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1 **Estimating babassu palm density using automatic palm tree detection with very high**  
2 **spatial resolution satellite images**

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19

20 **Abstract**

21 High spatial resolution images as well as image processing and object detection algorithms  
22 are recent technologies that aid the study of biodiversity and commercial plantations of forest  
23 species. This paper seeks to contribute knowledge regarding the use of these technologies by  
24 studying randomly dispersed native palm tree. Here, we analyze the automatic detection of  
25 large circular crown (LCC) palm tree using a high spatial resolution panchromatic GeoEye  
26 image (0.50 m) taken on the area of a community of small agricultural farms in the Brazilian  
27 Amazon. We also propose auxiliary methods to estimate the density of the LCC palm tree  
28 *Attalea speciosa* (babassu) based on the detection results. We used the “Compt-palm”  
29 algorithm based on the detection of palm tree shadows in open areas via mathematical  
30 morphology techniques and the spatial information was validated using field methods (i.e.  
31 structural census and georeferencing). The algorithm recognized individuals in life stages 5  
32 and 6, and the extraction percentage, branching factor and quality percentage factors were  
33 used to evaluate its performance. A principal components analysis showed that the structure  
34 of the studied species differs from other species. Approximately 96% of the babassu  
35 individuals in stage 6 were detected. These individuals had significantly smaller stipes than  
36 the undetected ones. In turn, 60% of the stage 5 babassu individuals were detected, showing  
37 significantly a different total height and a different number of leaves from the undetected  
38 ones. Our calculations regarding resource availability indicate that 6,870 ha contained 25,015  
39 adult babassu palm tree, with an annual potential productivity of 27.4 t of almond oil. The  
40 detection of LCC palm tree and the implementation of auxiliary field methods to estimate  
41 babassu density is an important first step to monitor this industry resource that is extremely  
42 important to the Brazilian economy and thousands of families over a large scale.

43 **Keywords:** Shadow detection; Mathematical morphology; Density estimate; Remote sensing;  
44 Brazilian Amazon

45

## 46 **1. Introduction**

47         The babassu (*Attalea speciosa* Mart. ex Spreng.) is a palm tree species native to dense  
48 and humid forests that is distributed across approximately 200,000 km<sup>2</sup> of forests and  
49 savannas in Brazil, with optimal development in secondary environments (Anderson and  
50 Anderson, 1985; May et al., 1985; Barot et al., 2005; Santos and Mitja, 2011; Coelho et al.,  
51 2012). Recent research emphasized the importance of this palm tree to industry, given its  
52 potential for biodiesel production (Da Rós et al., 2014) and bioenergy (Protásio et al., 2014);  
53 to ethnobotany, given its use diversity (Araujo and Lopes, 2012; Martins et al., 2014); to  
54 anthropology, given its economic and social importance for small farmers (Porro and Porro,  
55 2014); and to medicine because babassu palm trees can become infested with triatomines,  
56 which transmit Chagas disease (Dias et al., 2014). Recently, babassu oleaginous almonds  
57 were considered as the third most important non-wood product of plant extractivism in Brazil  
58 (89,739 t/\$56.7 million in 2013; IBGE, 2013). Nevertheless, a gap exists between the  
59 knowledge of this species and use of technologies that might aid in its management and  
60 sustainable exploitation.

61         In forest plantations, information on tree or palm tree density is obtained using remote-  
62 sensing techniques that aid in productivity monitoring, planning and management of African  
63 oil palm tree (Shafri et al., 2011; Srestasathiern and Rakwatin, 2014) and eucalypt (Whiteside  
64 et al., 2011; Zhou et al., 2013) plantations. The spatial information provided regarding the  
65 number of trees or palm trees enables (among other things) the identification of excessive  
66 mortality areas (Zhou et al., 2013) and the prediction of production dates (Malek et al., 2014),  
67 which are essential for resource management and conservation (Engler et al., 2013).

