



HAL
open science

Mapping local density of young *Eucalyptus* plantations by individual tree detection in high spatial resolution satellite images

Jia Zhou, Christophe Proisy, Xavier Descombes, Gueric Le Maire, Yann Nouvellon, Jose-Luiz Stape, Gaëlle Viennois, Josiane Zerubia, Pierre Couteron

► To cite this version:

Jia Zhou, Christophe Proisy, Xavier Descombes, Gueric Le Maire, Yann Nouvellon, et al.. Mapping local density of young *Eucalyptus* plantations by individual tree detection in high spatial resolution satellite images. *Forest Ecology and Management*, 2013, 301, pp.129-141. 10.1016/j.foreco.2012.10.007 . hal-00741010v1

HAL Id: hal-00741010

<https://inria.hal.science/hal-00741010v1>

Submitted on 11 Oct 2012 (v1), last revised 6 Nov 2012 (v2)

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 destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

1 **Mapping local density of young *Eucalyptus* plantations by**
2 **individual tree detection in high spatial resolution satellite**
3 **images**
4

5 ***Jia Zhou^{a,b}, Christophe Proisy^c, Xavier Descombes^b, Gueric le Maire^{d,e}, Yann***
6 ***Nouvellon^{d,f}, José-Luiz Stape^g, Gaëlle Viennois^h, Josiane Zerubia^b, Pierre***
7 ***Couteron^c***
8

9 a. Université de Montpellier 2, UMR AMAP, Boulevard de la Lironde, TA-A51/PS2,
10 Montpellier Cedex 5, F-34398 France

11 jia.zhou@cirad.fr

12 b. Institut National de Recherche en Informatique et Automatique (INRIA), Sophia-
13 Antipolis Méditerranée, BP 93, 2004 Route des Lucioles, Sophia-Antipolis
14 Cedex, F-06902 - France

15 xavier.descombes@inria.fr; josiane.zerubia@inria.fr

16 c. Institut de Recherche pour le Développement (IRD), UMR AMAP, Boulevard de
17 la Lironde, TA-A51/PS2, Montpellier Cedex 5, F-34398 France

18 christophe.proisy@ird.fr; pierre.couteron@ird.fr

19 d. CIRAD, UMR Eco&Sols, 2 Place Viala, Montpellier, F-34060 France

20 gueric.le_maire@cirad.fr; yann.nouvellon@cirad.fr

21 e. CIRAD, UMR TETIS, Maison de la Télédétection, Montpellier Cedex 5, F-34093
22 France

23 f. Atmospheric Sciences Department, Universidade de São Paulo, Rua do Matão
24 1226, 05508-090 São Paulo, Brazil

25 g. Department of Forestry and Environmental Sciences, North Carolina State
26 University, Raleigh, NC 27695, United States

27 stape@ncsfnc.cfr.ncsu.edu

28 h. Centre Nationale de la Recherche Scientifique (CNRS), UMR AMAP, TA A51 PS
29 2, Boulevard de la Lironde, Montpellier Cedex 5, F-34398, France

30 gaelle.viennois@cirad.fr
31

32 **Abstract**

33 Local tree density may vary in young *Eucalyptus* plantations under the effects of
34 environmental conditions or inadequate management, and these variations need to be
35 mapped over large areas as they have a significant impact on the final biomass
36 harvested. High spatial resolution optical satellite images have the potential to provide
37 crucial information on tree density at an affordable cost for forest management. Here, we
38 test the capacity of this promising technique to map the local density of young and small
39 *Eucalyptus* trees in a large plantation in Brazil. We use three Worldview panchromatic
40 images acquired at a 50 cm resolution on different dates corresponding to trees aged 6,
41 9 and 13 months and define an overall accuracy index to evaluate the quality of the
42 detection results. The best agreement between the local densities obtained by visual
43 detection and by marked point process modeling was found at 9 months, with only small
44 omission and commission errors and a stable 4% underestimation of the number of trees
45 across the density gradient. We validated the capability of the MPP approach to detect
46 trees aged 9 months by making a comparison with local densities recorded on 112 plots
47 of ~590 m² and ranging between 1360 and 1700 trees per hectare. We obtained a good
48 correlation ($r^2=0.88$) with a root mean square error of 31 trees/ha. We generalized
49 detection by computing a consistent map over the whole plantation. Our results showed
50 that local tree density was not uniformly distributed even in a well-controlled intensively-
51 managed *Eucalyptus* plantation and therefore needed to be monitored and mapped. Use
52 of the marked point process approach is then discussed with respect to stand
53 characteristics (canopy closure), acquisition dates and recommendations for algorithm
54 parameterization.

55

56

57

58 **Keywords: crown identification, object detection, stochastic point process,**
59 **forests, remote sensing, Brazil**

60

61 1. Introduction

62

63 Local density in forest plantations corresponds to a planting density from which local
64 mortality is substrated. It is one of the most important factors controlling the productivity
65 of managed *Eucalyptus* forests (e.g. [Walters, 1980](#)). It directly affects inter-tree
66 competition for light, water and soil nutrients for the whole rotation period ([Gonçalves et
67 al. 2004](#)). As young trees are the most sensitive to adverse environmental conditions
68 and inappropriate practices, mortality is likely to occur at early stages. There is thus a
69 silvicultural challenge specifically to locate areas of excessive tree mortality or
70 insufficient growth as soon as possible during the first year in order to decide on
71 replanting accordingly. Areas of strong mortality or poor growth are generally conserved
72 up to the end of the rotation and result in overall lower productivity ([Stape et al., 2010](#)).
73 Spatially explicit information about individual *Eucalyptus* trees may therefore be of great
74 value for pinpointing problems that are often encountered even in intensive plantations
75 due to inadequate management, heterogeneous soil conditions (e.g. [Garau et al., 2008](#)),
76 competition with herbaceous vegetation, seed genetic capacity, nutrients supply
77 problems or other local damage ([Pallett and Sale, 2004](#); [du Toit et al., 2005](#)). For
78 instance, trees that are rachitic in their early stages are later totally dominated by
79 'regular' trees, and by the end of the rotation their crown is expected to be under the
80 canopy. Those trees are generally neglected in biomass estimates by companies.
81 Therefore, monitoring the actual number of regular-sized live trees in order to make
82 comparisons with planned density turns out to be of prime importance in the
83 management of extensive forest plantations. However, counting and positioning such
84 young individual trees in the field is generally an unaffordable business when dealing
85 with hundreds of hectares of plantation, as it is frequently observed in Brazil.

86 The potential of sub-metric spatial resolution remotely sensed data needs to be
87 examined carefully with a view to count young trees at an affordable cost. Published
88 studies have used airborne Light Detection and Ranging (Lidar) and optical satellite
89 instruments. Both types of data can provide fine-scale information on canopy
90 characteristics (e.g. [Richardson et al. 2011](#); [Hirschmugl. et al. 2007](#)). The Lidar
91 instruments have a good potential for single tree detection in open canopies (e.g.
92 [Tesfamichael et al. 2009](#); [Vauhkonen et al. 2012](#)) or for a forest carbon inventory (e.g.
93 [Stephens et al. 2012](#)) due to their ability to measure the vertical structure of forests by

94 determining the distance between the sensor and a target within the canopy. However,
95 the cost of airborne Lidar data collection remains high. In Brazil, it ranges from US\$
96 15/ha to US\$ 200/ha depending on the location inside the country, the area covered and
97 the signal density of points (E. Gorgens, pers. comm.). The additional time and cost
98 required for data processing cannot be ignored (Hummel et al. 2011). Consequently,
99 operational use of Lidar remote sensing over extensive Eucalyptus plantations in Brazil
100 is still limited to one-off and well-funded research activities.

