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► **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-02566581>

Submitted on 7 May 2020

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

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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.

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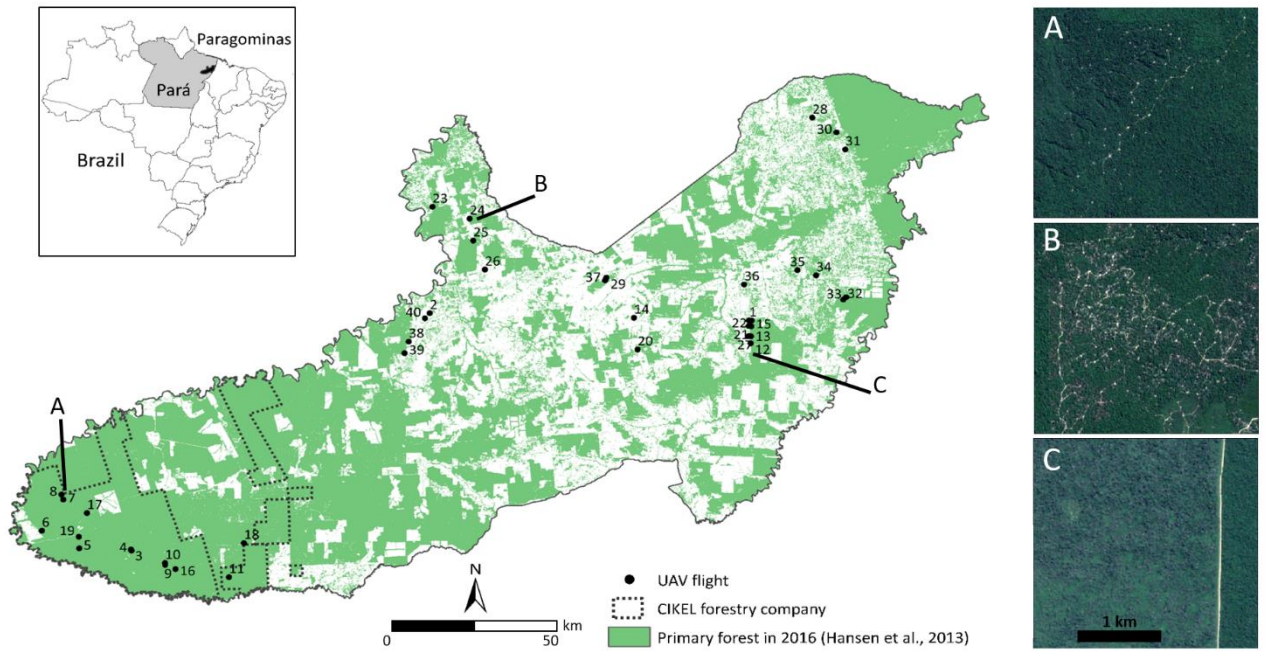
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117 **2. Materials and Methods**

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 km² (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.

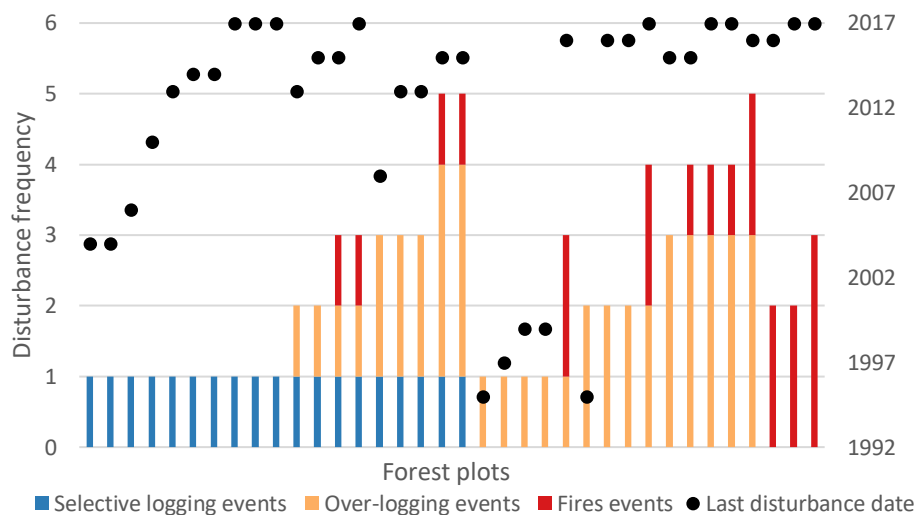
159 Raw image data were processed to the highest density point cloud using structure from motion (SfM)
160 followed by densification using multi-view stereo algorithms in the Pix4D software (Alonzo et al., 2018;
161 Westoby et al., 2012). Final point cloud densities were ~ 27 pts.m⁻³ depending on the 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 $NDMI = \frac{NIR - SWIR}{NIR + SWIR}$
 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.

