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Linking canopy images to forest structural parameters : potential of a modeling framework

Nicolas Barbier, Pierre Couteron, Jean-Philippe Gastellu-Etchegorry, Christophe Proisy

► **To cite this version:**

Nicolas Barbier, Pierre Couteron, Jean-Philippe Gastellu-Etchegorry, Christophe Proisy. Linking canopy images to forest structural parameters : potential of a modeling framework. *Annals of Forest Science*, 2012, 69 (2), pp.305-311. <10.1007/s13595-011-0116-9>. <ird-00657316v2>

HAL Id: ird-00657316

<https://ird.hal.science/ird-00657316v2>

Submitted on 9 Jan 2012

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Editorial Manager(tm) for Annals of Forest Science
Manuscript Draft

Manuscript Number:

Title: Linking canopy images to forest structural parameters: potential of a modeling framework

Article Type: Research Paper

Keywords: texture analysis; remote sensing; 3D forest model; radiative transfer model; broad-leaf tropical forests.

Corresponding Author: Nicolas Barbier

Corresponding Author's Institution: IRD

First Author: Nicolas Barbier

Order of Authors: Nicolas Barbier; Pierre Couteron, PhD; Jean-Philippe Gastellu-Etchegorry, PhD; Christophe Proisy, PhD

Abstract: Remote sensing methods, and in particular very high (metric) resolution optical imagery, are essential assets to obtain forest structure data that cannot be measured from the ground, because they are too difficult to measure, or because the areas to sample are too large or inaccessible. To understand what kind of, and how precisely and accurately, information on forest structure can be inverted from RS data, we propose a modeling framework combining a simple 3D forest model, Allostand, based on empirical or theoretically-derived DBH distributions and allometry rules, with a well-established radiative transfer model, DART. This framework allows producing forest canopy images for any type of forest based on widely available information of inventory data. Image texture can then be quantified, for instance using the Fourier Transform Textural Ordination (FOTO) method, and the derived textural indices compared with stand parameters for inversion and sensitivity analyses, as well as to indices from real world remote sensing images. The potential of the approach for the development of quantitative methods to assess forest structure, dynamics, matter and energy budgets and degradation, including in tropical contexts, is illustrated emphasizing broadleaf natural forests and discussed.

Suggested Reviewers: André Beaudoin
Andre.Beaudoin@RNCAN-NRCAN.gc.ca

Laurent Saint-André
laurent.saint_andre@cirad.fr

Richard Lucas
rml@aber.ac.uk

Sylvie Durrieu
sylvie@teledetection.fr

Uta Berger
uta.berger@forst.tu-dresden.de

Sassan Saatchi

saatchi@congo.jpl.nasa.gov

FOR PEER REVIEW

1 **Abstract**

2 Remote sensing methods, and in particular very high (metric) resolution optical imagery, are
3 essential assets to obtain forest structure data that cannot be measured from the ground, because
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5 understand what kind of, and how precisely and accurately, information on forest structure can be
6 inverted from RS data, we propose a modeling framework combining a simple 3D forest model,
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8 well-established radiative transfer model, DART. This framework allows producing forest canopy
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14 energy budgets and degradation, including in tropical contexts, is illustrated emphasizing broadleaf
15 natural forests and discussed.

16 **Introduction**

17 Zenithal views of the earth surface have long contributed to forest resource inventory and planning
18 of forest management operations (Küchler, 1967; Holdridge, 1971). Visual interpretation of aerial
19 photographs has been used worldwide for decades to a priori delineate inventory sampling strata or
20 to map the mosaic of forest stands on criteria relating to age, structure or dominant species (see
21 Polidori et al., 2004 for examples of tropical applications). The classical practice shows that skilled
22 interpreters can go beyond the mapping of strongly contrasting forest types and analyze subtler
23 gradients of canopy aspect and map them into meaningful qualitative classes of operational
24 value (Husch et Harrison, 1971). An important fraction of the criteria sustaining such interpretations
25 relates to sizes and spatial distribution of both tree crowns and inter-crown gaps, which are

26 observable on printed panchromatic outlooks of classical scale and resolution (1/30 000 or less), and
27 are here referred to as canopy texture. Colour photos, including “false-colour” ones that display the
28 near-infrared response of the vegetation can provide additional insights on species compositions.
29 The practical, implicit message of this long-standing expertise on photo interpreting is that forest
30 canopy aspect does convey valuable information about the forest stands.