101 On the other hand, space-borne imagery acquired at 0.5 to 1-m resolutions and provided
102 by recent satellites such as Geoeye, Ikonos, Worldview or Quickbird is now increasingly
103 available at reasonable costs ranging from US\$ 0.10 for archived images to a maximum
104 of US\$ 0.80/ha in tasking mode (e.g. e-GEOS, 2011). Fast delivery of data, daily revisit
105 and viewing agility are also key characteristics of a forthcoming constellation of small
106 satellites such as Pleiades. In sub-metric optical images, individual tree crowns are
107 visible because of the contrasting sunlit and shadowed parts of the crown itself and also
108 the gaps between neighboring trees. These data can therefore be used to study the
109 canopy aspect of natural tropical forests by conducting a textural analysis and extracting
110 texture indices that correlate with above-ground stand parameters (Couteron et al.,
111 2005; Barbier et al. 2010; Song et al. 2010) and biomass (Proisy et al., 2007). However,
112 canopy texture approaches usually yielded less accurate estimations of stand density
113 than other stand variables such as mean quadratic diameter (e.g. Ploton et al. 2012)

114 The possibility of automatically detecting individual tree crowns from optical images has
115 been investigated by a variety of techniques, but they all work on pixel intensity to
116 delineate tree crowns from their surrounding environment (Korpela, 2004; Erikson and
117 Olofsson 2005). A first family of techniques includes local maxima detection (e.g.
118 Pitkänen, 2001; Wulder et al., 2004; Gebreslasie et al. 2011), valley following or region
119 growing (e.g. Gougeon, 1995; Culvenor, 2002), 3D template matching (e.g. Larsen and
120 Rudemo, 1998) or a combination of several of the above (Pouliot and King, 2005).
121 Another family of approaches applies stochastic geometry models to forest scenes.
122 These models can efficiently detect objects by considering both the noise in data and
123 object variability. In remote sensing, marked point process modeling, a subfield of
124 stochastic geometry, would appear to be well suited to the analysis of very high
125 resolution images since it adjusts a random process by considering groups of pixels as
126 parametric, a priori defined objects located in the geographic space (Descombes, 2012).
127 The different possibilities opened up by this approach include the counting of items as

128 diverse as brain lesions (Descombes et al., 2004), trees (Perrin et al., 2006) and
129 flamingos (Descamps et al., 2011). Although the review of Larsen et al. (2011)
130 concludes that the above-mentioned individual tree detection techniques show
131 decreasing accuracy with the heterogeneity of forest stands, the marked point process
132 has been found to yield the best results over a forest plantation. The latter study was
133 based on aerial photographs with pixel sizes ranging from 10 to 50 cm. To our
134 knowledge, young stand density has not yet been assessed through individual tree
135 detection from satellite optical imagery.

136 In this paper, we assess the potential of marked point processes (MPP) to detect
137 individual tree as a contribution to the monitoring of young *Eucalyptus* plantations from
138 three Worldview images acquired at the ages of 6, 9 and 13 months. We first used the
139 results of visual detection by independent assessors to measure the performance of the
140 MPP approach and its sensitivity to parameter values. We then validated the MPP
141 estimations of local tree density using figures from a ground truth dataset of 112 plots.
142 Finally, a local density map was produced across the entire study area i.e. 170 ha. The
143 usefulness and performance of MPP for mapping the early stages of *Eucalyptus*
144 plantations are finally discussed.

145

146 **2. Data**

147

148 *2.1. Main characteristics of the Eucalyptus plantation*

149

150 This study took place in a plantation managed by the Duratex company. It is located in
151 southeastern Brazil at approximately 22°58'S and 48°43.75'W (Fig. 1). The area is
152 currently the subject of several research investigations aimed at monitoring and
153 improving the growth of *Eucalyptus* trees (e.g. Laclau et al., 2010; le Maire et al.,
154 2011a). Mean annual rainfall in the area is around 1300 mm, occurring mainly between
155 October and March. Annual temperatures range from 13.3°C in the coldest months (June
156 to August) to 27.2°C in the warmest season (December to February), with 19°C being
157 the average. In addition, temperatures in the cold season rarely drop below 5°C. The
158 study area is almost entirely flat except in the western and northwestern part of the stand
159 where the land slopes gently down to a stream. This part of the stand has also a higher
160 percentage of clay content and is more prone to encroachment by herbaceous
161 vegetation (Campoe et al., 2012).

162 The study concerned a surface area of about 170 hectares, as shown in [Figure 1](#). This
163 stand is planted with a company-improved, highly productive clone of *Eucalyptus grandis*
164 (W. Hill ex Maiden). Clone cuttings have been planted in rows approximately 3 meters
165 apart, and the trees in the rows are about 2 m apart. This gives a target density of 1666
166 trees per hectare. Planting operations took place over a period of 3 to 4 weeks from the
167 end of November 2009. The soil was fertilized and chemical weeding was carried out to
168 remove competitors ([Garau et al., 2008](#)).

169 Unloading tracks clearly divide the area into 4 zones labeled A to D ([Fig. 1](#)). The four
170 zones have specific plantation row azimuths ([Fig. 2](#)) of about 159°, 72°, 7° and 8° from
171 the East. Despite uniform plant material, soil preparation and fertilization ([le Maire et al.,](#)
172 [2011b](#); [Campoe et al., 2012](#)), each zone shows local productivity gradients related to
173 local differences in topography, soil water, nutrient availability or insufficient weed
174 control. This alters final planting performance by reducing growth or increasing mortality
175 during juvenile stages in the least favorable contexts.

176 The growth of these trees averages 20-25 Mg of dry matter ha⁻¹ year⁻¹, i.e. one of the
177 highest forest productivities in the world ([Marsden et al., 2010](#); [le Maire et al., 2011a](#)).
178 Tree crown extension was recorded in four inventory plots of 84 trees each ([Fig. 1](#)) in
179 from May to October 2010 by measuring ground projections of both row and inter-row
180 tree crown axes (diameters). Our measurements in May, August and October showed
181 that crown radii were 0.80m ± 0.22m, 0.99m ± 0.21m and 1.1m ± 0.16m in the plantation
182 row direction and 0.82m ± 0.24m, 1.06m ± 0.22m and 1.15m ± 0.16m in the orthogonal
183 direction. Interestingly, the dissimilarity between the two directions proved weak over the
184 growing sequence (less than 6%) and crown projection to ground was therefore
185 approximated as circular discs. After October, no measurements were available but we
186 assumed relative stable crown projections to ground due to the canopy closeness.

