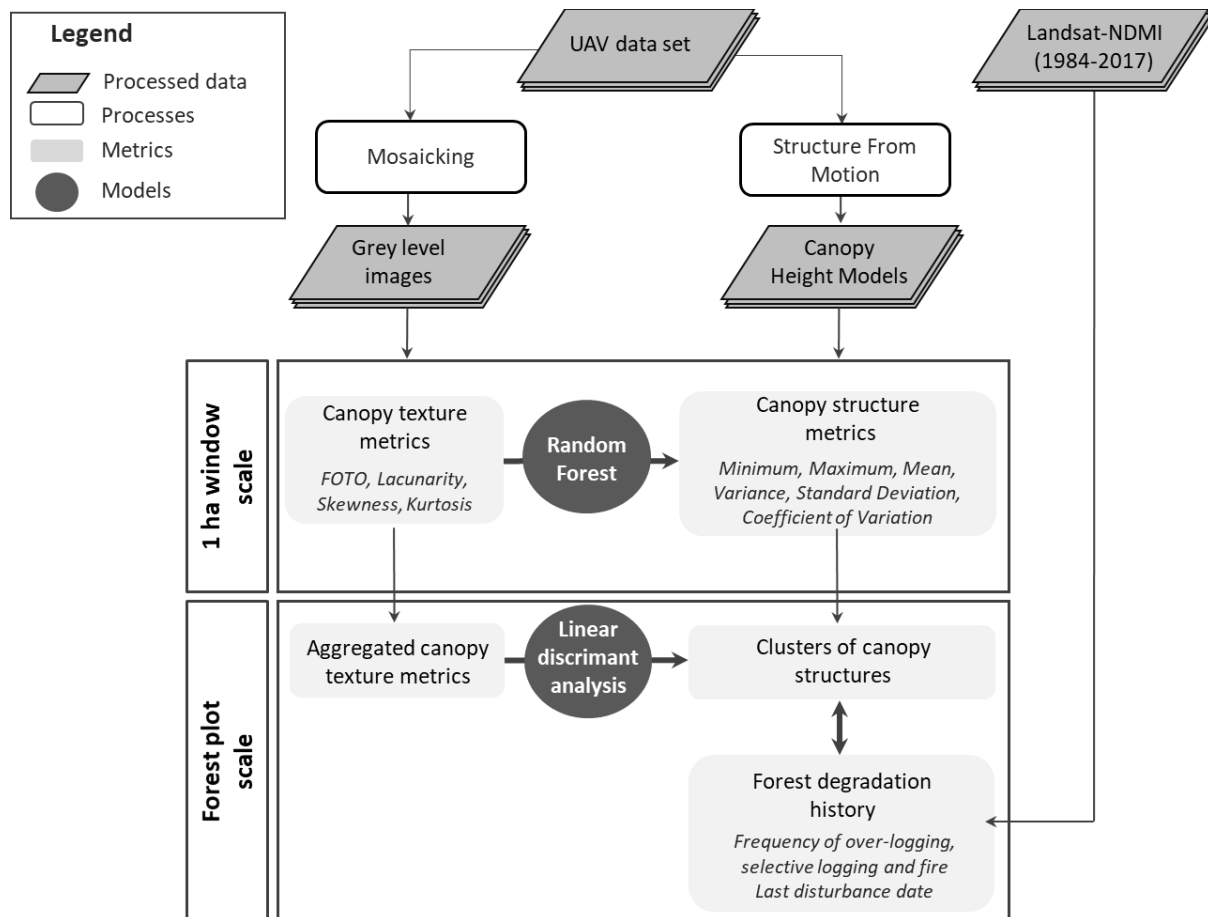


185  
 186  
 187 Figure 2: Forest degradation history of the 40 forest plots based on the frequency of selective logging,  
 188 over-logging, fire events and date of last disturbance (4 plots are not shown as they are secondary  
 189 forests).

190 **2.3. Methods**

191 The data analysis was based on two steps: (1) use canopy texture metrics derived from grey-level UAV  
 192 images to retrieve canopy structure metrics (based on canopy height models) derived from UAV

193 structure from motion within a large range of degraded forest types at 1 ha scale and (2) potential of  
 194 canopy texture metrics to discriminate degradation history and the resulting changes in forest  
 195 structures at the forest plot scale (Fig. 3).



196  
 197 Figure 3: Workflow of the method used to evaluate the potential of canopy texture metrics to retrieve  
 198 the canopy structure along the gradient of forest degradation and their relation with forest  
 199 degradation history.

200

201 2.3.1. Computation of forest canopy texture metrics from grey level UAV images at 1 ha scale

202 We performed texture analysis of grey level canopy images using FOTO (Couteron, 2002) and  
 203 lacunarity (Frazer et al., 2005) algorithms. We also used basic descriptors of statistical grey level  
 204 distributions such as skewness and kurtosis. Each of the UAV canopy images was divided into canopy  
 205 100\*100 m windows (fixed grid) for texture analysis. This size was shown in previous studies to be

206 appropriate to capture several repetitions of the largest tree crowns (in our case 45 meters of  
207 maximum tree crown diameter) in forest stands (Ploton et al., 2017).

208 The FOTO method is extensively described elsewhere (Couteron, 2002; Couteron et al., 2005; Ploton  
209 et al., 2017), hence we only give here a brief outline of the procedure. When applying FOTO, each of  
210 the windows originating from the UAV images is subjected to a two-dimensional Fourier transform to  
211 enable computation of the two-dimensional periodogram. 'Radial-' or 'r-spectra' are extracted from  
212 the periodogram to provide simplified, azimuthally-averaged textural characterization. Spectra are  
213 systematically compared using the two first axes of a principal component analysis (FOTO\_PCA1,  
214 FOTO\_PCA2), providing an ordination along a limited number of coarseness vs. fineness gradients. In  
215 this process, windows are treated as statistical observations that are characterized and compared on  
216 the basis of their spectral profile, i.e., the way in which window grey scale variance is broken down in  
217 relation to Fourier harmonic spatial frequencies (ranging from 50 to 240 cycles/km for this study). PCA  
218 captures gradients of variation between windows spectra opposing those concentrating most variance  
219 in low frequencies (i.e. coarse textures) and those in which high frequencies retain a substantial share  
220 of variance (i.e. fine textures).

221

222 Lacunarity was defined following Frazer et al. (2005) and Malhi and Roman-Cuesta (2008). For each  
223 100\*100 m window, a moving square box of size 's' was glided by one pixel at a time and the sum of  
224 all pixel spectral radiance, called the mass, was computed at each gliding position. The frequency  
225 distribution of the mass divided by the number of boxes' positions is computed, and Lacunarity at box  
226 size 's' is the squared ratio of the first and second moment of this distribution. This process was  
227 repeated for 100 box sizes ranging from 1 to 99 m and the resulting lacunarity spectrum was  
228 normalized by lacunarity at size 1. Finally, the spectra were compared using the two first axes of a PCA  
229 (Lacu\_PCA1 and Lacu\_PCA2 respectively), to provide an ordination of windows along inter-crown  
230 canopy openness gradients.

231 Routines for both FOTO (<http://doi.org/10.5281/zenodo.1216005>) and lacunarity methods were  
232 developed in the MatLab® environment (The MathWorks, Inc., Natick, Massachusetts, USA).

233

#### 234 2.3.2. Computation of forest canopy structure metrics from canopy height models at 1 ha scale

235 From the canopy height model, six Canopy Structure Metrics (CSM) were computed in the same  
236 100\*100m window grid previously described: mean elevation (mean), minimum (min), maximum  
237 (max), variance (var), Standard Deviation (SD) and Coefficient of Variation (CV) defined as the ratio  
238 between standard deviation and mean elevation. We then compiled the six Canopy Texture Metrics,  
239 noted CTM, (FOTO\_PCA1, FOTO\_PCA2, Lacu\_PCA1, Lacu\_PCA2, Skewness, Kurtosis) and the 6 CSM.