31 However, this empirical expertise did neither translate into the definition of objective indices to
32 quantify canopy aspect nor into the study of the relationship between canopy features and the most
33 classical structural variables used by foresters, especially those which are routinely measured in field
34 inventories. This is all the more regrettable that global challenges on climate and biodiversity urge
35 forest science to design cost-effective systems to consistently monitor forest structures (i.e. the
36 three dimensional arrangement of individual trees and tree parts) over extensive areas (Shugart et al.,
37 2010).

38 While means for field measures are limited and often insufficient to regularly sample large areas of
39 poor accessibility, especially in the tropics, the rapid improvement and diversification of satellite-
40 borne sensors suggests that monitoring methods combining field and remotely-sensed data could
41 provide cost-effective answers to the forest structure monitoring challenge (Asner et al., 2010). In
42 fact, remote sensing approaches have the potential not only to extrapolate field results, but also to
43 provide information that is near impossible to accurately measure on the ground, such as total height
44 or crown size of canopy trees in multi-strata natural forests. Such information is critical since canopy
45 structure conditions stand dynamics, gas and energy exchanges, forest feedbacks on the micro- and
46 macro-climates and habitat for the canopy-specialized biota (Birnbaum, 2001; Bonan, 2008). Even
47 though remote-sensing approaches using medium to high resolution data (pixels larger than 5 m)
48 have been hindered for decades by the saturation of all the physical signals at intermediate levels of
49 forest above-ground biomass (AGB, c. 200 t/ha, Imhoff, 1995; Proisy et al., 2000), the increasing
50 availability of very high resolution (VHR) data opens new prospects. Indeed, the VHR optical images

51 furnished by satellites (e.g. Ikonos, Quickbird or GeoEye) now approach the potential of airborne
52 photos for visual interpretation at a cheaper cost which will keep decreasing in the future. As a
53 consequence, several studies endeavoured to extract quantitative information on canopy structure
54 from such imagery (Bruniquel-Pinel et Gastellu-Etchegorry, 1998; Asner et al., 2002; Frazer et al.,
55 2005; Gougeon et Leckie, 2006; Malhi et Roman-Cuesta, 2008). In particular, texture indices provided
56 by the FOTO method (Fourier Transform Textural Ordination) showed good correlations with usual
57 stand parameters (Couteron et al., 2005) and even biomass (Proisy et al., 2007) in some case studies
58 carried out in natural tropical forests. These relationships remarkably appeared to hold without
59 saturation even for very high biomass values (above 500 t/ha).

60 Validating at large scale those encouraging local results is made difficult by the present lack of
61 extensive datasets simultaneously featuring reliable field data and canopy images of sufficient spatial
62 resolution, i.e. with pixels of 1 m or less. Moreover, the regional to global stability of the
63 relationships between canopy structure (mostly pertaining to crowns) and other forest structural
64 parameters (largely deriving from trunks diameters) remains to be assessed, despite some
65 theoretical and empirical efforts to uncover general allometry rules at the individual and stand
66 levels (Coomes et al., 2003; Muller-Landau, Condit, Chave, et al., 2006; Poorter et al., 2006; Enquist et
67 al., 2009). Similarly, the influence on image texture of tree architecture, crown shape, physiology,
68 phenology, and their variation across species, as well as the effect of different perturbation types on
69 stand structure calls for in depth studies. Another issue is that acquisition conditions, and in
70 particular the sun-scene-sensor angles which determines shadowing, do have an influence on texture
71 which must be accounted for when using several or numerous images, or in the presence of marked
72 topography (Barbier, Proisy, et al., 2010).