187

188 2.2. Validation data

189

190 The validation data included local tree densities collected in May 2010 on 112 plots
191 located at the periphery of the plantation zones ([Fig. 1](#)). These plots corresponded to
192 seven replications of clone trials involving sixteen different clones commonly used in
193 commercial *Eucalyptus* plantations. The 16 clones were very different in terms of leaf
194 properties (reflectance, transmittance) and canopy structural characteristics (leaf angles,
195 leaf area index, crown diameters, height, etc.). On each of these 112 plots, 12 rows with

196 16 trees per row were planted on an approximately 3*2 m regular grid at the same time
197 as the rest of the plantation. Within the central area of each plot, we measured the crown
198 diameters of a total of 96 trees (12 trees per row). The area over which density was
199 actually assessed in each plot was thus around 590 m². In some plots, mortality
200 occurred between the planting date and the inventory date, and some trees though
201 surviving, had almost no growth. For the study, we considered as 'regular' only the trees
202 that had a crown diameter above 20 cm in May 2010. The local density on the 112 plots
203 of these regular trees ranged between 1360 and 1700 trees per hectare.

204

205 2.3. *Remote sensing images and preprocessing*

206

207 The study involved three high spatial resolution Worldview images acquired from May
208 2010 to January 2011 (Table 1). Only panchromatic data were used. The images were
209 acquired at different viewing angles (Table 1) and were provided in a GeoTiff format at a
210 spatial resolution of 50 centimeters. Sun elevation in the January image was 25° higher
211 than for May and August. Sun-viewing angle values indicated an almost rear illumination
212 (sun behind) of 20° for the May acquisition whereas illumination in August and January
213 was from the side, with angles of about 95 and 105° (Table 1). A preliminary visual
214 examination of the images (Fig. 2) showed how the January image contrasted sharply
215 with the two previously acquired images as being slightly blurred in appearance with
216 plantation rows no longer visible, especially in zones A and C. We interpreted this as a
217 consequence of high sun elevation combined with the relative azimuth angle of the
218 sensor while the distance between the crowns of *Eucalypt* trees in adjacent rows had
219 narrowed since August (and crowns adjoined along a row). Indeed, rows in the zone B
220 image were still clearly visible in the January image because the sunlight was coming
221 from a near orthogonal direction of 80°.

222 The registration of the Worldview-2 images needed to be corrected in order to reach the
223 pixel size precision required to superimpose the three images of the same area. To do
224 this, we took the May image as the reference image for superimposition and located
225 about 100 image-to-image landmarks spread over the stand and the neighboring region
226 in both the August and January images. We then used a third order polynomial to reach
227 a spatial superimposition error of less than 50 cm.

228 Lastly, we re-sampled the three superimposed images into 10 cm pixel images by
229 applying a cubic convolution fit to keep the rectification smooth. This oversampling, as

230 routinely accomplishable by all image processing software, was required to improve the
231 flexibility of disc radius parameter adjustments to the crown in the MPP analysis.

232

233 **3. Methods**

234

235 The study comprised several operations (Fig. 3) applied to the preprocessed images that
236 could be grouped into five main steps: tree positioning by visual analysis (3.1); automatic
237 detection of trees by MPP (3.2); identification of the best sets of parameters by an
238 analysis of detection quality (3.3); validation from ground-assessed densities before
239 generalization to the whole plantation (3.4). These operations were implemented in
240 Matlab® language.

241

242 *3.1. Visual tree positioning*

243

244 In our study we assumed that a careful visual analysis of the Worldview images would
245 provide an adequate reference dataset of tree positions for comparison with MPP results
246 (Fig.3; step 2). This is reasonable provided that tree crowns are neither too small
247 (compared to pixel size) nor sufficiently large to fill the inter-crown gaps along the rows.
248 We therefore visually analyzed the August image (9-month-old trees), which was
249 immune to both difficulties and used the May image (6-month-old trees) only for
250 additional comparisons. In addition, we restricted the tedious work of visual interpretation
251 to a sample of training/validation zones given that not only the affordability but also the
252 quality and objectivity of the interpretation process were likely to decrease with the
253 interpreted area. We thus arbitrarily located and delineated a total of 18 square 50x50 m
254 plots in zones A, B, C and D (Fig. 1) with the aim of interpreting a sample that featured
255 all the different plantation row angles.

256 Visual detection was carried out by two experts working independently on GIS-based
257 data and consisted in determining latitude and longitude projections of apparent crown
258 centers for all identifiable trees located in each of the 18 plots. About 7,000 trees were
259 located by each of the two experts with close agreement between the two for the number
260 of trees in the plots (correlation coefficient 0.95). On the other hand, tree density across
261 the 18 plots varied substantially, but independently of the zones as the number of
262 visually detected trees ranged from 358 to 417, i.e. the maximum number of trees
263 imposed by the plantation scheme for 2500 m².

264

265 3.2. Tree detection by the marked point process

266

267 The point process theory can be used to build random spatial patterns of points and is
268 part of stochastic geometry. As the reader can find abundant literature on the subject
269 from the mathematical point of view (e.g. [Stoyan et al, 1995](#); [van Lieshout, 2000](#);
270 [Jacobsen, 2006](#)), or from an image processing point of view ([Descombes, 2012](#)), we
271 present here only the basics of marked point process modeling along with specificities
272 for application to high spatial resolution images of *Eucalyptus* plantations ([Fig. 3](#); [step 2](#)).

273

274 3.2.1. Marked point process modeling from zenithal images of forests

275 A high-resolution image of a forest canopy is a two dimensional lattice of spectral
276 reflectance where tree crowns are distinguishable from their surrounding environment by
277 intensity contrasts between sunlit and shadowed canopy portions or soil portions ([Proisy
278 et al., 2007](#)). As visual analysis naturally tends to individualize tree crowns, it is sensible
279 and logical to model the image scene as a particular production of a point process
280 having as marks discs that approximate the crown shapes ([Fig. 4](#); [left](#)). Each MPP
281 corresponds to a random configuration of discs belonging to the configuration
282 space $X = P \times M$, where P is the space containing the geographic positions of the crown
283 centers, and M is the space containing the marks. In our study, the mark was regarded
284 as the ground-projected crown half-diameter (or radius). Space X was thus defined as:

$$285 \quad X = P \times M = [0; X_M] \times [0; Y_M] \times [r_{min}; r_{max}] \quad (1)$$

286 where X_M is the width and Y_M the length of the image scene, and r_{min} is the minimum
287 value and r_{max} the maximum value considered for the radius of the discs. The PPM
288 model was defined through a probability density with respect to the Poisson measure
289 ([van Lieshout, 2000](#)) and an energy function was stated using a Gibbs formulation
290 ([Descombes et al., 2009](#); [Descombes, 2012](#)). Finding the best configuration for the
291 model then became an energy minimization exercise through the space of all possible
292 random configurations featuring a finite number of disc-objects. The total energy $U(x)$ of
293 a given configuration was defined as the sum of two terms, namely:

$$294 \quad U(x) = U_p(x) + U_d(x) \quad (2)$$

295 where $U_p(x)$ is a term introducing constraints between two adjacent objects (prior
296 energy) and $U_d(x)$ is a term that expressed how well the system made by the objects and

297 their neighborhood fitted image reflectance (data energy). The first term $U_p(x)$ cumulates
 298 the elementary energy computed for each adjacent pair of objects while the second
 299 $U_d(x)$ cumulates the local energy and includes variations in pixel values within and
 300 around each object in the configuration.