240

#### 241 2.3.3. Canopy texture - structure relations within a large range of degraded forest types at 1 ha scale

242 The ability of CTM to predict forest canopy structures was tested using regression models for each  
243 CSM based on Random Forest machine learning (RF) (Breiman, 2001).

244 The learning set is randomly partitioned into  $k$  equal size sub-samples with  $k=10$ . Each regression  
245 process is then applied where  $k-1$  sub samples are used as training data and the remaining ones for  
246 validation. This process is repeated by changing the training/validation sub-samples in such a way that  
247 all learning samples are used for validation. Cross-validation is a common and sound procedure in  
248 machine learning processes (Arlot and Celisse, 2010; Kohavi, 1995). The R-squared, average Root  
249 Mean Square Error (RMSE) and relative RMSE were utilized to evaluate the performance of the model.

250 The number of trees and the number of variables used for tree nodes splitting were randomly  
251 determined using the tune function implemented in the R randomForest package, version 4.6-14 (Liaw  
252 and Wiener, 2002). The number of tree was set to 500 to reduce computation times without notable  
253 loss in accuracy.

254

#### 255 2.3.4. Potential of canopy texture metrics to discriminate forest degradation histories at the plot scale

256 The forest plot scale was used to combine canopy texture and canopy structure metrics with forest  
257 degradation history. We first classified forest plots according to their canopy structures (mean CSM  
258 calculated at the plot scale) using PCA and hierarchical clustering (Ward's criterion). The number of  
259 clusters was optimized by calculating the inter-cluster variance (Ketchen Jr. and Shook, 1996). Each  
260 cluster of forest canopy structure was then related to forest degradation history by calculating the  
261 average disturbance frequency of over-logging, selective logging and fire events. We then used Linear  
262 Discriminant Analysis (LDA) to predict membership of forest structure clusters from averaged value of  
263 CTM at the plot scale. LDA algorithm tries to find a linear combination within the canopy textural  
264 metrics averaged at plot scale that maximizes separation between the barycenters of the clusters  
265 while minimizing the variation within each group of the dataset (Hamsici and Martinez, 2008; Kuhn  
266 and Johnson, 2013). We used MANOVA with Pillai's Trace tests to evaluate the significance of the  
267 multivariate inter-cluster difference computed from the 6 CTM. All processes were computed using  
268 the R packages FactoMineR (Husson et al., 2010; Lê et al., 2008) and the MASS package (Venables and  
269 Ripley, 2002).

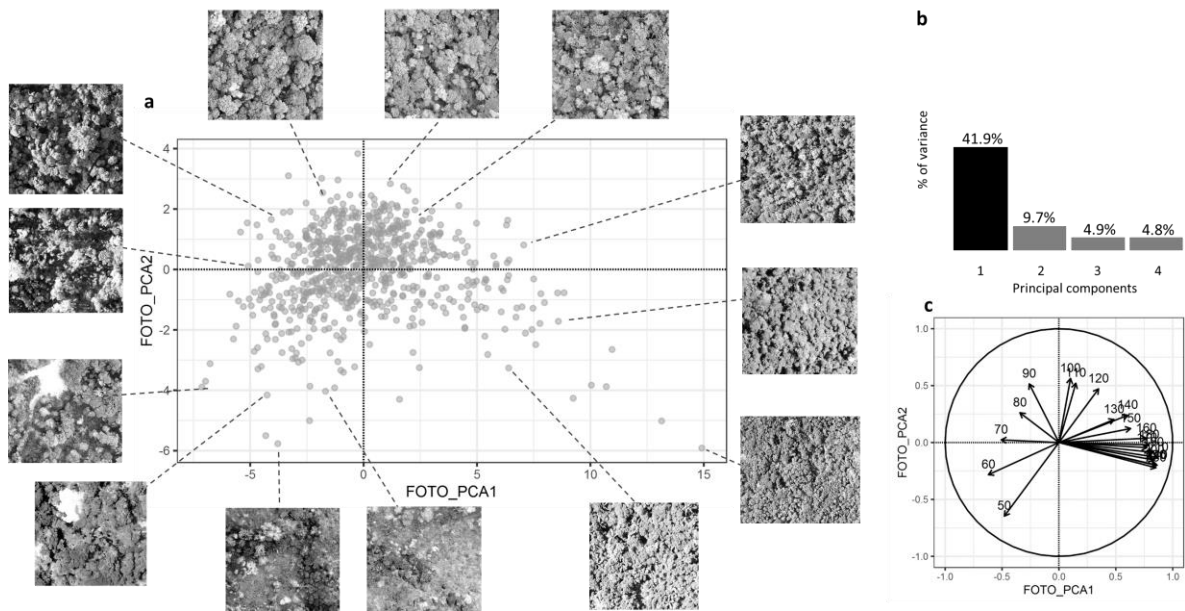
270

### 271 **3. Results**

#### 272 **3.1. Forest canopy texture metrics from grey level UAV images at 1 ha scale**

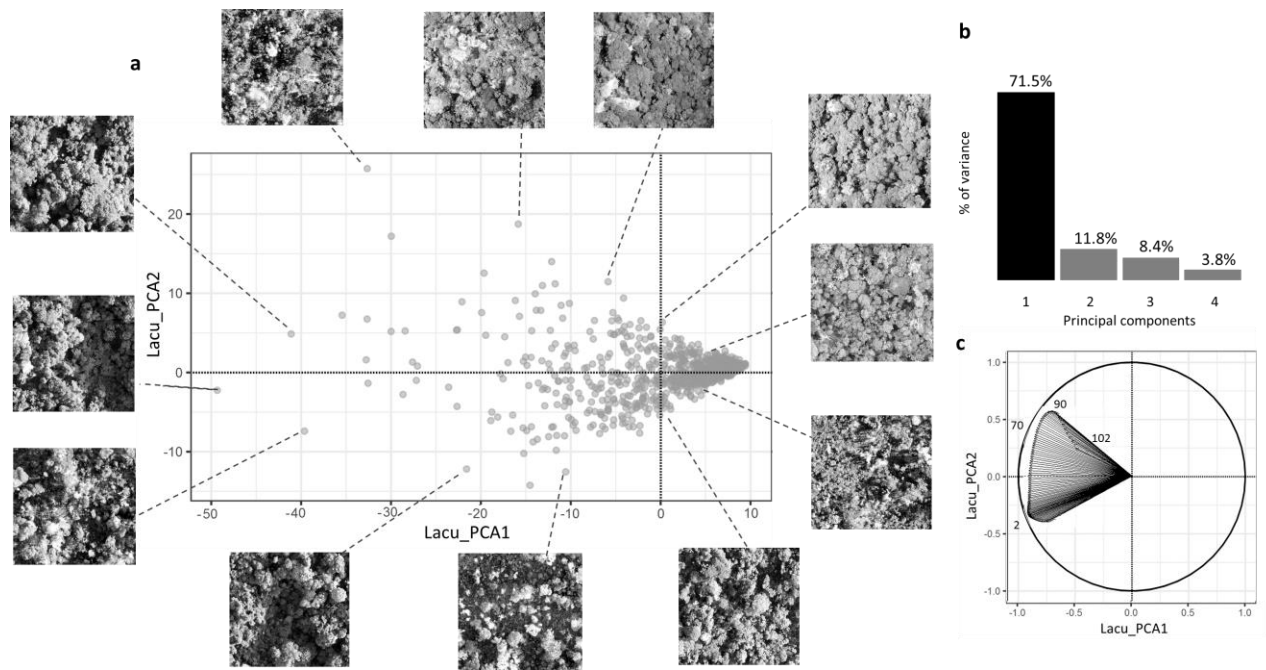
273 The two first factorial axes of the PCA accounted for 51.6% of the total variability of the r-spectra  
274 observed (Fig. 4b). FOTO\_PCA1 expresses a gradient between coarse and fine texture corresponding  
275 to spatial frequencies of less than 90 cycles/km and more than 120 cycles/km, respectively (Fig. 4c).  
276 FOTO\_PCA2 expresses a gradient leading from heterogeneous textures with the coexistence of low  
277 and high frequencies (negative scores) toward homogeneous intermediate frequencies in the range  
278 90-120 cycles/km (high scores). Fine textures correspond to homogeneous distribution of small tree  
279 crowns reflecting ongoing regeneration after probable over-logging. Intermediate textures along axis  
280 1 associate large and smaller tree crowns that characterize preserved forest with the natural  
281 distribution of high emergent trees and lower canopy trees. The left part of the scatter plot groups