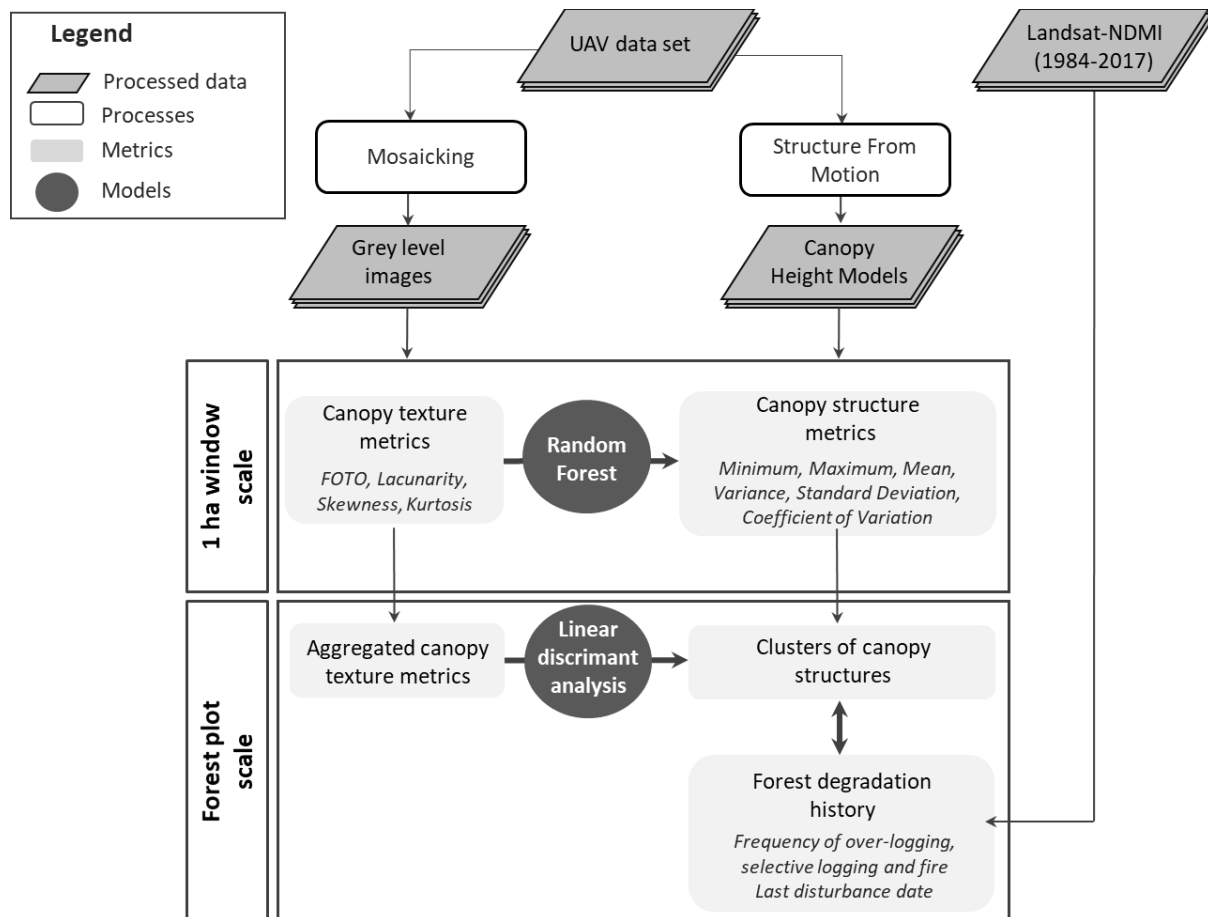


185
 186
 187 Figure 2: Forest degradation history of the 40 forest plots based on the frequency of selective logging,
 188 over-logging, fire events and date of last disturbance (4 plots are not shown as they are secondary
 189 forests).