73 Thus, simulating canopy images from forest mockups of known 3D structure is appealing to
74 anticipate the increasing availability of relevant satellite data, and extensively assess the extent to
75 and the conditions under which forest structural stand parameters could be retrieved from canopy

76 image analysis. The objectives of the approach which will be illustrated in the present paper can be
77 summarized in four steps: (i) simulating 3D explicit mockups of forest stands from the most basic
78 information provided by field inventories, namely distributions of diameter at breast height values
79 (dbh) ; (ii) applying a radiative transfer model on the mockups to generate canopy images; (iii)
80 characterizing the texture of the generated canopy images using the FOTO method; (iv) analyzing the
81 covariation of FOTO-based texture indices and the stand parameters corresponding to the 3D
82 mockups in order to test the potential of model inversion.

83

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84 **Modelling 3D stands – The Allostand model**

85 The Allostand model aims at producing simple 3D forest simulations (Fig. 1) on the basis of
86 information generally available out of classical forest inventories, i.e. densities of trees according to
87 classes of trunk diameters at breast heights (DBH). The basic model input is therefore either an
88 observed or a theoretical diameter frequency distribution, such as the inverse square law of Enquist
89 et al.(2009) or alternative laws(Coomes et al., 2003). From there,the spatial distribution and sizes of
90 trunks and crowns are produced on the basis of measured allometry rules at the individual stand
91 scales (see below).

92 To ensure its applicability over extents of poorly known forests, the present version of the model is
93 kept at the simplest possible level(or “zeroth order” sensu West et al., 2009): tree crowns are
94 modeled as ellipsoids, and no plastic deformations are implemented.From the DBH, allometry rules
95 obtained, for instance from rainforest trees(Poorter et al., 2006; Muller-Landau, Condit, Chave, et al.,
96 2006), allow computing tree height and crown dimensions. For instance one can compute crown area
97 and tree height from DBH using the allometric exponents provided in table 2 of (2006). In absence of
98 measured (x,y) positions for each tree, these positions are obtained using an iterative hard-
99 core(Matérn, 1986) birth/death procedure. In other words, starting from the largest tree in the DBH
100 distribution, at each iteration step a new individual of lesser or equal size is placed at random. It is
101 kept only if it happens to be located beyond a certain distance from preexistingtrees, otherwise a
102 new location is taken, up to a chosen maximal attempt number. If this number is reached, a failed
103 birth is counted. Hard core distance between trees of the same size class is taken from the
104 isometricrelationshiplinkinginter-tree distance to DBH as derived by Enquist et al.(2009) on
105 theoretical grounds. Minimum distance between trees of different size classes are defined
106 empirically according to a decreasing function of the diameter difference, in a way minimizing the
107 number of failed births. The above procedure is repeated within each size class for the number of

108 individuals requested to match the DBH frequency distribution. Model output takes the form of a
109 table listing tree individuals, their XY positions and dimensions (height plus trunk and crown radii).

110 To illustrate the result of a tropical rainforest simulation produced by the Allostand model, a
111 tridimensional representation is shown in figure 1. This simulation was created using a DBH
112 frequency distribution following the inverse square law (-2 power law with intercept = 5000 trees/ha)
113 and with a bin width of 1 cm, a minimum DBH of 5 cm and a maximum DBH (DBH_{max}) of 100 cm.