68           As an alternative to time-demanding tasks of individually counting trees or palm trees  
69 in the field, automatic-detection methods were developed using high spatial resolution  
70 images. The primary objective of this detection is to determine the location of the tree or palm  
71 tree crowns in an image (Srestasathien and Rakwatin, 2014). Studies apply different  
72 techniques to delimit tree and palm tree crowns based on the value of each pixel in the image  
73 (Erikson and Olofsson, 2005). Some of the techniques used include the marked-point process  
74 (MPP) via Worldview 1 and Worldview 2 multispectral images (Zhou et al., 2013), the  
75 maximum local detection method using Kodak DCS 460 CIR and UltracamD digital camera  
76 images (Pouliot et al., 2002; Hirschmugl et al., 2007), and a technique based on the structure  
77 of the elements using an airborne AISA hyperspectral image (Shafri et al., 2011). These  
78 techniques are generally used for homogeneous forest plantations disposed along a line; not  
79 having other species within the plantation avoids confusion when analyzing the images.

80           The mapping of tree crowns in non-planted areas (i.e., those dispersed in cultivated  
81 areas or in homogeneous or heterogeneous natural forests) can be based on the detection of  
82 crowns via object-oriented classification using IKONOS and GeoEye images (Aouragh et al.,  
83 2013), the wavelet-transform technique (Zhang et al., 2006; Ghiyamat and Shafri, 2010), or  
84 via supervised classification techniques such as spectral angle mapper, a linear discriminant  
85 analysis, and the maximum likelihood method (Clark et al., 2005), both techniques use an  
86 airborne HYDICE hyperspectral image.

87           Few studies have used image-based palm tree detection directed toward regular  
88 African oil palm tree plantations. Currently, babassu plantations are not found in Brazil,  
89 which might explain why this species has not yet been evaluated using automatic detection  
90 via images from recent satellites such as GeoEye, Ikonos, Worldview or Quickbird (which  
91 offer a spatial resolution of less than 1 m). The development of images with a resolution of  
92 less than 1 m enabled the more precise detection of small objects such as tree crowns in

93 agricultural areas and their different shapes (Aouragh et al., 2013) using canopy delineation  
94 algorithms (Culvenor, 2002).

95         Although the classic algorithms developed for crown delineation fundamentally  
96 assume that the center of a crown appears radiometrically brighter than its edge (Culvenor,  
97 2002), the algorithm developed by Demagistri et al. (2014), adapted for open environments,  
98 extracts the image pixels that correspond to shadows using the mathematical morphology  
99 technique (Serra, 1982; Haralick et al., 1987). This algorithm permits the detection of palm  
100 trees in pastures and agricultural plantations with low-to-average palm tree density. This  
101 image analysis technique is important (Soille and Pesaresi, 2002; Giada et al., 2003) for the  
102 detection of individual trees (Jiang and Lin, 2013) and other objectives. This technique is  
103 known as “morphology” because it analyses the content and shape of the object and called  
104 “mathematical” because it is based on set theory, integral geometry, and algebraic structure  
105 (Giada et al., 2003). Therefore, this algorithm has been used to detect the babassu palm tree in  
106 open agricultural environments.

107         Studies on tree and palm tree-crown detection do not usually employ field methods to  
108 validate the spatial information (Clark et al., 2005; Zhang et al., 2006; Hirschmugl et al.,  
109 2007; Ghiyamat and Shari, 2010; Shafri et al., 2011; Aouragh et al., 2013; Malek et al., 2014;  
110 Srestasathiern and Rakwatin, 2014). When used, these methods are typically restricted to  
111 measure crown diameter and individual density (Pouliot et al., 2002, Zhou et al., 2013),  
112 although other structural characteristics of the individuals might affect their detection using  
113 the algorithm. Therefore, understanding these characteristics is an important step to improve  
114 the reliability of spatial information.

115         A large diversity of palm trees exists in the Amazon region, including 195 species and  
116 35 genera. The most important genera include *Attalea* and *Astrocaryum*, each with 28 species  
117 (Pintaud et al., 2008). In addition to *Attalea speciosa* (babassu), other large circular crown

118 (LCC) species such as *Attalea maripa* (inajá), *Astrocaryum aculeatum* (tucumã), *Oenocarpus*  
119 *bacaba* (bacaba) and *Mauricia flexuosa* (buriti) are distributed in an isolated and random  
120 manner (D. Mitja, Personal communication). Because no methods are described in the  
121 literature that enable differentiation among LCC palm tree types using a high-resolution  
122 image, estimating the density of a species of interest (e.g., the babassu) using automatic  
123 detection is a real challenge.