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).

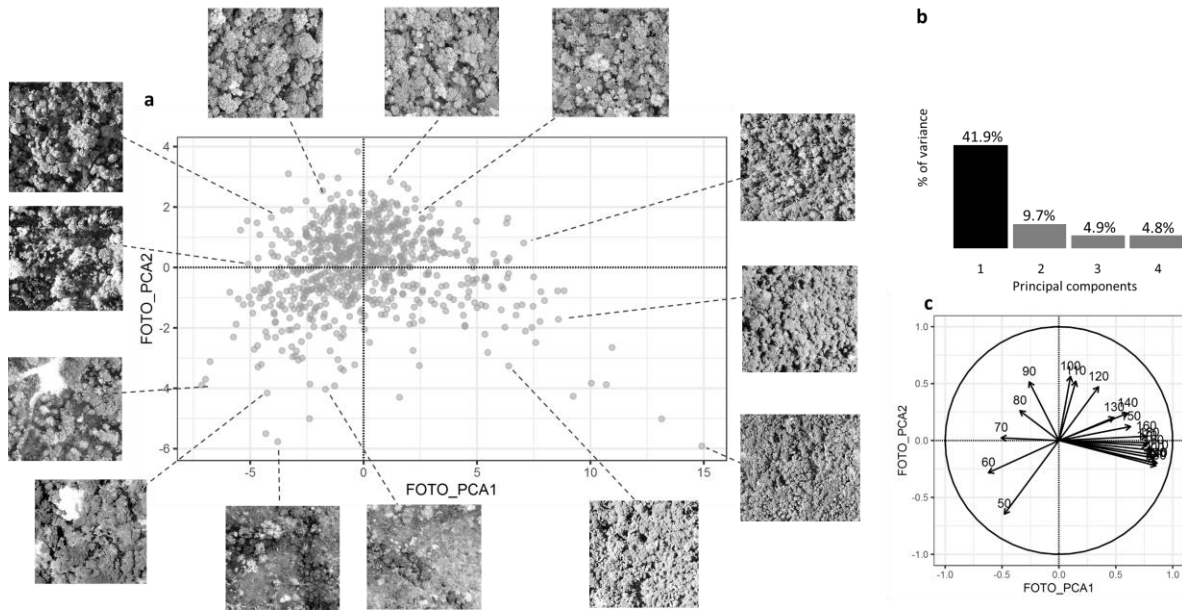
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271 **3. Results**

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

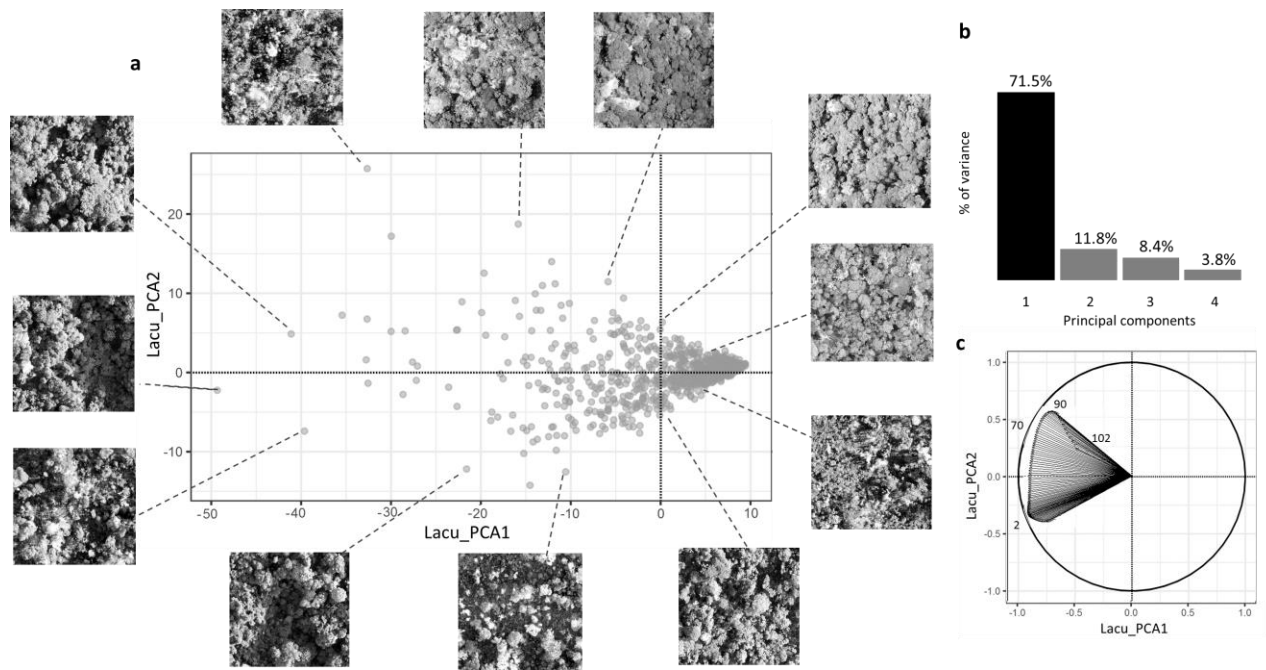
273 The two first factorial axes of the PCA accounted for 51.6% of the total variability of the r-spectra
274 observed (Fig. 4b). FOTO_PCA1 expresses a gradient between coarse and fine texture corresponding
275 to spatial frequencies of less than 90 cycles/km and more than 120 cycles/km, respectively (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.