114 **Modelling radiative transfer– DART model**

115 From the 3D stands, it is possible to simulate spectral images of the scene as viewed from air- or
116 space-borne sensors (Fig. 2). The Discrete Anisotropic Radiative Transfer (DART) model (Gastellu-
117 Etchegorry, 2008), is used to simulate the interaction between scene components and
118 electromagnetic signals of various natures (e.g., of varying wavelengths, active or passive signals, of
119 varying sun-scene-sensor configurations, etc.). The DART model involves an iterative tracing of rays in
120 a discrete number of directions within a scene constituted by parallelepipedic voxels. Light transfer
121 within a voxel depends on the proportion and orientation of volume elements (modeled as turbid,
122 e.g. foliage, atmosphere) and surface elements (solid, e.g. trunks, soil) it contains.

123 From the positions and dimensions of trees produced by the Allostand model, DART first computes
124 the voxelized (discrete) scene, which involves computing the fractions and orientation of the main
125 scene elements present in each voxel. The reflectance of each scene element in different spectral
126 bands can be parameterized at the desired or accessible level of precision, from either general
127 estimations or from specific measurements made for the area of interest (for instance, for foliage,
128 from radiometric information and technical specifications of modern satellite imagery such as
129 GeoEye®). Other relevant parameters used by DART are the leaves angular distribution and density
130 within foliage voxels, as well as the distribution of empty voxels within a tree crown. As these
131 parameters are difficult to measure, they are usually taken empirically, in order to achieve realistic
132 values of the Leaf Area Index (LAI) at the stand scale (e.g., LAI between 6 and 8 (Richards, 1995)).

133 **Image analysis – FOTO method**

134 The Fourier Transform Textural Ordination (FOTO) method basically ordines digital images along
135 coarseness-fineness texture gradients in a way congruent with the visual appraisal (see (Couteron,
136 2002)for details). It showed promising results(Couteron et al., 2005; Proisy et al., 2007; Barbier,
137 Couteron, Proisy, et Malhi, 2010) for the characterization and measure of canopy texture on very
138 high (metric) resolution air- and space-borne panchromatic imagery. The FOTO method uses a
139 windowed 2D Fourier transform and the derived periodograms(power spectrum; Diggle, 1989;
140 Mugglestone et Renshaw, 1998)to characterize the textural properties of image extracts of about 1
141 ha. Each 2D periodogram is simplified to account only for spatial frequency (scale) information and
142 not for possible anisotropic variations of texture. This simplification (averaging of periodogram values
143 over the azimuths) leads to a so-called r-spectrum(Mugglestone et Renshaw, 1998)representing, for
144 each image, the broken-down of the panchromatic reflectance variance accounted for by successive
145 bins of spatial frequencies. Principal component analysis is then applied on the set of standardized r-
146 spectra (which may include spectra from hundreds to thousands of images)to identify the main
147 gradients of canopy textural variation and ordinate the images accordingly. The first PCA axis
148 generally approximates the fineness-coarseness gradient of canopy grain, most frequently linked to
149 variations in crown sizes. Subsequent axes, when notable, may point towards specific ranges of
150 dominant spatial frequencies (related to crown or gap sizes). PCA scores of the images against such
151 gradients are used as continuous indices of textural variation of canopy aspect.

152 **Example**

153 To illustrate the interest of the Allostand+DART modeling framework, we simulated 144
154 panchromatic reflectance images using the same parameterization as the stands presented in figures
155 1 and 2, for a rangeof maximum DBH values (DBH_{max} from 50 to 100 cm by steps of 10 cm). To assess
156 the sensitivity of the results to perturbations of the DBH distribution, we also madethe density in the

157 largest DBH class vary by a factor of either 0.33, 0.5, 1 or 2. For each combination of these two factors
158 (i.e., maximum DBH and density modulation in the largest DBH class), six replicates were produced.
159 If we investigate the relationships (Fig. 3) between stand parameters and the main textural gradient
160 (*PCA1*) identified over the 144 images by the FOTO method, we find that the correlation with stand
161 density is the most sensible to the perturbation introduced in stand structure by changing the tree
162 density in the largest DBH classes. The r^2 of the regression is indeed only of 0.35 (Fig. 3a). On the
163 other hand, the correlation with mean crown diameter (Fig. 3b) or with the mean DBH or mean
164 quadratic DBH are fairly good in this case, with r^2 above 0.6. The best correlations are found with the
165 maximum DBH or the average crown size (Fig. 3c). This is no surprise since what is captured by
166 texture analysis concerns the structure of the top canopy and the crown size distribution of canopy
167 trees.