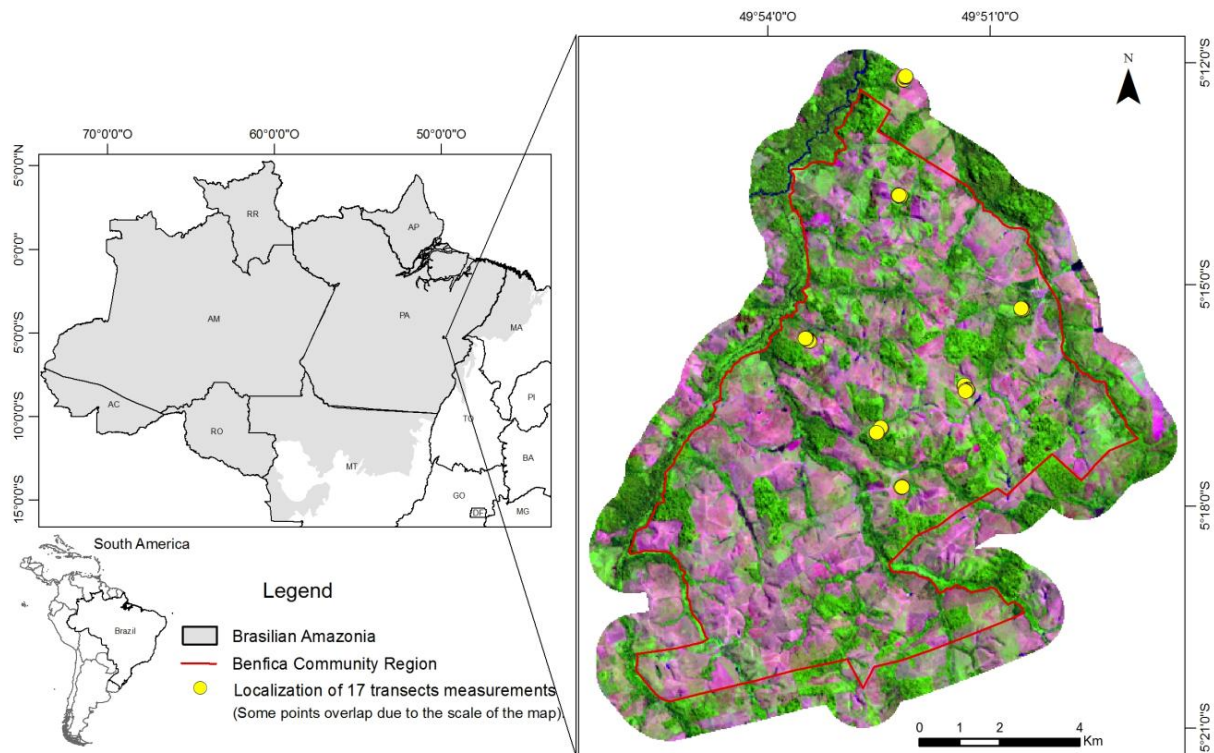
124 In the present study, we analyzed the automatic detection of LCC palm trees using a  
125 high spatial resolution panchromatic image (GeoEye1 sensor, 0.50-m resolution, July/2013)  
126 taken on a community of small farms in the Brazilian Amazon after validating the remote-  
127 sensing data using photo-interpretation and field methods. Based on the automatic detection  
128 results, we implemented auxiliary field methods to estimate babassu density.

129

## 130 **2. Material and Methods**

### 131 2.1. Characterization of the study area

132 This study was conducted in small farmlands in Benfica (S 05°16'20", W 49°50'25"),  
133 (Itupiranga State of Pará (PA), southeast of the Brazilian Amazon) (Fig. 1). This site has  
134 9,501 ha, and its occupation started in 1986 successively by farmers and settlers. Its land  
135 regularization was consolidated by the National Institute of Colonization and Agrarian  
136 Reform (Instituto Nacional de Colonização e Reforma Agrária; INCRA) in 1996 (Arnauld de  
137 Sartre, 2004). The latest estimate indicated 183 agricultural establishments and approximately  
138 1,000 people in the community (Ritter et al., 2009).