282 coarse textures corresponding to large gaps in the canopy related to logging activities. Finally, the two  
 283 examples at the bottom of the plot show mixed coarse (remaining trees) and fine (low understory or  
 284 shrub stratum) textures that characterize over-logged and recently burned forests.  
 285



286  
 287 *Figure 4: Canopy texture ordination based on the FOTO method applied to UAV-acquired grey level images. (a) Scatter plots*  
 288 *of PCA scores along F1 and F2 and windows selected as illustrations. (b) Histogram of eigenvalues expressed as % of total*  
 289 *variance. (c) Correlation circles with frequencies ranging from 50 to 240 (cycles/km).*

290 The first factorial axe of the PCA on the lacunarity spectra account for more than 70% of total  
 291 variability (Fig. 5b). Lacu\_PCA1 expresses a gradient of gapiness with large gaps appearing in the  
 292 extreme left part of the scatter plot (Fig. 5a) and closed canopy forest with no gaps in the extreme  
 293 right part. Large gaps are tree shadows projected over large canopy gaps. Homogeneous canopies, i.e.  
 294 smooth grain and a closed canopy characterizing low degradation forests were found on the positive  
 295 side of the second axis (Lacu\_PCA2)(11% of total variability) and vice versa for heterogeneous  
 296 canopies. These are highly degraded forests (over-logged at different ages and recently burned  
 297 forests) with destroyed canopies and patches of small crowns linked to the understory or to  
 298 regeneration. Other axes did not reveal other structures. Substantial analogy can be observed  
 299 between the main texture gradients provided by FOTO and by the lacunarity analyses.



300

301 *Figure 5: Canopy texture ordination based on the lacunarity method. (a) Scatter plots of PCA scores along F1 and F2 and*  
 302 *windows selected as illustrations. (b) Histogram of eigenvalues expressed as % of total variance. (c) Correlation circles with*  
 303 *sub-window sizes ranging from 2 to 102 pixels.*

304 **3.2. Relationships between canopy textures and forest structure parameters at 1 ha scale**

305 The standard deviation and variance of canopy height were the CSM best explained by texture with a  
 306  $R^2$  of 0.58 and 0.54 respectively (Table 1). These metrics pointing to the variability of canopy structure  
 307 directly reflect the different processes of degradation and the associated gradients of canopy grain  
 308 texture. Maximum and mean canopy height and coefficient of variation show lower relationship (resp.  
 309  $R^2$  of 0.43, 0.38 and 0.31). The minimum height showed a low  $R^2$  of 0.13 with CTM.

310 *Table 1: Random forest regression models for the prediction of canopy structure metrics (CSM) from canopy texture metrics*  
 311 *(CTM) on grey level images.*

CSM	$R^2$	RMSE	Relative RMSE
Minimum (m)	0.13	3.49	0.94
Maximum (m)	0.43	5.66	0.76
Mean (m)	0.38	4.88	0.79
Variance	0.54	13.03	0.68



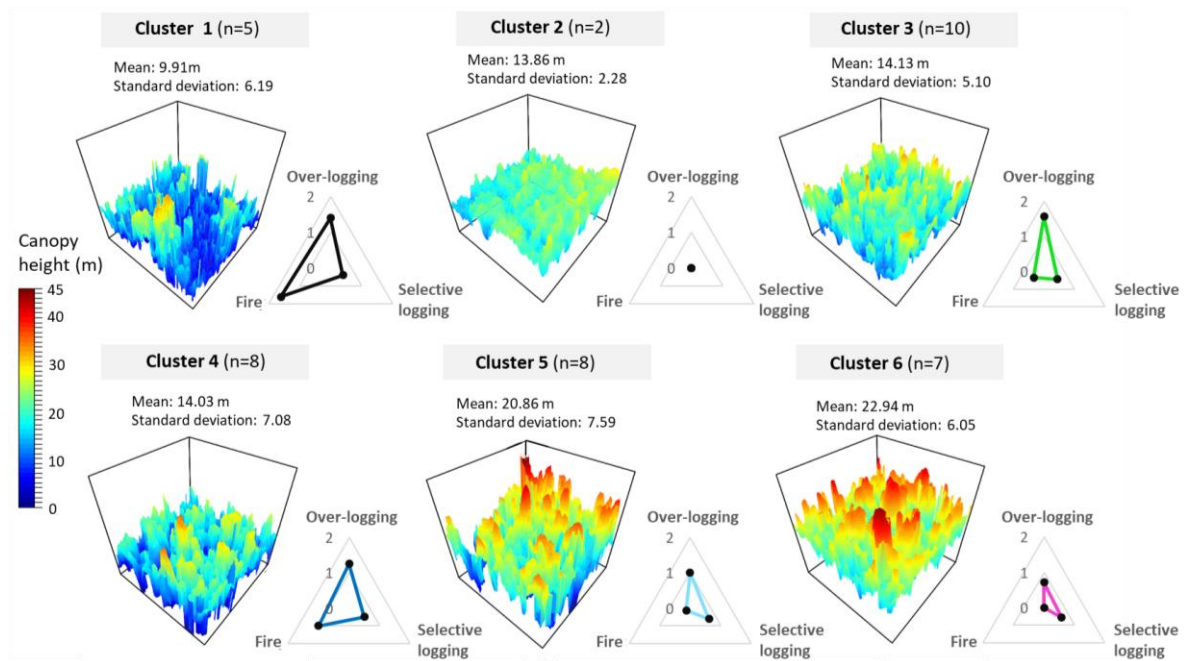
Standard deviation	0.58	1.01	0.65
Coefficient of variation	0.31	0.17	0.83

312

313 **3.3. Potential of canopy texture metrics to discriminate forest degradation histories at the plot scale**

314 3.3.1. Clusters of canopy structures and related degradation history

315 The clustering method allowed identifying six clusters of canopy structures (Fig. 6). **Cluster 1** groups  
316 wide open and low canopy forests with a significantly lower average canopy height (9.9 m) than the  
317 other clusters and high Standard Deviation (SD) values (6.19 m). It groups forest plots that have mainly  
318 experienced over-logging (~1.4 events) and recent fire events identified between 2015 and 2017 (1.6  
319 in average). **Cluster 2** groups 23-year-old secondary forests characterized by a homogeneous and low  
320 canopy (average height of 13.86m and SD of 2.28). **Cluster 3** groups forest plots with homogeneous  
321 (SD of 5.10), low average canopy height (14.13m) mainly marked by over-logging (~1.5 events). **Cluster**  
322 **4** has a heterogeneous canopy structure characterized by high standard deviation (SD of 7.03) which  
323 is explained by recent logging events detected in 2017 (~1.2 events) and other previous disturbances  
324 such as fire (~1 event). **Clusters 5 and 6** have similar canopy height (~22 m) but variable canopy  
325 roughness (SD ranging from 6.05 to 7.59). Their degradation histories differ as cluster 5 groups  
326 recently selectively logged forest (~0.6 events) or over-logged forests (~1 event) while cluster 6 mostly  
327 groups undisturbed forest and old selectively logged forests (more than 10 years ago). However both  
328 clusters are marked by very low (~0.1 events for cluster 5) to none fire disturbances detected. Further  
329 explanation on the different steps of the method and on the statistical results can be found in  
330 Appendix D and E.