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

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

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

Table 1: Random forest regression models for the prediction of canopy structure metrics (CSM) from canopy texture metrics (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

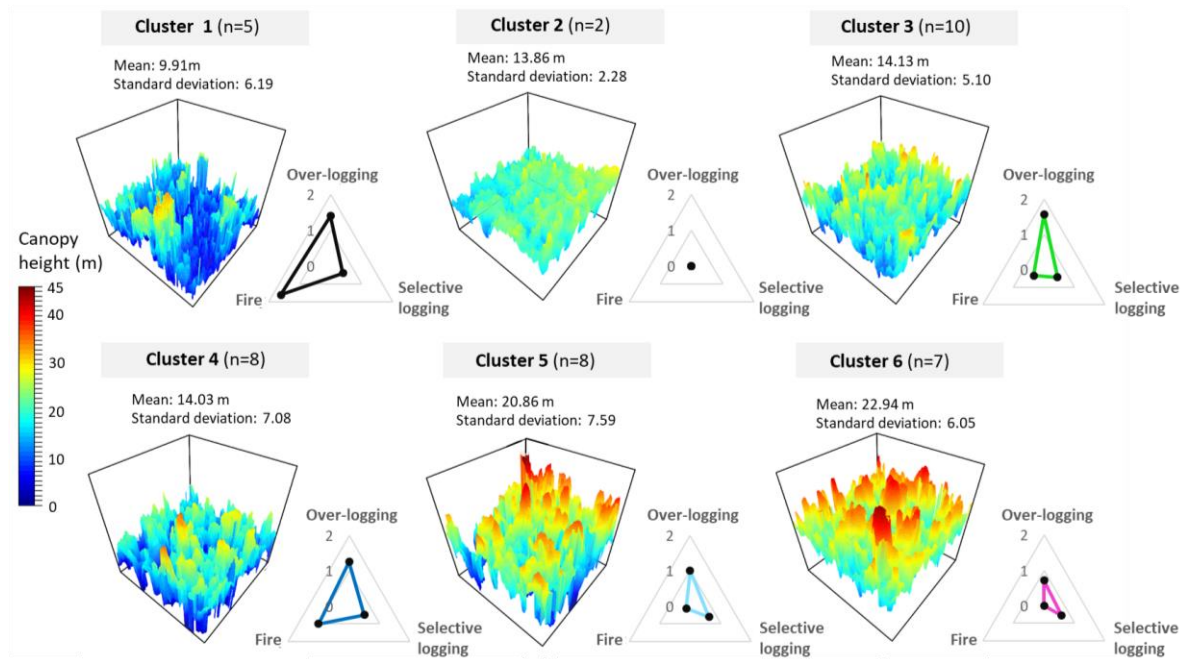
Standard deviation	0.58	1.01	0.65
Coefficient of variation	0.31	0.17	0.83