301 This local data energy $U_d(x)$ was computed through a function of the radiometric contrast
 302 between the pixels inside a given disc-object and the pixels composing its surrounding
 303 annulus. The higher this contrast, the more likely was the existence of a sunlit crown
 304 over a shadowed background. Let us note as μ_i , σ_i , n_i and μ_0 , σ_0 , n_0 the mean intensity,
 305 standard deviation and number of pixels inside a given disc-object and inside its
 306 surrounding ring, respectively. For every disc brighter than its corona i.e. $\mu_0 < \mu_i$, a
 307 contrast function derived from a Student's mean-comparison test is computed as follows:

$$308 \quad S(x) = \frac{\mu_i - \mu_0}{\sqrt{\frac{n_i \sigma_i^2 + n_0 \sigma_0^2}{n_i + n_0 - 2}} \sqrt{\frac{1}{n_i} + \frac{1}{n_0}}} \quad (3)$$

309 Then, data energy is derived from the comparison of $S(x)$ with a contrast threshold T
 310 ($T > 0$ and $T \leq 1$) defined and used as part of model parameterization:

$$311 \quad U_d(x) = \begin{cases} \frac{T - S(x)}{T}, & \text{if } S(x) > 1 - T \\ S(x) - 1, & \text{otherwise} \end{cases} \quad (4)$$

312 when $S(x) < 1 - T$, $U_d(x) < 0$, the disc fits the data. Setting the contrast threshold to a low
 313 value tends to increase the number of discs accepted around the same location, while
 314 high values of T may increase omissions in the event of low contrasts.

315 The prior energy term $U_p(x)$ is defined here to penalize any overlap between two objects
 316 and is a function of the normalized extent of the discs' intersection (Fig. 4; left). This
 317 function is parameterized using an overlapping threshold value, noted θ , that must be
 318 adjusted in relation to both image characteristics and forest type. Finally, overall prior
 319 energy is described as $U_p(x) = \gamma \eta(x)$, where $\eta(x)$ is the number of disc pairs with non-
 320 null intersection in the current configuration and γ is a parameter that weights prior
 321 energy comparatively to data energy $U_d(x)$.

322

323 3.2.2. Multiple Births and Deaths optimization algorithm

324 In order to find the x configuration that minimized total energy $U(x)$, we used a '*multiple
 325 births and deaths*' process. The algorithm, embedding an annealing technique, was first
 326 proposed in [Descombes et al. \(2009\)](#) and consists of the following steps:

- 327 1) Initialize both a temperature β to 1 and a birth rate $\delta = \frac{X_M \times Y_M}{r_{max}}$
- 328 2) Select image pixels randomly from those not yet associated with a disc. Then, select
329 discs with radius between r_{min} and r_{max} randomly from the newly born disc radius. a
330 uniform distribution.
- 331 3) Sort the discs of the current configuration with respect to their data energy in
332 decreasing order (i.e. from the worst to the best cases).
- 333 4) Remove each disc with a probability depending on both the temperature parameter
334 and the total energy difference between the configurations with and without this object.
- 335 5) If the process has not converged (i.e. if total energy changes significantly during the
336 last iteration), both temperature and birth rate are decreased.

337

338 3.3. *Identifying the best sets of parameters*

339

340 MPP modeling was applied to the 18 image extracts (each of 50x50m). The range of
341 disc radius variations was adjusted based on field measurements of the radii of a sample
342 of crowns at the three plantation ages considered (see 2.1). The $[r_{min}, r_{max}]$ pairs values
343 used to analyze the January image were taken according to the October measurements,
344 assuming minor changes in canopy dimensions afterwards due to canopy closure. The
345 largest interval range for $[r_{min}, r_{max}]$ pairs was thus set to [5, 10], [7, 12] and [9, 15] pixels
346 in the analysis of the May, August and January 10 cm oversampled images,
347 respectively. Various values for γ , T and θ were also used (see 4.1). For each
348 parameters combination, all detected disc-objects (center coordinates plus radius) were
349 drawn and overlaid on the analogue patterns provided by the visual interpretation of
350 each expert (Fig. 3; step 3). A search was conducted for all detected discs located within
351 a capture distance of less than the maximum radius of the tree crown expected at a
352 given observation date. Capture distance was taken from field measurements to be the
353 average tree crown half diameter at the considered age plus one standard deviation of
354 the related crown radius distribution.

355 When only one disc was captured in the neighborhood of a known tree, the detection
356 was considered as validated (situation 1). Detection process limitations generated three
357 other possible situations: no discs captured (situation 2), multiple captures (situation 3),
358 and false detection i.e. no reference position could be associated with a given detected
359 disc (situation 4). We therefore defined four variables for characterizing the quality of

360 detection for any given set of parameters. Situation 1 (one tree, one disc) was described
361 through the number of validated discs (noted nbv). Situation 2 informs on omission error
362 as quantified by the number of omitted discs (nbo) whereas situations 3 and 4 contribute
363 to the commission error through the number of multiple detections (nbm) and the
364 number of false detections (nbf). The number of trees visually detected was noted nbr .
365 Associated rates were then computed from ratios of nbv , nbo , nbl or nbv on nbr .
366 Finally, and as done in several other studies (e.g. Pitkänen, 2001; Pouliot et al., 2005)
367 we used an overall accuracy index, noted AI , to measure the performance of any given
368 set of parameters:

$$369 \quad AI(\%) = \frac{nbv}{nbv + nbo + nbm + nbf} \times 100 \quad (5)$$

370 This index corrects the validated rate by taking account both of omission and
371 commission errors. It should be noted that computation of this overall index was strictly
372 dependent upon the availability of reference data for tree locations.

373

374 3.4. Local density validation and large-scale mapping

375

376

377 We validated the potential of the MPP to detect young *Eucalyptus* trees by comparing
378 local density values estimated by MPP with fully independent data coming from the 112
379 field plots measuring ~590 m² as previously presented. Only the best set of parameters
380 that minimized unavoidable omission and commission errors was used (Fig. 3; step 4).

381 Our last aim was to compute a MPP-derived local density map for the entire plantation
382 area from the number of MPP-detected discs (Fig. 3; step 5). In order to cover the whole
383 *Eucalyptus* plantation imaged by Worldview, the local density index had to be computed
384 over approximately 800 image windows (each of 50x50m), i.e. about 170 hectares of
385 plantation. We also indicated an error index for MPP-detection by averaging the number
386 of omitted, redundant and false discs, noted $nboe$, $nbme$ and $nbfe$, respectively.

387 For information, it takes around 20 minutes to process a 50x50m image (500x500 pixels)
388 extracted using a Matlab® routine on a 3.5GHz 64 bit PC running with a conventional
389 RAM configuration of a few gigabytes. Processing time increases with the specified
390 range of radii.

391

392 4. Results

393 The quality of MPP detections was analyzed in two steps. The first aimed to identify both
394 the parameters (γ, T, θ) and observation dates that maximized the overall accuracy index.
395 It was carried out using broad ranges of crown radius values. The second step evaluated
396 how the range of crown values, i.e. $[r_{min}, r_{max}]$ pairs affected the final results.

397

398 4.1. *Selecting tree detection parameters*

399

400 4.1.1. MPP parameters

401 The May, August and January images were analyzed using various pairs of minimum
402 and maximum radius values, i.e. [5, 8], [8, 10] and [10, 12] pixels, respectively. Detection
403 scores were systematically computed in reference to the two visual expert appraisals.
404 For the sake of conciseness, only a subset of the results and figures obtained is
405 presented in this paper.