331

332 *Figure 6: Three-dimensional plots of canopy height models of the 100 x 100 m windows selected to illustrate the six forest*  
 333 *structure clusters. Radar chart shows the average frequency of over-logging, selective logging and fire disturbances detected*  
 334 *in all forest plots within a given cluster.*

335

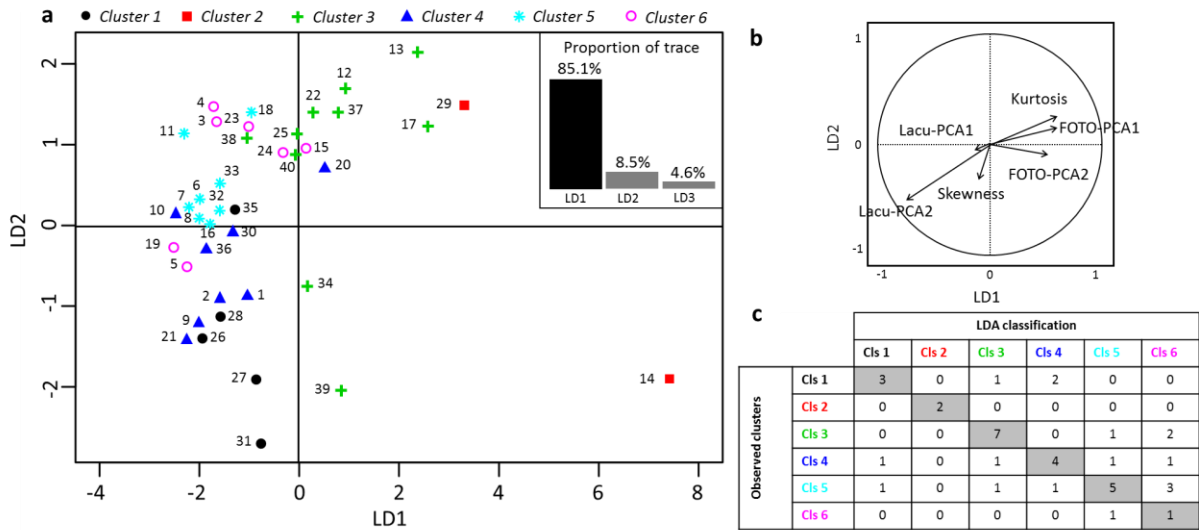
### 336 3.4.2. Linear discriminant analysis at the forest plot scale

337 The two first discriminant components (LD1 and LD2) account for 93.6% of the total proportion of the  
 338 trace i.e. the proportion of inter-cluster discrimination of the LDA based on texture (MANOVA test  
 339 with  $p$ -value  $< 0.05$ )(Fig. 7a). The prominent first discriminant component is mainly correlated with  
 340 FOTO\_PCA1 ( $r=0.55$  in LD1), FOTO\_PCA2 (0.49 in LD1) and LACU\_PCA2 (-0.79 in LD1) (Fig. 7b). The  
 341 second discriminant component is mainly correlated with LACU\_PCA2.

342 In the LD1-LD2 plane, clusters 2 and 3 are mainly separated from the rest of clusters thanks to axis  
 343 LDA1. Cluster 1, 4 and 5 are discriminated along LD2. Cluster 6 has less discriminating capacity,  
 344 especially compared with cluster 5.

345 LDA results include misclassification errors corresponding to disagreement between texture-based  
 346 and structural classifications of the plots (Fig. 7a). The confusion matrix shows an overall accuracy of  
 347 55% and kappa index at 0.44 (Fig 7c). The LDA classification performed well for all clusters except

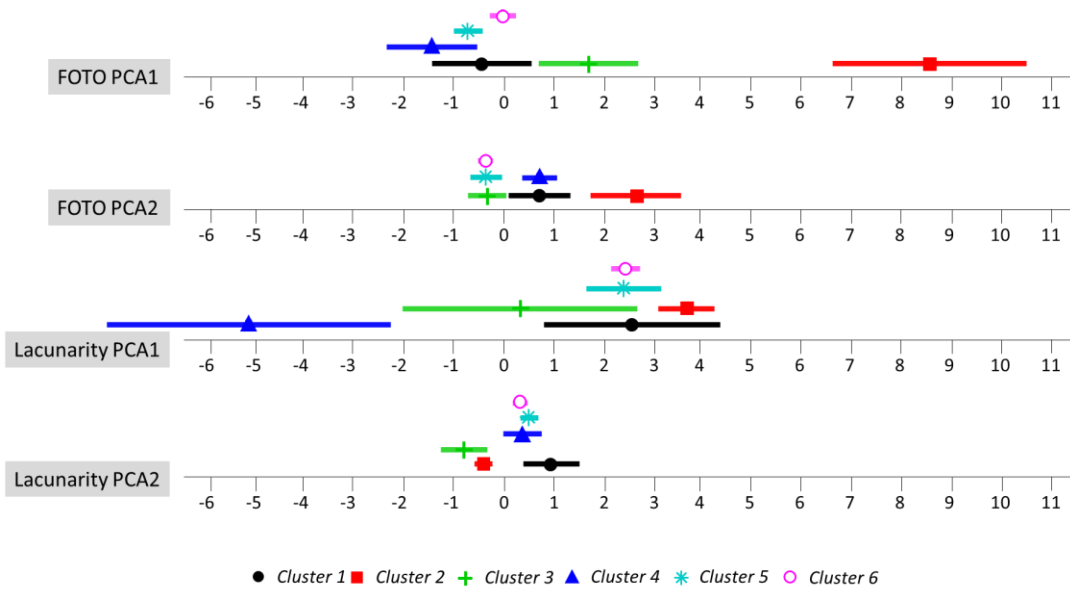
348 cluster 6 which has the highest misclassification rate with a high rate of confusion with cluster 5. Based  
 349 on CTM, clusters 5 and 6 appeared to be similar because they mainly differ in their minimum height,  
 350 which logically is difficult to predict from canopy texture metrics on 2D images.  
 351



352  
 353 *Figure 7: (a) Scatter plot showing the distribution of the 40 forest plots with color based on the color of canopy clusters on*  
 354 *the linear discriminant plane (LD1-2). Inset: proportions of LDA trace (b) Correlation circle of CTM with respect to the two*  
 355 *main components (axes) of the LDA (c) Confusion matrix between observed and predicted clusters for the 40 plots (LDA*  
 356 *classifications)*

357 Clusters 2, 3 and 5 are distinguished along a gradient of canopy textural grain that spans from fine to  
 358 coarse (FOTO-PCA1) (Fig. 8). Cluster 4 mainly presents the lowest FOTO-PCA1 and Lacunarity-PCA1  
 359 values, which correspond to the coarse texture and large gaps, respectively, typical of recent logging  
 360 events. Cluster 1 has on average the coarse grain and homogeneous texture (FOTO-PCA1 and -PCA2)  
 361 that characterize low vegetation strata. Finally cluster 6 (well preserved forest) has intermediate  
 362 canopy grain (FOTO-PCA1 and 2) and canopy openness (Lacunarity-PCA2).