168 Discussion

169 The main purpose of this paper is to draw the attention of forest scientists and modelers on the
170 potential of simulating canopy panchromatic images from forest mockups of known 3D structure.
171 Simulating such images could be a decisive step to help forest monitoring and forest ecology benefit
172 from the increasing availability of very high resolution space-borne imagery through a thorough
173 process of model calibration and inversion. As it has been illustrated here using a very simple
174 structure model, the simulation allows assessing the extent to which the entire modeling chain can
175 be inverted to retrieve forest structure variables from canopy reflectance information. From such an
176 approach it is possible to have some a priori knowledge on the magnitude of the prediction error
177 that is to be expected for the different variables and to efficiently design how field data should be
178 acquired to validate the inversion process in a given ecological context. In fact, the confrontation of
179 space-borne information to field inventory data has often been hindered by field sampling units
180 having size, shape or spacing properties irrelevant to that purpose. This hindrance adding to the well-
181 documented signal saturation problem (Imhoff, 1995; Foody, 2003) has made the results of forest

182 variable prediction from spatial observation often disappointing and at best revealing local
183 agreements of unwarranted extrapolation. Whatever the type of signal and the kind of signal analysis
184 technique, progress in forest monitoring now requests simulations of signal interactions with a wide
185 range of known forest structures for inversion testing. This necessity has long been recognized for
186 radar applications (Kasischke et Christensen, 1990; Proisy et al., 2000) but has been overlooked by
187 most users of optical imagery (but see Bruniquel-Pinel et Gastellu-Etchegorry, 1998; Frazer et al.,
188 2005; Widłowski et al., 2007). Developing and validating forest application for the more recent full-
189 waveform LiDAR (Light Detection and Ranging) techniques also requests signal simulation on forest
190 mockups in a way similar to what is presented here, which can be done by adapting existing radiative
191 transfer models (Rubio et al., 2009).

192 Since canopy information mostly pertains to the dominant fraction of the tree population, it is
193 obvious that the best predictions are to be expected for stand variables that are the most strongly
194 influenced by this dominant subpopulation (e.g. basal area, quadratic mean diameter and, of
195 course, total above-ground biomass). As illustrated here (Fig.3), less accuracy is probable for variables
196 related to stand density which directly integrates understory trees that are not visible in the canopy.
197 In even-aged stands, most trees are dominant or co-dominant and logically the FOTO method yielded
198 good predictions of total AGB for even-aged mangroves (Proisy et al., 2007).

199 In mixed-aged stands, canopy trees only account for a small share of the overall tree number. Yet, this
200 fraction is expected to capture most of the limiting resource (usually light) and to condition gas and
201 energy exchanges with the atmosphere (Bonan, 2008) and thereby strongly influence the whole stand
202 dynamics. Enquist et al. (2009) assumed one of the simplest models of stand demography, which can
203 be traced back to de Liocourt (1898), to reach the prediction that the diameter density distribution
204 should scale as a -2 power of DBH. In the present modeling illustration, we referred to it for simplicity
205 sake, although such a distribution is not satisfactory (Muller-Landau, Condit, Harms, et al.,
206 2006). Other simple functions of diameter distribution predicted by competing theories (Coomes et