139

140 Fig. 1. The study area (Benfica, PA), located southeast of the Brazilian Amazon, shown by a  
 141 Landsat 8-OLI 2013 image (RGB: B6, B5, B4).

142 \*Two transects were near but outside the limit of Benfica community.

143

144 The vegetation in this area is upland tropical forest, characterized by the presence of  
 145 lianas and palm trees (Mitja and Miranda, 2010). The dense forest has a canopy between 25  
 146 and 30 m in height, although some trees (e.g., *Bertholletia excelsa* H.B.K) reach a height of  
 147 over 50 m (Bertrand, 2009). Landsat 8-OLI images taken in 2013 (Fig. 1) showed that  
 148 primary and old secondary forests (in dark green colors) covered 34% of the area in Benfica,  
 149 whereas degraded pastures or pastures with little cover (in purple and pink colors) represented  
 150 31%; pastures in good states and young secondary forests (in light green colors) accounted for  
 151 31% of the area (Eric Delaître, Personal communication).

152 When forests are converted into pastures, some palm trees and timber species are  
 153 maintained (Mitja et al., 2008; Santos and Mitja, 2011), thereby contributing to the



154 composition of the local landscape that includes pastures containing woody species (15%) and  
155 pastures with babassu (12%; Sampaio, 2008). The high reproductive plasticity of babassu  
156 favors its development in agricultural areas (Barot et al., 2005) because the use of fire for  
157 agricultural management contributes to the germination and regeneration of babassu  
158 individuals (Mitja and Ferraz, 2001). Thus, the different densities of the babassu in the study  
159 area are partially a result of its resilience to natural and anthropogenic disturbances, insofar as  
160 (similar to some other species) it has particular morphological characteristics and reproductive  
161 strategies that influence its phenology and gene flow (Montúfar et al., 2011).

162         The climate is tropical humid with average temperature of 26°C. The average annual  
163 rainfall is 1,700 mm, distributed irregularly throughout the year. The region's two seasons are  
164 defined by the movements of the intertropical convergence zone: the rainy season, which  
165 typically lasts approximately 8 months (October to May); and the dry season, which typically  
166 lasts 4 months (June to September; Bertrand, 2009).

167         A variety of soils exists along the toposequences: (i) oxisol, with a thick B horizon  
168 rich in ferruginous nodules; (ii) cambisol, with an incipient B horizon and a C horizon located  
169 close to the surface; and (iii) gleysol, with an A horizon rich in organic matter, A and B  
170 horizons with little clay, and hydromorphy along the entire profile (Ritter et al., 2009). As is  
171 the norm for most arable lands in the Amazon, the soil fertility of the study area is low (Ritter  
172 et al., 2009).

173

## 174         2.2. Field data

175         The information obtained in the field enabled the definition of the proportion of  
176 babassu in the set of LCC palm trees. There are five LCC palm tree species in Benfica, three  
177 are more frequent, babassu, inajá and tucumã, and two rare species, bacaba and buriti (Santos

178 and Mitja, 2011; Danielle Mitja, Personal communication). In a 487 ha pasture area of the  
179 study site (=62-plots), we observed that 93.6% of the LCC palm trees found were babassu.  
180 This result was used to estimate the babassu density based on the automatic LCC palm tree  
181 detection results.