363



364

365 *Figure 8: Mean and SD values of CTM calculated within the 6 predicted clusters using LDA.*

366

367

## 368 **4. Discussion**

369 A better characterization of forest structure is crucial to tailoring forest management plans (Goldstein,  
370 2014). In this paper, we show that canopy texture metrics extracted from very-high spatial resolution  
371 optical images acquired by unmanned aerial vehicle are clearly related to forest canopy height models  
372 and can reveal different and complex degradation history. The canopy texture metrics provide  
373 complementary information on degraded forest states compared to other remotely sensed indicators  
374 based on vegetation photosynthesis activity (Asner et al., 2009; Bullock et al., 2018; Mitchell et al.,  
375 2017). The canopy texture metrics can also be used in multidisciplinary approaches such as for the  
376 assessment of forest ecosystem services that require detailed information on forest structure (Barlow  
377 et al., 2016; Berenguer et al., 2014).

378

### 379 **4.1. Potential of canopy texture metrics to assess degraded canopy structures**

380 We showed that CTM can assess forest structure variability that reflects both horizontal and vertical  
381 heterogeneity induced by degradation. Through the expression of canopy grain and heterogeneity  
382 gradients, CTM provides reliable estimations of canopy roughness (standard deviation of canopy  
383 height) at 1 ha-scale. At the forest plot scale, we demonstrated the complementarity of FOTO and  
384 lacunarity metrics in distinguishing between the different clusters. While FOTO and lacunarity express  
385 similar gradients of canopy texture (Figs. 4 and 5), the measure of canopy openness in lacunarity  
386 provide useful additional information to distinguish large canopy gaps from large crowns, as  
387 underlined by Ploton et al. (2017). However, the first axis of lacunarity reveals a gradient of canopy  
388 textures that could be influenced by sun-angle conditions during the UAV data acquisition. Early  
389 morning and late afternoon data acquisitions generate higher projected shadow, which drives the  
390 distribution of the data towards the negative values of the first axis. Data acquisition parameters (sun  
391 and sensor angles, clouds etc.) are known to be able to disturb grey level values and textures (Barbier  
392 and Coueron, 2015). One advantage of using UAV is that they allow better control of acquisition  
393 conditions than do satellites.

394  
395  
396  
397  
398  
399  
400  
401  
402  
403  
404  
405  
406  
407  
408  
409  
410  
411  
412  
413  
414  
415  
416  
417  
418

#### **4.2. Long-term forest degradation consequences on structure explained using current canopy textures**

In this study, we demonstrate the potential of single shot UAV-based canopy altimetry and texture to correlate with current structure that can reveal both past disturbances and recovery processes (Herold et al. 2011, Ghazoul and Chazdon 2017). At the forest plot scale (~24 ha), the average CSM and the variability of CSM enabled the identification of six forest clusters with specific degradation history. The link between long term degradation history and canopy structure has already been identified in previous studies that quantified carbon densities of Amazonian forests following successive logging and/or fire events (Berenguer et al., 2014; Longo et al., 2016; Rappaport et al., 2018). CTM proved to be able to differentiate between five types of degradation, although with some confusion between the less degraded forest types.

Undisturbed forests have a high closed canopy, and are homogeneous in texture with an intermediate grain associating large and medium-sized tree crowns (cluster 6). Any logging event will disrupt the canopy and create a coarse texture with greater variation in canopy height (cluster 4). Under a management plan, logging intensity is moderate (< 5 to 8 trees/ha) and the recovery time (35 years in Brazil) is expected. In that case, the coarse texture will recover and will turn back into intermediate grain (cluster 5 or 6). We showed that after seven years, the canopy texture of a logged forest resembles that of undisturbed forest (Fig. 6 and Appendix C). For unmanaged forests, subject to higher uptake, the time for the forest to recover a canopy texture of intermediate grain will be longer (e.g. plots 23 and 24). In the case of additional impacts (progressive disappearance of large crowns), the coarse canopy texture will also be maintained longer. Repetitive and intense logging have therefore triggered the complete harvesting of emergent trees, thereby weakening the capacity of forests to cope with further disturbances (Asner et al., 2002). During the recovery process, canopy is of low height and its texture is dominated by a fine and heterogeneous grain (cluster 3).

419 Additionally, we found that recent fire (single or multiple events) has a major impact on the damaged  
420 forest structure. The resulting highly degraded forests are characterized by coarse textures  
421 corresponding to large gaps and/or homogeneous regeneration stratum and highly damaged canopy  
422 (cluster 1). Moreover, most fires were detected in 2015, which correlated with the El Nino drought  
423 event (Berenguer et al., 2018). These findings underline the importance of the synergetic effects of  
424 logging and fire on forest structure (Dwomoh et al., 2019; Morton et al., 2013). We also found that  
425 fire was never detected (i.e. did not occur) in closed canopy and relatively low degradation forests.  
426 This confirms that heavily logged forests are more vulnerable to fire due to the presence of dead and  
427 dry vegetation resulting from logging. At a larger scale, this vulnerability is linked with the  
428 fragmentation of forest patches, which facilitates access to forest resources, accentuates dry edge  
429 effects and increases potential pressure caused by agricultural expansion (Briant et al., 2010;  
430 Broadbent et al., 2008; Silva Junior et al., 2018). The mitigation of fire occurrence through improved  
431 landscape management is therefore a priority in order to prevent further degradation and forest  
432 carbon losses (Berenguer et al., 2014).

433 The results of the present study reveal possible ways to address questions concerning the future  
434 management of primary degraded forests by analyzing the structure and texture of their canopy in  
435 order to better differentiate forest states and the associated degradation history. This study also  
436 opens the way for further analysis of secondary forests in abandoned lands which will certainly play a  
437 crucial role in future scenarios of landscape restoration (Chazdon et al., 2016).

438

### 439 **4.3. UAV technology: from data acquisition to limitations and perspectives**

440 This paper reports the first large-scale application of low cost UAV to retrieve quantitative information  
441 on closed canopy forest structures. The UAV used is inexpensive (<2,000 US\$) and a highly efficient  
442 cost/time ratio was found for data acquisition in the field. In a 20 minutes flight, around 25 hectares  
443 of forest was mapped at a resolution of 10 centimeters. Other studies using UAV produced results that  
444 are comparable with LiDAR in terms of point cloud densities (Chung et al., 2019; Dandois et al., 2015)

445 and estimations of forest structural parameters (Alonzo et al., 2018). Finally, the computation of CTM  
446 using open-source Matlab® routines is automatic and only requires the window size used for texture  
447 analysis as the user input. Window size can be adapted to forest canopy crown size and distribution,  
448 although limited variations do not alter the results much. Consequently, the workflow described here  
449 has great promise for future monitoring of tropical forest at low cost, which is interesting when  
450 airborne LiDAR is not affordable or available.

451 However, UAV remain limited by their inability to cover regions as large as those covered by satellite  
452 images, and climatic conditions (wind, cloud shadows) are likely to disturb the consistency of image  
453 texture and thus the automatic mapping process. Finally, regulations strongly limit the use of UAV in  
454 certain countries. Nonetheless, UAVs appears to be an efficient tool at the interface between field  
455 inventory and satellite characterization of forest structure (Koh and Wich, 2012). Unmanned aerial  
456 vehicle acquired reference data could be the basis of upscaling chains that would allow the use of  
457 spaceborne data of decreasing resolution yet increasing swath and affordability so as to reach broad  
458 scale, wall to wall mapping of forest state indicators of known accuracy.