406 Detection scores varied only by a few percentage points when data energy threshold
407 value T was varied from 0.05 to 0.8 (not shown). This parameter was therefore set to
408 0.1 in subsequent analyses, without any great loss of generality. The effect of the γ
409 parameter that weights prior energy relative to data energy was also tested by
410 considering values ranging from 0.5 to 6. For each value of γ , we simultaneously
411 examined the effect of the overlapping threshold by taking $0 \leq \theta \leq 0.5$. The results
412 obtained for all observation dates and all θ values showed that setting γ below 1
413 generated far too many multiple detections while γ values above 1 reduced multiple
414 detections to less than 15% for the May image and to around 10% for both the August
415 and January images (result not shown). Also, overall detection quality was stable for all
416 values of $\gamma \geq 1$. Thus, for the remainder of the study, γ was set to 2.

417 Variations in detection scores were analyzed by considering a range of overlapping
418 threshold θ values from 0 (no overlap) to very high values of up to 0.5 for May and
419 August (50% overlapping) and 0.7 for January. We observed that the overall accuracy
420 index for the May image (Fig 5; top) was relatively stable at about 60%, with θ less than
421 0.2. Beyond this value, the overall accuracy index rapidly deteriorated due to a
422 simultaneous decrease in validated detections and an increase in multiple detections.

423

424 4.1.2. Image acquisition date

425 As shown in [figure 5](#), the accuracy index A_I for MPP-based detections was clearly higher
426 when using the August image than when using the May and January images, with mean
427 values of 82%, 51% and 30%, respectively.

428 Considering the May acquisition, index values were about 70% as long as the
429 overlapping threshold θ remained below 0.2, but then fell to 40% ([Fig 5; top](#)). The rate of
430 missed detections exceeded 15% while that of validated detections (single detections)
431 was less than 60%. Conversely, the August image clearly provided good overall scores
432 exceeding 80% when using $0.05 \leq \theta \leq 0.3$ ([Fig 5; middle](#)). Very poor detection quality
433 was obtained from the January image, with the overall accuracy index peaking at no
434 more than 35% for $\theta = 0.4$ ([Fig 5; bottom](#)). Canopy closure along plantation rows due to
435 crown enlargement ([Fig. 2](#)) is a likely explanation for this poor performance of the MPP
436 analysis at this plantation age.

437 However, it should be noted that false detections (disc-objects that cannot be associated
438 with a visually detected tree) were zero for all tested parameters and all observation
439 dates, indicating that the marked point process had been appropriately parameterized.

440

441 4.1.3. Range of disc radii using the August image

442 Here we focused on analyzing the August image. The main parameters were set to the
443 previously established values of γ , T and θ in order to determine how the choice of
444 minimal/maximal radius values impacted omission and commission errors and overall
445 detection quality ([Table 2](#)) for the four zones with different plantation row orientations
446 ([Fig. 6](#)).

447 Since no significant difference was found between the tree density values provided by
448 the two independent visual expert appraisals (see 3.1), densities were considered as a
449 sound basis to compute overall detection scores. Interestingly, the validated detections
450 rate exceeded 82% for all four zones, showing that row orientation had little or no impact
451 on this result. However, the overall accuracy index indicated that median density values
452 were about 15% lower in A and B than those observed for zones C and D. Rates of no
453 detection and multiple detection ranged from 5 to 8% in zones A and B while in zones C
454 and D these values did not exceed 3%.

455 A detailed analysis using various $[r_{min}, r_{max}]$ pairs ([Table 2](#)) indicated that the MPP
456 analysis performed least well taking values in the upper part of the realistic tree crown
457 radius interval, i.e. with $r_{min} \geq 10$ pixels (1 m), whereas using $[r_{min}, r_{max}]$ pairs close to the
458 lower boundary i.e. $[7, 11]$, $[8, 11]$ or $[9, 11]$ boosted both the overall index and the

459 validated rate to values above 90% by minimizing omission and commissions errors to a
460 few percent. The potential of the MPP analysis is illustrated in [Figure 7](#) which shows
461 examples of the detection results obtained with $[r_{min}, r_{max}] = [9, 11]$.

462 Additionally, a comparison of visually- vs. MPP-detected trees pointed to MPP detection
463 providing a 4% underestimation, but despite this difference the two assessments
464 appeared to be linearly correlated throughout the range of *Eucalyptus* tree densities.
465 This indicates that the discrepancy between the visual- and MPP-based density
466 estimates is not density-dependent when considering Worldview images acquired for 9-
467 month old *Eucalyptus* plantations.

468

469 4.2. Validation of MPP-derived local density

470

471 We computed the local density on the 112 validation plots using the best parameter
472 combinations i.e. $T=0.1$, $\gamma=2$ and $\theta=0.1$ and using one of the best radius ranges, i.e. [7,
473 11] pixels. The comparison of the MPP-derived and ground truth collected local density
474 values correlated well ($r^2=0.88$) with a root mean square error of 31 trees/ha ([Fig. 8](#)). The
475 slope coefficient of the regression between both datasets did not significantly depart
476 from 1 with a 95% confidence interval. There was no mean to quantify omissions or
477 commission errors, since ground truth plots did not feature XY locations of trees.
478 However, this result validated the ability of MPP detection to assess tree density using
479 the parameter values previously identified by visual detection. It also confirmed the
480 robustness of MPP density estimates across gradients of tree densities, tree structural
481 characteristics and row orientations.

482

483 4.3. Large-scale mapping of local density

484

485 Lastly, we generated a local tree density map for the entire plantation (~800 image
486 windows of 50x50m) using one of the best radius ranges, i.e. [8, 11] pixels. This
487 parameterization yielded a number of trees ranging from 333 to 420 trees to compare
488 with the 415 theoretically planted trees for a 50x50m planted area. The associated
489 values for *nboe*, *nbme*, *nbfe* corresponded to 17, 14 and 0 trees, respectively. The
490 resulting map showed local density variations ranging from 316 trees mainly in the
491 northwestern part (zone A) to maximum density values in zone D ([Fig. 9](#)). Local density
492 across the plantation was clearly not uniformly distributed.

493

494 5. Discussion

495

496 5.1. Potentialities and further improvements of MPP analysis

497

498 High spatial resolution satellite images can supply useful quantitative information for
499 forest management as they can be used to analyze the forest scene on an individual
500 tree scale. For instance, pixelwise classification algorithms based on optical image
501 radiometry are generally ill-suited to detect young individual trees and measure their
502 characteristics. The problem of tree crown delineation in fine spatial resolution images
503 calls for methods that combine both an analysis of radiometric contrast and *a priori*
504 knowledge of tree size and physiognomy. In response to this, and once it had been
505 verified that tree crowns can be represented by circular discs, the marked point process
506 modeling of forest image properties has an undeniable potential for monitoring
507 *Eucalyptus* forest plantations. One particular advantage of using this MPP method is its
508 ability to integrate *a priori* and ideally field-derived data on forest characteristics when
509 setting the ranges of parameter values that determine point process configurations.
510 Values for disc radii must match realistic ranges of tree crown half-diameters on the
511 observation date in order to avoid false detections and improve MPP performance. Data
512 on tree crown overlapping area are crucial for MPP analysis and can be deduced from
513 ground-truth references in one or more plots. Yet, very little crown overlap is observed in
514 this kind of even-aged *Eucalyptus* plantation, and, over time, overlap is of very limited
515 importance. The overlap parameter, θ , is therefore more intended to express possible
516 crown deformation that may occur from tree-tree interactions along the plantation rows.
517 Crown modeling via circles cannot account for such deformation plasticity, but
518 allowances made for some overlapping provide the necessary plasticity. However, in our
519 study, field data showed that little crown deformation occurred, and interpretation of the
520 optimal overlap values is probably related to sun and/or sensor position distorting
521 apparent tree position or crown shape.