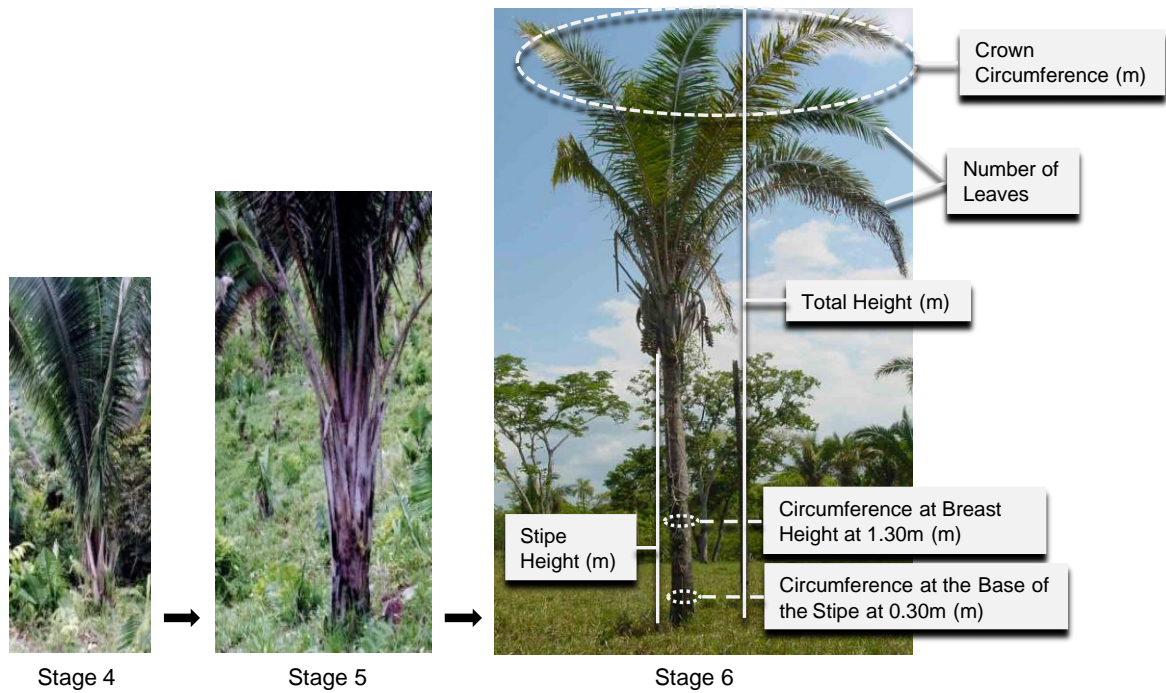
182 A total of 17 transects were sampled in pastures of different ages (1, 3, 5, 7 and 9  
183 years), with a total sampling area of 1.3 ha (Fig. 1). In these transects, we noted that 46.51%  
184 of the detected palm trees belonged to stage 5, whereas 53.49% belonged to stage 6.

185 A total of 150 babassu across three development stages were inventoried in the pasture  
186 areas. Out of these babassu, 105 were in stage 6 (adults with an aerial stipe and signs of male  
187 and/or female reproductive organs), 30 were in stage 5 (juvenile with an aerial stipe,  
188 regardless of sheath coverage, and without the signs of male or female reproductive organs),  
189 and 15 were in stage 4 (juvenile with a terminal bud at the soil surface level, with well-visible  
190 leaf sheaths).

191 The structural information obtained in the field included circumference at breast  
192 height, circumference at the base of the stipe, number of leaves, total height, stipe height, and  
193 crown circumference (Fig. 2). This structural information was also obtained for two other  
194 LCC palm trees species, inajá (31 individuals) and tucumã (30 individuals).

195 All these palm trees were georeferenced using the global positioning system (GPS;  
196 model: GARMIN 62stc) to be located in the GeoEye 2013 image and identify the individuals  
197 that had been detected using the detection algorithm.

198



199

200 Fig. 2. Life-cycle stages of the babassu palm trees studied in Benfica and the  
 201 structural information obtained

202

203 2.3. Remote sensing image

204

205

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211

212

213 2.4. LCC palm tree detection algorithm development and evaluation

214 An “Compt-palm” algorithm adapted to open environments was developed to detect  
215 the following LCC palm trees: babassu, inajá, tucumã, bacaba and buriti (Demagistri et al.,  
216 2014). A panchromatic GeoEye 2009 image of Benfica was used in the algorithm-  
217 development process. At first, shadows palm trees are extracted using mathematical  
218 morphology techniques; then each shadow object (which corresponds to a potential palm tree)  
219 undergoes a supervised classification by calculating a decision coefficient used to assign that  
220 object a particular class label between “palm tree shadow” and “other shadow”.