459

#### 460 **Authors' contributions**

461 *CB, JB, LB, JO, LR, PL and VG conceived the ideas and designed methodology; CB, JB, LB and VB collected*  
462 *the data; CB, JB, PC, LB, HD, LR and VG analyzed the data; CB, PC, VG, LB and PS led the writing of the*  
463 *manuscript. All authors contributed critically to the drafts and gave final approval for publication.*

#### 464 **Acknowledgements**

465 *This work was supported by 1) the European Union through the H2020-MSCA-RISE-2015 ODYSSEA*  
466 *project (Project Reference: 691053), by 2) the CNES (France) through the TOSCA CASTAFIOR project (ID*  
467 *4310), by 3) the EIT through the Climate-KIC ForLand Restoration project and by 4) the CGIAR Research*  
468 *Program on Forest Trees and Agroforestry (FTA) and on Climate Change, Agriculture and Food Security*  
469 *(CAAFS), the latter with support from CGIAR Fund Donors and through bilateral funding agreements.*



470 For details, please visit <https://ccafs.cgiar.org/donors>. The views expressed in this document cannot  
471 be taken to reflect the official opinions of these organizations

472 **Conflicts of Interest:** *The authors declare no conflict of interest.*

473

## 474 **References**

- 475 Alonzo, M., Andersen, H.-E., Morton, D., Cook, B., 2018. Quantifying Boreal Forest Structure  
476 and Composition Using UAV Structure from Motion. *Forests* 9, 119.  
477 <https://doi.org/10.3390/f9030119>
- 478 Arlot, S., Celisse, A., 2010. A survey of cross-validation procedures for model selection.  
479 *Statist. Surv.* 4, 40–79. <https://doi.org/10.1214/09-SS054>
- 480 Asner, G.P., Keller, M., Pereira, R., Zweede, J.C., 2002. Remote sensing of selective  
481 logging in Amazonia: Assessing limitations based on detailed field observations,  
482 Landsat ETM+, and textural analysis. *Remote Sensing of Environment* 80, 483–496.
- 483 Asner, G.P., Knapp, D.E., Balaji, A., Páez-Acosta, G., 2009. Automated mapping of tropical  
484 deforestation and forest degradation: CLASlite. *Journal of Applied Remote Sensing*  
485 3, 033543–033543.
- 486 Asner, G.P., Mascaró, J., Muller-Landau, H.C., Vieilledent, G., Vaudry, R., Rasamoelina, M.,  
487 Hall, J.S., van Breugel, M., 2012. A universal airborne LiDAR approach for tropical  
488 forest carbon mapping. *Oecologia* 168, 1147–1160. [https://doi.org/10.1007/s00442-](https://doi.org/10.1007/s00442-011-2165-z)  
489 [011-2165-z](https://doi.org/10.1007/s00442-011-2165-z)
- 490 Baccini, A., Walker, W., Carvalho, L., Farina, M., Sulla-Menashe, D., Houghton, R.A., 2017.  
491 Tropical forests are a net carbon source based on aboveground measurements of  
492 gain and loss. *Science* 358, 230–234. <https://doi.org/10.1126/science.aam5962>
- 493 Barbier, N., Couteron, P., 2015. Attenuating the bidirectional texture variation of satellite  
494 images of tropical forest canopies. *Remote Sensing of Environment* 171, 245–260.  
495 <https://doi.org/10.1016/j.rse.2015.10.007>
- 496 Barbier, N., Couteron, P., Proisy, C., Malhi, Y., Gastellu-Etchegorry, J.-P., 2010. The  
497 variation of apparent crown size and canopy heterogeneity across lowland  
498 Amazonian forests: Amazon forest canopy properties. *Global Ecology and*  
499 *Biogeography* 19, 72–84. <https://doi.org/10.1111/j.1466-8238.2009.00493.x>
- 500 Barlow, J., Lennox, G.D., Ferreira, J., Berenguer, E., Lees, A.C., Nally, R.M., Thomson, J.R.,  
501 Ferraz, S.F. de B., Louzada, J., Oliveira, V.H.F., Parry, L., Ribeiro de Castro Solar,  
502 R., Vieira, I.C.G., Aragão, L.E.O.C., Begotti, R.A., Braga, R.F., Cardoso, T.M., Jr,  
503 R.C. de O., Souza Jr, C.M., Moura, N.G., Nunes, S.S., Siqueira, J.V., Pardini, R.,  
504 Silveira, J.M., Vaz-de-Mello, F.Z., Veiga, R.C.S., Venturieri, A., Gardner, T.A., 2016.  
505 Anthropogenic disturbance in tropical forests can double biodiversity loss from  
506 deforestation. *Nature* 535, 144–147. <https://doi.org/10.1038/nature18326>
- 507 Bastin, J.-F., Barbier, N., Couteron, P., Adams, B., Shapero, A., Bogaert, J., De Cannière, C.,  
508 2014. Aboveground biomass mapping of African forest mosaics using canopy texture  
509 analysis: toward a regional approach. *Ecological applications* 24, 1984–2001.
- 510 Berenguer, E., Ferreira, J., Gardner, T.A., Aragão, L.E.O.C., De Camargo, P.B., Cerri, C.E.,  
511 Durigan, M., Oliveira, R.C.D., Vieira, I.C.G., Barlow, J., 2014. A large-scale field  
512 assessment of carbon stocks in human-modified tropical forests. *Global Change*  
513 *Biology* 20, 3713–3726. <https://doi.org/10.1111/gcb.12627>
- 514 Berenguer, E., Malhi, Y., Brando, P., Cardoso, A., Cordeiro, N., Ferreira, J., Franca, F.,  
515 Rossi, L.C., 2018. Tree growth and stem carbon accumulation in human-modified  
516 Amazonian forests following drought and fire 8.

517 Bourgoin, C., Blanc, L., Bailly, J.-S., Cornu, G., Berenguer, E., Oszwald, J., Tritsch, I.,  
518 Laurent, F., Hasan, A.F., Sist, P., Gond, V., 2018. The Potential of Multisource  
519 Remote Sensing for Mapping the Biomass of a Degraded Amazonian Forest 21.  
520 Breiman, L., 2001. Random forests. *Machine learning* 45, 5–32.  
521 Briant, G., Gond, V., Laurance, S.G.W., 2010. Habitat fragmentation and the desiccation of  
522 forest canopies: A case study from eastern Amazonia. *Biological Conservation* 143,  
523 2763–2769. <https://doi.org/10.1016/j.biocon.2010.07.024>  
524 Broadbent, E., Asner, G., Keller, M., Knapp, D., Oliveira, P., Silva, J., 2008. Forest  
525 fragmentation and edge effects from deforestation and selective logging in the  
526 Brazilian Amazon. *Biological Conservation* 141, 1745–1757.  
527 <https://doi.org/10.1016/j.biocon.2008.04.024>  
528 Bullock, E.L., Woodcock, C.E., Olofsson, P., 2018. Monitoring tropical forest degradation  
529 using spectral unmixing and Landsat time series analysis. *Remote Sensing of*  
530 *Environment*. <https://doi.org/10.1016/j.rse.2018.11.011>  
531 Chazdon, R.L., Brancalion, P.H.S., Laestadius, L., Bennett-Curry, A., Buckingham, K.,  
532 Kumar, C., Moll-Rocek, J., Vieira, I.C.G., Wilson, S.J., 2016. When is a forest a  
533 forest? Forest concepts and definitions in the era of forest and landscape restoration.  
534 *Ambio* 45, 538–550. <https://doi.org/10.1007/s13280-016-0772-y>  
535 Chung, C.-H., Wang, C.-H., Hsieh, H.-C., Huang, C.-Y., 2019. Comparison of forest canopy  
536 height profiles in a mountainous region of Taiwan derived from airborne lidar and  
537 unmanned aerial vehicle imagery. *GIScience & Remote Sensing* 56, 1289–1304.  
538 <https://doi.org/10.1080/15481603.2019.1627044>  
539 Couteron, P., 2002. Quantifying change in patterned semi-arid vegetation by Fourier  
540 analysis of digitized aerial photographs. *International Journal of Remote Sensing* 23,  
541 3407–3425. <https://doi.org/10.1080/01431160110107699>  
542 Couteron, P., Pelissier, R., Nicolini, E.A., Paget, D., 2005. Predicting tropical forest stand  
543 structure parameters from Fourier transform of very high-resolution remotely sensed  
544 canopy images. *Journal of applied ecology* 42, 1121–1128.  
545 Couteron, Pierre, Pelissier, R., Nicolini, E.A., Paget, D., 2005. Predicting tropical forest stand  
546 structure parameters from Fourier transform of very high-resolution remotely sensed  
547 canopy images: *Predicting tropical forest stand structure*. *Journal of Applied Ecology*  
548 42, 1121–1128. <https://doi.org/10.1111/j.1365-2664.2005.01097.x>  
549 Dandois, J., Olano, M., Ellis, E., 2015. Optimal Altitude, Overlap, and Weather Conditions for  
550 Computer Vision UAV Estimates of Forest Structure. *Remote Sensing* 7, 13895–  
551 13920. <https://doi.org/10.3390/rs71013895>  
552 DeVries, B., Decuyper, M., Verbesselt, J., Zeileis, A., Herold, M., Joseph, S., 2015. Tracking  
553 disturbance-regrowth dynamics in tropical forests using structural change detection  
554 and Landsat time series. *Remote Sensing of Environment* 169, 320–334.  
555 <https://doi.org/10.1016/j.rse.2015.08.020>  
556 Dwomoh, F.K., Wimberly, M.C., Cochrane, M.A., Numata, I., 2019. Forest degradation  
557 promotes fire during drought in moist tropical forests of Ghana. *Forest Ecology and*  
558 *Management* 440, 158–168. <https://doi.org/10.1016/j.foreco.2019.03.014>  
559 Frazer, G.W., Wulder, M.A., Niemann, K.O., 2005. Simulation and quantification of the fine-  
560 scale spatial pattern and heterogeneity of forest canopy structure: A lacunarity-based  
561 method designed for analysis of continuous canopy heights. *Forest Ecology and*  
562 *Management* 214, 65–90. <https://doi.org/10.1016/j.foreco.2005.03.056>  
563 Frolking, S., Palace, M.W., Clark, D.B., Chambers, J.Q., Shugart, H.H., Hurtt, G.C., 2009.  
564 Forest disturbance and recovery: A general review in the context of spaceborne  
565 remote sensing of impacts on aboveground biomass and canopy structure. *Journal of*  
566 *Geophysical Research* 114. <https://doi.org/10.1029/2008JG000911>  
567 Gao, B., 1996. NDWI—A normalized difference water index for remote sensing of vegetation  
568 liquid water from space. *Remote Sensing of Environment* 58, 257–266.  
569 [https://doi.org/10.1016/S0034-4257\(96\)00067-3](https://doi.org/10.1016/S0034-4257(96)00067-3)