207 al., 2003) may have been used as well to create families of 3D mockups. Above all, as underlined by
208 Coomes et al. (2003) the size distribution of the largest trees is probably shaped by disturbances
209 rather than neighborhood competition and is therefore barely predictable from a general reasoning.
210 Since there is a top-down control on the stand structure (as in our Allostand simulation process),
211 random variations in the abundances of larger trees also propagate into the size distribution of
212 smaller individuals. This is what we illustrated here by letting the density vary in the largest DBH class
213 as a rudimentary way to parameterize a family of mockups. Ongoing developments include the
214 simulations of mockups and canopy images from real-world diameter distributions observed by
215 extensive inventories in central Africa. They also feature the prospect to deduce the mockups as
216 outputs of more realistic simulators of forest dynamics (e.g. STRETCH, Vincent et Harja, 2008).
217 However, most existing simulators are still highly context-specific and demanding in terms of costly
218 diachronic data. They may also feature structural rules of unknown robustness outside the particular
219 situation they have been devised to mimic.

220 As a consequence, simple modeling rules are still relevant to address the linking of stand structure
221 and canopy images over extensive areas which are still devoid of reference data and simulators,
222 especially in the tropics. The suite of modeling steps leading to canopy images should and could
223 nevertheless be parsimoniously improved by verifying or calibrating the fundamental parameters for
224 tree allometries and foliage reflectance for broad classes of forest. Simple simulation-based modeling
225 approaches coupled with field case studies (Couteron et al., 2005; Proisy et al., 2007; Barbier,
226 Couteron, Proisy, Malhi, et Gastellu-Etchegorry, 2010) have already demonstrated that some
227 important stand parameters, including AGB, can be predicted from canopy images in heterogeneous
228 natural forests. Enhanced modeling procedures will contribute to better assess the validity domains
229 and the errors to be expected for such predictions.

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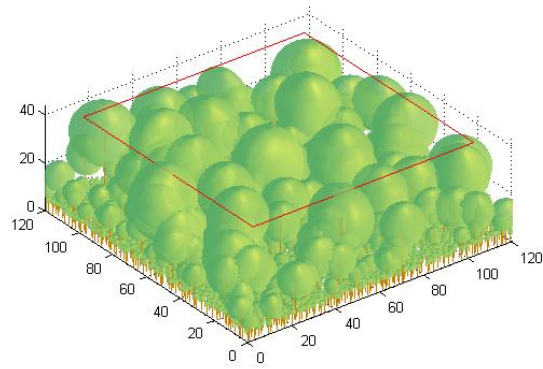
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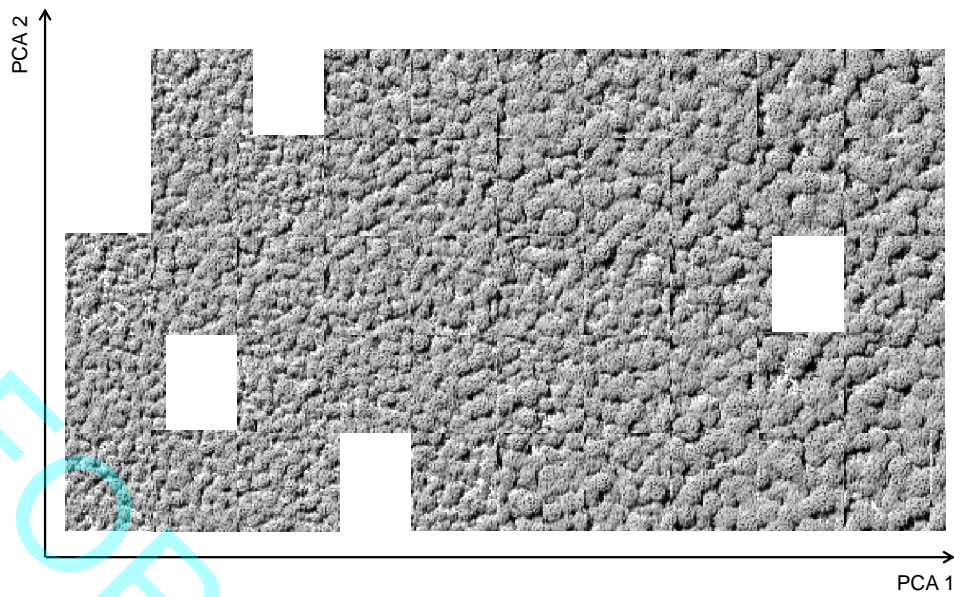
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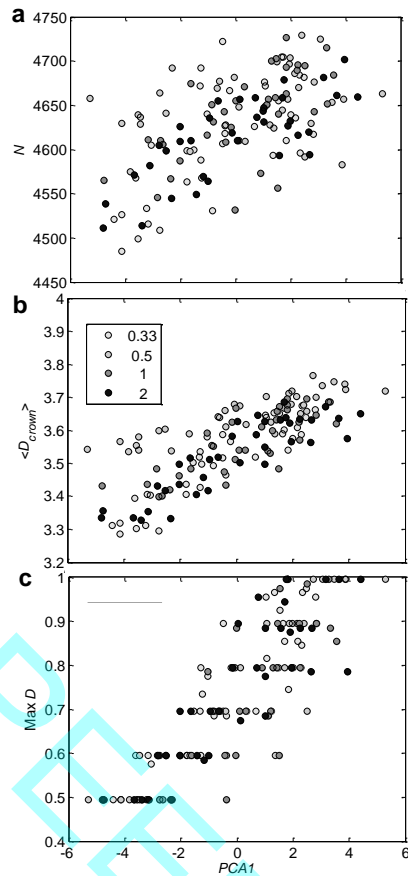
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Figure 1. View of a forest stand produced by the Allostand model on the basis of a inverse square law DBH distribution(Enquist et al., 2009), and using rainforest tree allometries(Poorter et al., 2006; Muller-Landau, Condit, Chave, et al., 2006). The superimposed square area represents the 1 ha plot used in subsequent analyses.