522 Some difficulties may arise when transforming radiometric variations expressed as
523 square pixels into disc-objects of adequate size. Here, we found in our preliminary tests
524 that simply oversampling the original image up to 10 cm pixels greatly improved
525 detection as the marked point process functions better when disc-objects are described
526 by tens of pixels rather than a few pixels. More accurate disc positioning through to a

527 finer evaluation of the radiometric distance between a crown and its periphery may
528 improve data energy minimization. This of course relies on choosing an appropriate
529 value for threshold parameter T . In our case of *Eucalyptus* crown detection in Worldview
530 panchromatic images and for the 10 cm resolution used, a sensitivity analysis led us to
531 the conclusion that substantial variations in T do not significantly affect detection.
532 Dealing with other images such as infrared channels or Lidar-derived canopy-height
533 models would require additional sensitivity testing. Additionally, computation of the
534 radiometric distances needed to evaluate the data energy term may be improved,
535 especially if spatial resolution and pixel numbers are high.

536

537 5.2. *Prospects and limitations*

538

539 Although the set of parameters used to implement the method is theoretically large, we
540 have shown here that, for a specific class of application (i.e., a certain type of tree stand
541 and a given type of image), most parameters have a limited effect on the result and can
542 be safely assigned to predetermined values. In our study of a *Eucalyptus* plantation, we
543 noted that we could take $T=0.1$ and $\gamma=2$ as the energy threshold and weighting of data
544 energy, respectively. We also propose that the overlapping parameter may be taken in
545 further studies as $0.1 \leq \theta \leq 0.2$ in the absence of more specific information. The only
546 remaining parameters concern the range of disc radii, which has been shown to have a
547 substantial effect on the results, but which can easily be adapted to each specific case
548 by field measurements of crown radii.

549 This work highlights that the number of trees and possibly tree locations can be mapped
550 from metric spaceborne images during early growth stages before tree crowns join.
551 Considering *Eucalyptus* plantations, mapping can be used to illustrate that planting
552 success is heterogeneous in space and pinpoint where the problem of tree mortality or
553 insufficient growth is the most acute. The potential for stand density mapping from
554 individual tree detection must now be tested in diverse types of even-aged, open-canopy
555 stands. For instance, the monitoring of ecosystems marked by frequent primary
556 successions, such as Amazonian mangroves, could benefit from the mapping of natural
557 colonization over extensive mud banks by fast-spreading species such as *Avicennia*
558 *germinans* (Proisy et al., 2009). The method could also be used to detect emergent tree
559 crowns sparsely distributed over a number of hectares of closed canopy forest, and this
560 could be tested by setting the overlapping threshold and disc radii at values distinct from

561 those observed for canopy trees. However, as suggested by the analysis of the January
562 image, corresponding to trees aged 13 months, tree canopy closeness makes detection
563 impossible with the available native image resolution. In comparison, [Vauhkonen et al.](#)
564 [\(2011\)](#) concluded that airborne scanning laser data allowed tree detection during the
565 whole rotation time in 4x3m *Eucalyptus* plantations. Moreover, when considering natural
566 tropical *terra firme* forests, tree crown size cannot be restricted to a given interval of a
567 few decimeters. In addition, tree crowns often overlap or closely adjust one to another,
568 resulting in non-circular shapes. Hence, any attempt to determine the number of trees
569 per hectare (except emergent/dominant trees) by MPP analysis on images with a spatial
570 resolution of 50 cm to 1m will probably fail in natural forests. A texture analysis providing
571 information on modal crown size on a forest hectare scale ([Couteron et al., 2005](#); [Proisy](#)
572 [et al., 2007](#)) may be the best way to extract information from images of closed canopies
573 at these resolutions.

574

575 5.3. *Prospects for improving the management of Eucalyptus plantations*

576

577 Large-scale automatic mapping of local tree density within commercial eucalypt
578 plantations is possible by MPP-based single tree detection. Generated maps contribute
579 to our overall knowledge of plantations, and could influence decision-making by locating
580 site-specific silvicultural failures that reduce productivity. An early detection of high
581 mortality areas could lead to modifications in current fertilization and weeding practices
582 to adapt them more to local low stand density (precision forestry). Local densities are a
583 good indicator of the potential volume at harvest, particularly when combined with
584 information about average individual tree volume obtained from adequate field
585 measurements. The advantage of using imagery compared to forest inventories is that
586 individual-scale and thus local information can be obtained over large areas. A lower
587 than expected tree density can inform the manager of possible problems occurring in
588 that area, and this can either be dealt with directly or at the next rotation. Since the best
589 detection results are obtained when trees are aged 6 to 9 months, this is too late to
590 replace missing trees, but the manager may decide to replant the local area entirely if
591 economically profitable, or change the clone, treatments or other operations at the next
592 rotation. The price of high spatial resolution satellite images will very likely decrease in
593 the future while availability will increase. Moreover, the application of such MPP-based
594 analyses at each successive rotation may provide a basis for building temporal archives

595 of plantation performance that may be useful for adjusting stocking densities and
596 management practices. Finally, the potential of the MPP approach will probably increase
597 with its application to fine-scale Lidar-derived canopy heights models that already proved
598 usefulness for monitoring *Eucalyptus* plantations (e.g. Packalén et al., 2011).

599

600 5.4. Concluding remarks

601

602 A better understanding of how the most influential MPP parameters need to be set for
603 different forest types, tree ages, crown forms and sun and viewing conditions may be
604 obtained by simulating reflectance images using 3D stand mockups and a radiative
605 transfer model, like for instance the DART model (Gastellu-Etchegorry, 2008). Here, as
606 explained by Barbier et al. (2012), realistic canopy images can be simulated by applying
607 the DART model to 3D forest mockups consisting of “lollipop” trees (ellipsoids on a stick)
608 built from field inventories and allometric relationships. This is a very convenient method
609 for developing and testing the robustness of remote sensing methods dedicated to the
610 application of high spatial resolution imagery to forests.

611 Simulating images of *Eucalyptus* plantations may help to both adjust the set of MPP
612 parameters for each age (and related levels of total height and crown development) and
613 determine optimal acquisition parameters in terms of sun and viewing angles (le Maire et
614 al. 2012). This approach may pave the way to providing key attributes for forest
615 management, such as trees location maps, an abacus of crown diameter growth during
616 early stages, and areas of poor growth or high mortality. Information such as this is
617 crucial when investigating the effect of planting density on yield (Vanclay 1994) or when
618 simulating competition for light (Binkley et al., 2010; le Maire, 2012; Binkley et al., 2012)
619 and when using a simple representation of tree crowns with geometrical volumes, such
620 as ellipsoids or cones (Medlyn, 2004).

621

622 Acknowledgements

623 This work was supported by the ORFEO program, a Centre National d'Etudes Spatiales
624 (CNES) Accompaniment Program for the use of PLEIADES images. We especially wish
625 to thank Claire Tinel for her help in image sorting and are grateful to the Eucflux project
626 (<http://www.ipef.br/eucflux/>) for providing inventories of the *Eucalyptus* plantation plots.
627 We thank Peter Biggins for the revision of the English.