570 Ghazoul, J., Chazdon, R., 2017. Degradation and Recovery in Changing Forest  
571 Landscapes: A Multiscale Conceptual Framework. *Annual Review of Environment  
572 and Resources* 42, 161–188.

573 Goetz, S., Hansen, M., Houghton, R.A., Walker, W., Laporte, N.T., Busch, J., 2014.  
574 Measurement and Monitoring for REDD+: The Needs, Current Technological  
575 Capabilities, and Future Potential. *SSRN Electronic Journal*.  
576 <https://doi.org/10.2139/ssrn.2623076>

577 Goldstein, J.E., 2014. The Afterlives of Degraded Tropical Forests: New Value for  
578 Conservation and Development. *Environment and Society: Advances in Research* 5,  
579 124–140. <https://doi.org/10.3167/ares.2014.050108>

580 Hamsici, O.C., Martinez, A.M., 2008. Bayes Optimality in Linear Discriminant Analysis. *IEEE  
581 Transactions on Pattern Analysis and Machine Intelligence* 30, 647–657.  
582 <https://doi.org/10.1109/TPAMI.2007.70717>

583 Hasan, A.F., Laurent, F., Messner, F., Bourgoïn, C., Blanc, L., 2019. Cumulative  
584 disturbances to assess forest degradation using spectral unmixing in the north-  
585 eastern Amazon. *Appl Veg Sci* avsc.12441. <https://doi.org/10.1111/avsc.12441>

586 Herold, M., Román-Cuesta, R.M., Mollicone, D., Hirata, Y., Van Laake, P., Asner, G.P.,  
587 Souza, C., Skutsch, M., Avitabile, V., MacDicken, K., 2011. Options for monitoring  
588 and estimating historical carbon emissions from forest degradation in the context of  
589 REDD+. *Carbon balance and management* 6, 13.

590 Hirschmugl, M., Gallaun, H., Dees, M., Datta, P., Deutscher, J., Koutsias, N., Schardt, M.,  
591 2017. Methods for mapping forest disturbance and degradation from optical earth  
592 observation data: A review. *Current Forestry Reports* 3, 32–45.

593 Husson, F., Josse, J., Pages, J., 2010. Principal component methods - hierarchical  
594 clustering - partitional clustering: why would we need to choose for visualizing data?  
595 17.

596 Ketchen Jr., D.J., Shook, C.L., 1996. The Application Of Cluster Analysis In Strategic  
597 Management Research: An Analysis And Critique. *Strategic Management Journal*  
598 17, 441–458. [https://doi.org/10.1002/\(SICI\)1097-0266\(199606\)17:6<441::AID-  
599 SMJ819>3.0.CO;2-G](https://doi.org/10.1002/(SICI)1097-0266(199606)17:6<441::AID-SMJ819>3.0.CO;2-G)

600 Koh, L.P., Wich, S.A., 2012. Dawn of Drone Ecology: Low-Cost Autonomous Aerial Vehicles  
601 for Conservation. *Tropical Conservation Science* 5, 121–132.  
602 <https://doi.org/10.1177/194008291200500202>

603 Kohavi, R., 1995. A Study of Cross-Validation and Bootstrap for Accuracy Estimation and  
604 Model Selection 7.

605 Kuhn, M., Johnson, K., 2013. *Applied predictive modeling*. Springer, New York.

606 Laurent, F., Arvor, D., Daugeard, M., Osis, R., Tritsch, I., Coudel, E., Piketty, M.-G., Piraux,  
607 M., Viana, C., Dubreuil, V., Hasan, A.F., Messner, F., 2017. Le tournant  
608 environnemental en Amazonie : ampleur et limites du découplage entre production et  
609 déforestation. *EchoGéo*. <https://doi.org/10.4000/echogeo.15035>

610 Lê, S., Josse, J., Husson, F., 2008. FactoMineR : An R Package for Multivariate Analysis.  
611 *Journal of Statistical Software* 25. <https://doi.org/10.18637/jss.v025.i01>

612 Lewis, S.L., Edwards, D.P., Galbraith, D., 2015. Increasing human dominance of tropical  
613 forests. *Science* 349, 827–832. <https://doi.org/10.1126/science.aaa9932>

614 Liaw, A., Wiener, M., 2002. Classification and regression by randomForest. *R news* 2, 18–  
615 22.

616 Longo, M., Keller, M., dos-Santos, M.N., Leitold, V., Pinagé, E.R., Baccini, A., Saatchi, S.,  
617 Nogueira, E.M., Batistella, M., Morton, D.C., 2016. Aboveground biomass variability  
618 across intact and degraded forests in the Brazilian Amazon: AMAZON INTACT AND  
619 DEGRADED FOREST BIOMASS. *Global Biogeochemical Cycles* 30, 1639–1660.  
620 <https://doi.org/10.1002/2016GB005465>

621 Malhi, Y., Gardner, T.A., Goldsmith, G.R., Silman, M.R., Zelazowski, P., 2014. Tropical  
622 Forests in the Anthropocene. *Annual Review of Environment and Resources* 39,  
623 125–159. <https://doi.org/10.1146/annurev-environ-030713-155141>

624 Malhi, Y., Román-Cuesta, R.M., 2008. Analysis of lacunarity and scales of spatial  
625 homogeneity in IKONOS images of Amazonian tropical forest canopies. *Remote*  
626 *Sensing of Environment* 112, 2074–2087. <https://doi.org/10.1016/j.rse.2008.01.009>

627 Mazzei, L., Sist, P., Ruschel, A., Putz, F.E., Marco, P., Pena, W., Ferreira, J.E.R., 2010.  
628 Above-ground biomass dynamics after reduced-impact logging in the Eastern  
629 Amazon. *Forest Ecology and Management* 259, 367–373.  
630 <https://doi.org/10.1016/j.foreco.2009.10.031>

631 Mercier, A., Betbeder, J., Rumiano, F., Gond, V., Blanc, L., Bourgoïn, C., Cornu, G.,  
632 Pocard-Chapuis, R., Baudry, J., Hubert-Moy, L., 2019. Evaluation of Sentinel-1 and  
633 2 Time Series for Land Cover Classification of Forest–Agriculture Mosaics in  
634 Temperate and Tropical Landscapes 20.