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

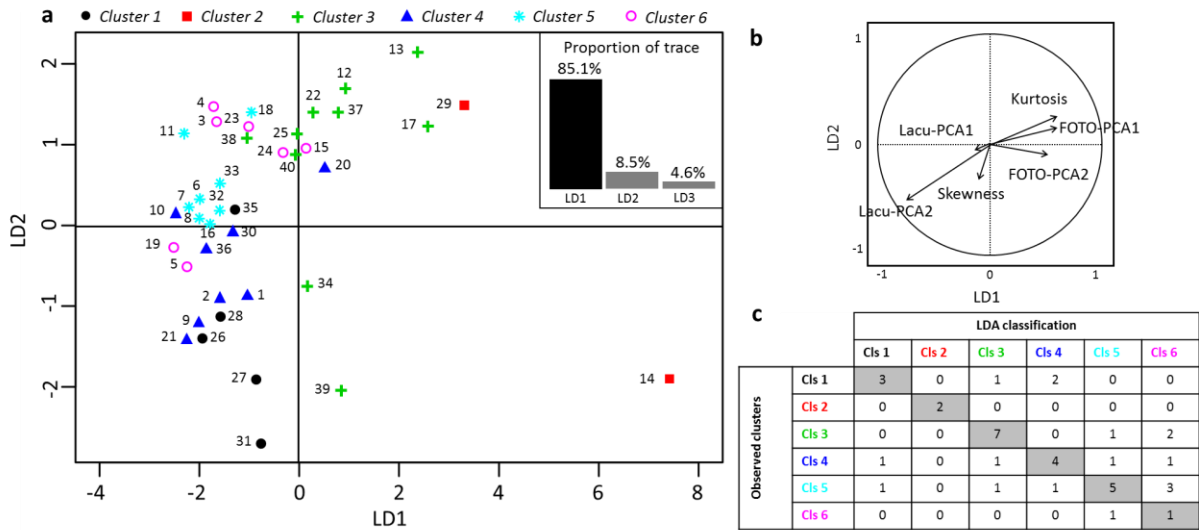
336 3.4.2. Linear discriminant analysis at the forest plot scale

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

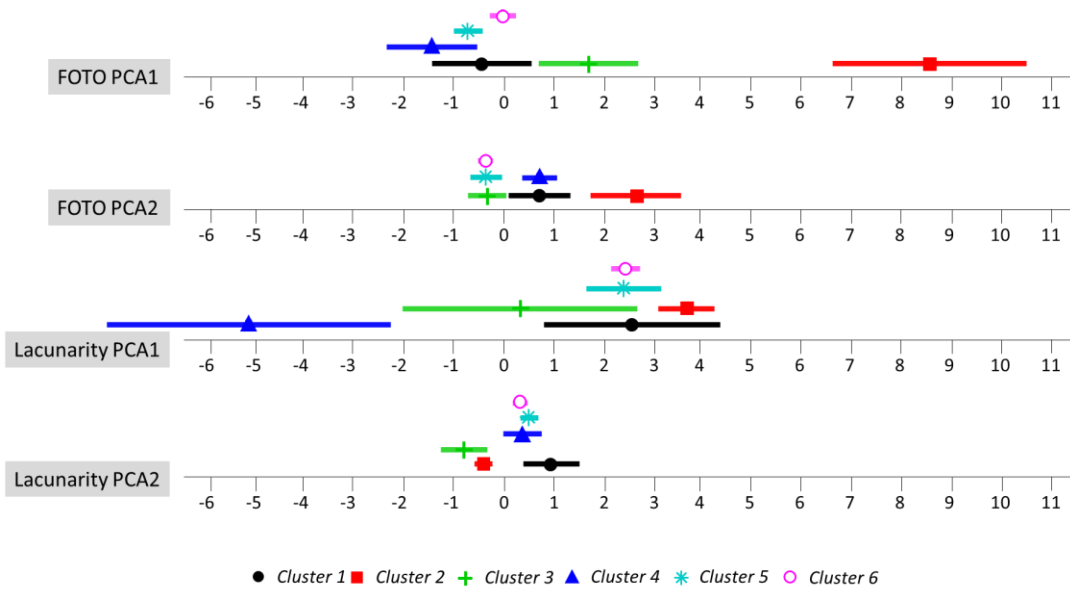
348 cluster 6 which has the highest misclassification rate with a high rate of confusion with cluster 5. Based
 349 on CTM, clusters 5 and 6 appeared to be similar because they mainly differ in their minimum height,
 350 which logically is difficult to predict from canopy texture metrics on 2D images.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

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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 complementary 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.

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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 *(CCAFS), 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.*

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