628

629 **References**

- 630 Barbier, N., Couteron, P., Proisy, C., Malhi, Y., & Gastellu-Etchegorry, J.-P., 2010. The
631 variation of apparent crown size and canopy heterogeneity across lowland
632 Amazonian forests. *Global Ecology and Biogeography*, 19, 72-84.
- 633 Barbier, N., Couteron, P., Gastelly-Etchegorry, J.-P., Proisy, C., 2012. Linking canopy
634 images to forest structural parameters: potential of a modeling framework. *Annals of*
635 *Forest Science* 69, 305-311.
- 636 Binkley, D., Stape, J.L., Bauerle, W.L., Ryan, M.G., 2010. Explaining growth of individual
637 trees: Light interception and efficiency of light use by Eucalyptus at four sites in
638 Brazil. *Forest Ecology and Management* 259, 1704-1713.
- 639 Binkley, D., Campoe, O.C., Gspaltl, M., Forrester, D.I., 2012. Light absorption and use
640 efficiency in forests: Why patterns differ for trees and stands. *Forest Ecology and*
641 *Management*. doi:10.1016/j.foreco.2011.11.002
- 642 Campoe, O.C., Stape, J.L., Laclau, J.-P., Marsden, C., Nouvellon, Y., 2012. Stand-level
643 patterns of carbon fluxes and partitioning in a Eucalyptus grandis plantation across
644 a gradient of productivity, in São Paulo State, Brazil. *Tree Physiology*.
645 doi:10.1093/treephys/tps038
- 646 Couteron, P., Pélissier, R., Nicolini, E., Paget, D., 2005. Predicting tropical forest stand
647 structure parameters from Fourier transform of very high-resolution remotely sensed
648 canopy figures. *Journal of Applied Ecology* 42, 1121-1128.
- 649 Culvenor, D.S., 2002. TIDA: an algorithm for the delineation of tree crowns in high
650 spatial resolution remotely sensed imagery. *Computers & Geosciences* 28, 33-44.
- 651 Descamps, S., Béchet, A., Descombes, X., Arnaud, A., Zerubia, J., 2011. An automatic
652 counter for aerial images of aggregations of large birds. *Bird Study* 58, 302-330.
- 653 Descombes, X., Kruggel, F., Wollny, G., Gertz, H.J., 2004. An object-based approach for
654 detecting small brain lesions: application to Virchow-Robin spaces *IEEE*
655 *Transactions on Medical Imaging* 23, 246-255.
- 656 Descombes, X., Minlos, R., Zhizhina, E., 2009. Object Extraction Using a Stochastic
657 Birth-and-Death Dynamics in Continuum. *Journal of Mathematical Imaging and*
658 *Vision* 33, 347-359.
- 659 Descombes, X. (Ed.), 2012. *Stochastic Geometry for Image Analysis*. ISTE & John Wiley
660 & Sons.

661 du Toit, B., Dovey, S.B., 2005. Effect of site management on leaf area, early biomass
662 development, and stand growth efficiency of a *Eucalyptus grandis* plantation in
663 South Africa. *Canadian Journal of Forest Research* 35, 891-900.

664 eGeos, 2011. Price List. http://www.eurimage.com/products/prices_terms.html

665 Erikson, M., Olofsson, K., 2005. Comparison of three individual tree crown detection
666 methods. *Machine Vision and Applications* 16, 258-265.

667 Garau, A.M., Lemcoff, J.H., Ghersa, C.M., Beadle, C.L., 2008. Water stress tolerance in
668 *Eucalyptus globulus* Labill. subsp. *maidenii* (F. Muell.) saplings induced by water
669 restrictions imposed by weeds. *Forest Ecology and Management* 255, 2811-2819.

670 Gastellu-Etchegorry, J.P., 2008. 3D modeling of satellite spectral images, radiation
671 budget and energy budget of urban landscapes. *Meteorol. Atmos. Phys.* 102, 187-
672 207.

673 Gebreslasie, M.T., Ahmed, F.B., Van Aardt, J.A.N., & Blakeway, F. (2011). Individual
674 tree detection based on variable and fixed window size local maxima filtering
675 applied to IKONOS imagery for even-aged *Eucalyptus* plantation forests.
676 *International Journal of Remote Sensing*, 32, 4141-4154.

677 Gonçalves, J.L.d.M., Stape, J.L., Laclau, J.-P., Smethurst, P., Gava, J.L., 2004.
678 Silvicultural effects on the productivity and wood quality of eucalypt plantations.
679 *Forest Ecology and Management* 193, 45-61.

680 Gougeon, F. A., 1995. A Crown-following approach to the automatic delineation of
681 individual tree crowns in high spatial resolution aerial Images. *Canadian Journal of*
682 *Remote Sensing*, 21, 274-284.

683 Hirschmugl, M., Ofner, M., Raggam, J., & Schardt, M. (2007). Single tree detection in
684 very high resolution remote sensing data. *Remote Sensing of Environment*, 110,
685 533-544.

686 Hummel, S., Hudak, A.T., Uebler, E.H., Falkowski, M.J., & Megown, K.A. (2011). A
687 comparison of accuracy and cost of LiDAR versus stand exam data for landscape
688 management on the Malheur National Forest. *Journal of forestry*, 267-273.

689 Jacobsen, M., 2006. Point process theory and applications: marked point and piecewise
690 deterministic processes. Springer Science & Business, New York, USA.

691 Korpela, I. (2004). Individual tree measurements by means of digital aerial
692 photogrammetry. *Silva Fennica Monograph*, 3, 93 pages.

693 Laclau, J.-P., Ranger, J., Gonçalves, J.L.M., Maquère, V., Krusche, A.V., M'Bou, A.T.,
694 Nouvellon, Y., Saint-André, L., Bouillet, J.-P., de Cassia Piccolo, M., Deleporte, P.,

695 2010. Biogeochemical cycles of nutrients in tropical Eucalyptus plantations: Main
696 features shown by intensive monitoring in Congo and Brazil. *Forest Ecology and*
697 *Management* 259, 1771-1785.

698 Larsen M., Rudemo, M., 1998. Optimizing templates for finding trees in aerial
699 photographs. *Pattern Recognition Letters*, 19, 1153-1162.

700 Larsen, M., Eriksson, M., Descombes, X., Perrin, G., Brandtberg, T., Gougeon, F.A.,
701 2011. Comparison of six individual tree crown detection algorithms evaluated under
702 varying forest conditions. *International Journal of Remote Sensing* 32, 5827-5852.

703 le Maire, G., Nouvellon, Y., Roupsard, O., Christina, M., Charbonnier, F., Zhou, J.,
704 Ponzoni, F., Stape, J.-L., Dauzat, J., Couteron, P., & Proisy, C. (2012). Very high
705 resolution satellite images for parameterization of tree-scale forest process-based
706 model. In: *IGARSS 2012*. Munich, Germany.

707 le Maire, G., Marsden, C., Nouvellon, Y., Grinand, C., Hakamada, R., Stape, J.-L.,
708 Laclau, J.-P., 2011a. MODIS NDVI time-series allow the monitoring of Eucalyptus
709 plantation biomass. *Remote Sensing of Environment* 115, 2613-2625.