635 Meyer, V., Saatchi, S., Clark, D.B., Keller, M., Vincent, G., Ferraz, A., Espírito-Santo, F.,  
636 d’Oliveira, M.V.N., Kaki, D., Chave, J., 2018. Canopy area of large trees  
637 explains aboveground biomass variations across neotropical forest landscapes.  
638 *Biogeosciences* 15, 3377–3390. <https://doi.org/10.5194/bg-15-3377-2018>

639 Mitchell, A.L., Rosenqvist, A., Mora, B., 2017. Current remote sensing approaches to  
640 monitoring forest degradation in support of countries measurement, reporting and  
641 verification (MRV) systems for REDD+. *Carbon Balance and Management* 12.  
642 <https://doi.org/10.1186/s13021-017-0078-9>

643 Morton, D.C., Le Page, Y., DeFries, R., Collatz, G.J., Hurtt, G.C., 2013. Understorey fire  
644 frequency and the fate of burned forests in southern Amazonia. *Philosophical*  
645 *Transactions of the Royal Society B: Biological Sciences* 368, 20120163–20120163.  
646 <https://doi.org/10.1098/rstb.2012.0163>

647 Panagiotidis, D., Abdollahnejad, A., Surový, P., Chiteculo, V., 2017. Determining tree height  
648 and crown diameter from high-resolution UAV imagery. *International Journal of*  
649 *Remote Sensing* 38, 2392–2410. <https://doi.org/10.1080/01431161.2016.1264028>

650 Ploton, P., Barbier, N., Coutron, P., Antin, C.M., Ayyappan, N., Balachandran, N.,  
651 Barathan, N., Bastin, J.-F., Chuyong, G., Dauby, G., Droissart, V., Gastellu-  
652 Etchegorry, J.-P., Kamdem, N.G., Kenfack, D., Libalah, M., Mofack, G., Momo, S.T.,  
653 Pargal, S., Petronelli, P., Proisy, C., Réjou-Méchain, M., Sonké, B., Texier, N.,  
654 Thomas, D., Verley, P., Zebaze Dongmo, D., Berger, U., Pélissier, R., 2017. Toward  
655 a general tropical forest biomass prediction model from very high resolution optical  
656 satellite images. *Remote Sensing of Environment* 200, 140–153.  
657 <https://doi.org/10.1016/j.rse.2017.08.001>

658 Ploton, P., Pélissier, R., Proisy, C., Flavenot, T., Barbier, N., Rai, S.N., Coutron, P., 2012.  
659 Assessing aboveground tropical forest biomass using Google Earth canopy images.  
660 *Ecological Applications* 22, 993–1003.

661 Potapov, P., Hansen, M.C., Laestadius, L., Turubanova, S., Yaroshenko, A., Thies, C.,  
662 Smith, W., Zhuravleva, I., Komarova, A., Minnemeyer, S., others, 2017. The last  
663 frontiers of wilderness: Tracking loss of intact forest landscapes from 2000 to 2013.  
664 *Science Advances* 3, e1600821.

665 Putz, F.E., Redford, K.H., 2010. The Importance of Defining ‘Forest’: Tropical Forest  
666 Degradation, Deforestation, Long-term Phase Shifts, and Further Transitions:  
667 Importance of Defining ‘Forest.’ *Biotropica* 42, 10–20. <https://doi.org/10.1111/j.1744-7429.2009.00567.x>

668 Rappaport, D.I., Morton, D.C., Longo, M., Keller, M., Dubayah, R., Nara dos-Santos, M.,  
669 2018. Quantifying long-term changes in carbon stocks and forest structure from  
670 Amazon forest degradation. *Environmental Research Letters*.  
671 <https://doi.org/10.1088/1748-9326/aac331>

672 Silva, C., Hudak, A., Vierling, L., Klauberg, C., Garcia, M., Ferraz, A., Keller, M., Eitel, J.,  
673 Saatchi, S., 2017. Impacts of Airborne Lidar Pulse Density on Estimating Biomass  
674 Stocks and Changes in a Selectively Logged Tropical Forest. *Remote Sensing* 9,  
675 1068. <https://doi.org/10.3390/rs9101068>

676

677 Silva, S.S. da, Fearnside, P.M., Graça, P.M.L. de A., Brown, I.F., Alencar, A., Melo, A.W.F.  
678 de, 2018. Dynamics of forest fires in the southwestern Amazon. *Forest Ecology and*  
679 *Management* 424, 312–322. <https://doi.org/10.1016/j.foreco.2018.04.041>  
680 Silva Junior, C., Aragão, L., Fonseca, M., Almeida, C., Vedovato, L., Anderson, L., 2018.  
681 Deforestation-Induced Fragmentation Increases Forest Fire Occurrence in Central  
682 Brazilian Amazonia. *Forests* 9, 305. <https://doi.org/10.3390/f9060305>  
683 Singh, M., Malhi, Y., Bhagwat, S., 2014. Biomass estimation of mixed forest landscape using  
684 a Fourier transform texture-based approach on very-high-resolution optical satellite  
685 imagery. *International Journal of Remote Sensing* 35, 3331–3349.  
686 <https://doi.org/10.1080/01431161.2014.903441>  
687 Souza, Jr, C., Siqueira, J., Sales, M., Fonseca, A., Ribeiro, J., Numata, I., Cochrane, M.,  
688 Barber, C., Roberts, D., Barlow, J., 2013. Ten-Year Landsat Classification of  
689 Deforestation and Forest Degradation in the Brazilian Amazon. *Remote Sensing* 5,  
690 5493–5513. <https://doi.org/10.3390/rs5115493>  
691 Thompson, I., Mackey, B., McNulty, S., Mosseler, A., Secretariat of the convention on the  
692 biological diversity, 2009. Forest resilience, biodiversity, and climate change: a  
693 synthesis of the biodiversity, resilience, stability relationship in forest ecosystems.  
694 Tritsch, I., Sist, P., Narvaes, I., Mazzei, L., Blanc, L., Bourgoin, C., Cornu, G., Gond, V.,  
695 2016. Multiple Patterns of Forest Disturbance and Logging Shape Forest  
696 Landscapes in Paragominas, Brazil. *Forests* 7, 315. <https://doi.org/10.3390/f7120315>  
697 Venables, W.N., Ripley, B.D., 2002. *Modern Applied Statistics with S* 504.  
698 Westoby, M.J., Brasington, J., Glasser, N.F., Hambrey, M.J., Reynolds, J.M., 2012.  
699 ‘Structure-from-Motion’ photogrammetry: A low-cost, effective tool for geoscience  
700 applications. *Geomorphology* 179, 300–314.  
701 <https://doi.org/10.1016/j.geomorph.2012.08.021>  
702 Zhang, J., Hu, J., Lian, J., Fan, Z., Ouyang, X., Ye, W., 2016. Seeing the forest from drones:  
703 Testing the potential of lightweight drones as a tool for long-term forest monitoring.  
704 *Biological Conservation* 198, 60–69. <https://doi.org/10.1016/j.biocon.2016.03.027>  
705