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339 Figure 2. Array of panchromatic images produced by the DART radiative transfer model using Allostand 3D
 340 forest simulations. The images are sampled and sorted along the two main textural gradients identified by the
 341 Fourier transform textural ordination (FOTO) method applied 144 images simulated with varying DBH_{max} and
 342 density values. The main gradient (PCA 1) corresponds to a clear fineness-coarseness gradient; visual
 343 interpretation of the second gradient (PCA 2) is more difficult, but it represents density variations (see text).



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Figure 3. Relationship between some classical forest parameters of the Allostand simulated forests and the main textural gradient identified by the FOTO method on the simulated images (*PCA1*). (a) Total stand density, [stems of DBH>2 cm ha⁻¹]; $r^2=0.35$. (b) Mean crown diameter [m]; $r^2=0.62$, (c) Maximum DBH value [m]; $r^2=0.75$.

Allostand simulations were produced on the basis of a -2 power law DBH distribution and with varying DBH max values (50 to 100 cm by steps of 10 cm). Noise has been introduced by varying the density in the largest DBH class by a factor of either 0.33, 0.5, 1 or 2 (see inset in (b) for the symbols of the four classes).

Linking canopy images to forest structural parameters: potential of a modeling framework

Nicolas BARBIER ^{1*}

Pierre COUTERON ¹

Jean-Philippe GASTELLY-ETCHEGORRY ²

Christophe PROISY ¹

¹IRD-UMR AMAP, Boulevard de la Lironde, TA A-51/PS2, 34398 Montpellier Cedex 05, France

* nicolas.barbier@ird.fr

²Centre d'Etudes Spatiales de la Biosphère (CESBIO). Université de Toulouse, UPS, CNRS, CNES, IRD,
18 Av. Ed. Belin, 31401, Toulouse, France

Running head: Linking forest canopy images to field inventory data

Keywords: texture analysis/remote sensing/ 3D forest model /radiative transfer model / broad-leaf
tropical forests

Characters: 31 166

Figures: 3