710 le Maire, G., Marsden, C., Verhoef, W., Ponzoni, F.J., Lo Seen, D., Bégué, A., Stape, J.-
711 L., Nouvellon, Y., 2011b. Leaf area index estimation with MODIS reflectance time
712 series and model inversion during full rotations of Eucalyptus plantations. *Remote*
713 *Sensing of Environment* 115, 586-599.

714 le Maire, G., Nouvellon, Y., Christina, M., Ponzoni, F.J., Gonçalves, J.L.M., Bouillet, J.P.,
715 Laclau, J.P., 2012. Tree and stand light use efficiencies over a full rotation of single-
716 and mixed-species Eucalyptus grandis and Acacia mangium plantations. *Forest*
717 *Ecology and Management*, <http://dx.doi.org/10.1016/j.foreco.2012.03.005>.

718 Marsden, C., le Maire, G., Stape, J.-L., Seen, D.L., Roupsard, O., Cabral, O., Epron, D.,
719 Lima, A.M.N., Nouvellon, Y., 2010. Relating MODIS vegetation index time-series
720 with structure, light absorption and stem production of fast-growing Eucalyptus
721 plantations. *Forest Ecology and Management* 259, 1741-1753.

722 Medlyn, B.E., 2004. A MAESTRO Retrospective. In: Mencuccini M., Moncrieff J.,
723 McNaughton K., J., G. (Eds.), *Forests at the Land-Atmosphere Interface*. CABI
724 Publishing, Wallingford, UK, pp. 105-122.

725 Nouvellon, Y., Laclau, J.-P., Epron, D., Kinana, A., Mabiata, A., Roupsard, O.,
726 Bonnefond, J.-M., le Maire, G., Marsden, C., Bontemps, J.-D., Saint-André, L.,
727 2010. Within-stand and seasonal variations of specific leaf area in a clonal

728 Eucalyptus plantation in the Republic of Congo. *Forest Ecology and Management*
729 259, 1796-1807.

730 Vauhkonen, J., Mehtätalo, L., & Packalén, P. (2011). Combining tree height samples
731 produced by airborne laser scanning and stand management records to estimate
732 plot volume in Eucalyptus plantations. *Canadian Journal of Forest Research*, 41,
733 1649-1658.

734 Packalén, P., Mehtätalo, L., Maltamo, M., 2011. ALS-based estimation of plot volume
735 and site index in a eucalyptus plantation with a nonlinear mixed-effect model that
736 accounts for the clone effect. *Annals of Forest Science* 68, 1085-1092.

737 Pallett, R.N., Sale, G., 2004. The relative contributions of tree improvement and cultural
738 practice toward productivity gains in Eucalyptus pulpwood stands. *Forest Ecology*
739 *and Management* 193, 33-43.

740 Perrin, G., Descombes, X., Zerubia, J., Boureau, J.G., 2006. Forest resource
741 assessment using stochastic geometry. In, *International Precision Forestry*
742 *Symposium*, South Africa.

743 Pitkänen, J., 2001. Individual tree detection in digital aerial images by combining locally
744 adaptive binarization and local maxima methods. *Canadian Journal of Forest*
745 *Research* 31, 832-844.

746 Ploton, P., Pélissier, R., Proisy, C., Flavenot, T., Barbier, N., Rai, S.N., Coueron, P.,
747 2012. Assessing aboveground tropical forest biomass using Google Earth canopy
748 images. *Ecological Applications* 22, 993-1003.

749 Pouliot, D., King, D., Pitt, D., 2005. Development and evaluation of an automated tree
750 detection-delineation algorithm for monitoring regenerating coniferous forests.
751 *Canadian Journal of Forest Research* 35, 2332-2345.

752 Pouliot, D., King, D., 2005. Approaches for optimal automated individual tree crown
753 detection in regenerating coniferous forests. *Canadian Journal of Remote Sensing*
754 31, 255-267.

755 Proisy, C., Coueron, P., Fromard, F., 2007. Predicting and mapping mangrove biomass
756 from canopy grain analysis using Fourier-based textural ordination of IKONOS
757 images. *Remote Sensing of Environment* 109, 379-392.

758 Proisy, C., Gratiot, N., Anthony, E.J., Gardel, A., Fromard, F., Heuret, P., 2009. Mud
759 bank colonization by opportunistic mangroves: A case study from French Guiana
760 using lidar data. *Continental Shelf Research*, 29, 632-641.

761 Richardson, J.J., & Moskal, L.M. (2011). Strengths and limitations of assessing forest
762 density and spatial configuration with aerial LiDAR. *Remote Sensing of*
763 *Environment*, 115, 2640-2651.

764 Song, C., Dickinson, M.B., Su, L., Zhang, S., & Yaussey, D. (2010). Estimating average
765 tree crown size using spatial information from Ikonos and QuickBird images: Across-
766 sensor and across-site comparisons. *Remote Sensing of Environment*, 114, 1099-
767 1107.

768 Stape, J.L., Binkley, D., Ryan, M.G., Fonseca, S., Loos, R.A., Takahashi, E.N., Silva,
769 C.R., Silva, S.R., Hakamada, R.E., Ferreira, J.M.d.A., Lima, A.M.N., Gava, J.L.,
770 Leite, F.P., Andrade, H.B., Alves, J.M., Silva, G.G.C., Azevedo, M.R., 2010. The
771 Brazil Eucalyptus Potential Productivity Project: Influence of water, nutrients and
772 stand uniformity on wood production. *Forest Ecology and Management* 259, 1684-
773 1694.

774 Stephens, P.R., Kimberley, M.O., Beets, P.N., Paul, T.S.H., Searles, N., Bell, A., Brack,
775 C., & Broadley, J. (2012). Airborne scanning LiDAR in a double sampling forest
776 carbon inventory. *Remote Sensing of Environment*, 117, 348-357.

777 Stoyan, D., Kendall, W.S., Mecke, J., Kendall, D.G., 1995. *Stochastic Geometry and Its*
778 *Applications*. John Wiley & Sons, Chichester.

779 Tesfamichael, S.G., Ahmed, F., van Aardt, J.A.N., & Blakeway, F. (2009). A semi-
780 variogram approach for estimating stems per hectare in *Eucalyptus grandis*
781 plantations using discrete-return lidar height data. *Forest Ecology and Management*,
782 258, 1188-1199.

783 Vanclay, J.K. 1994. *Modelling Forest Growth and Yield: Applications to Mixed Tropical*
784 *Forests*. CABI, Wallingford, UK. 312 p.

785 van Lieshout, M.N.M., 2000. *Markov point processes and their applications*. Imperial
786 College Press, London.

787 Vauhkonen, J., Ene, L., Gupta, S., Heinzl, J., Holmgren, J., Pitkänen, J., Solberg, S.,
788 Wang, Y., Weinacker, H., Hauglin, K.M., Lien, V., Packalén, P., Gobakken, T., Koch,
789 B., Næsset, E., Tokola, T., & Maltamo, M. (2012). Comparative testing of single-tree
790 detection algorithms under different types of forest. *Forestry*, 85, 27-40.

791 Walters, G.A. (1980). *Saligna eucalyptus growth in a 15-year-old spacing study in*
792 *Hawaii*. *Pacific Southwest Forest and Range Experiment Station*, 151, 1-6.

793 Wulder, M.A., White, J.C., Niemann, K.O., Nelson, T., 2004. Comparison of airborne and
794 satellite high spatial resolution data for the identification of individual trees with local
795 maxima filtering. *International Journal of Remote Sensing* 25, 2225-2232.
796