221 The shadow extraction protocol proceeds as follows:

- 222 i) Smoothing of the panchromatic image: this first filter removes the noise from the  
223 image;
- 224 ii) Local adaptive filtering based on the mean and standard deviation of a moving  
225 window: zones with a strong local contrast (i.e. the shadows) are extracted;
- 226 iii) Morphological closing: the first step in cleaning the shadow extraction results;
- 227 iv) Connected components extraction: labeling of independent shadow objects;
- 228 v) Object size thresholding: the second step in cleaning the shadow extraction results.

229 Afterwards, shadow objects are classified using a supervised classification based on a  
230 distance criterion and a decision rule process. These steps are detailed below:

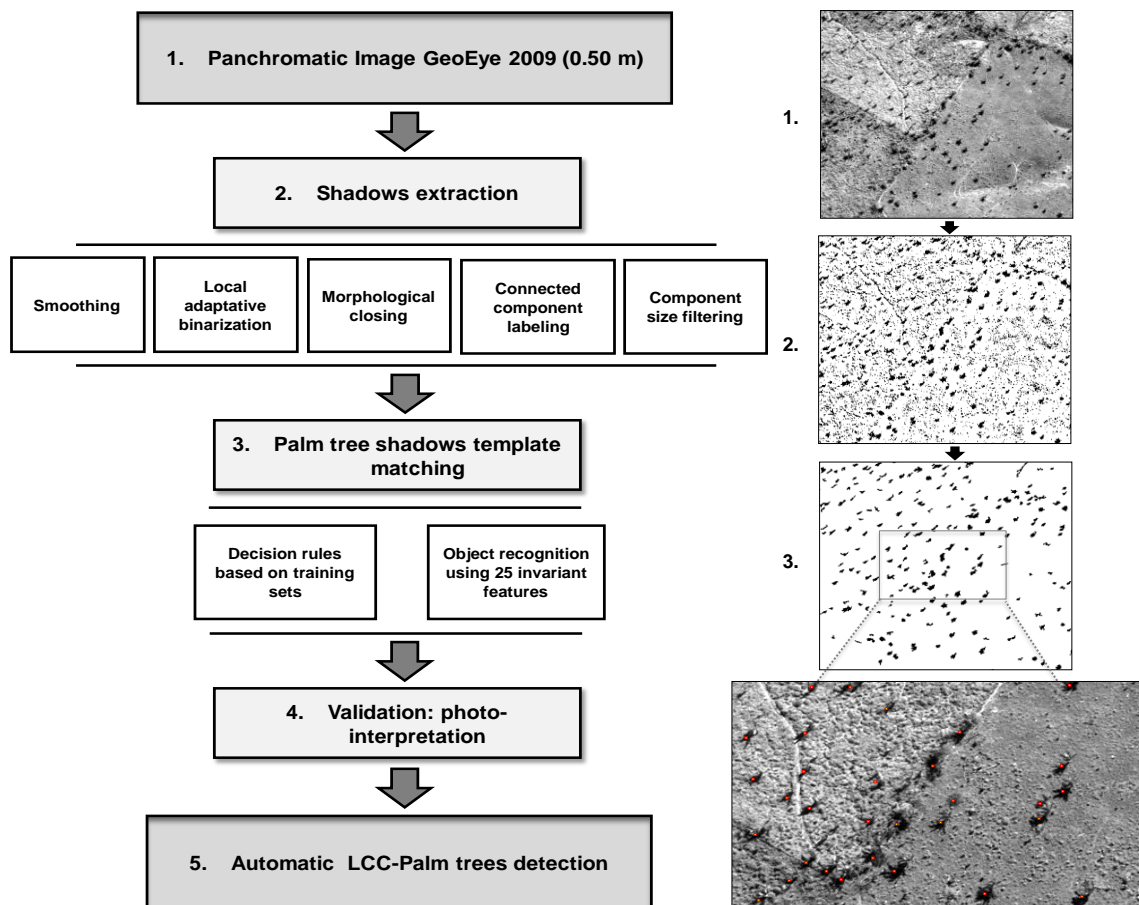
- 231 i) Classifier training with two sets of shadow images: 75 cropped images of “palm  
232 tree shadows” and 75 cropped images of “other shadows”; 25 normalized shape  
233 characteristics and invariants are computed on the whole set of the cropped images  
234 (see below for some details).
- 235 ii) Calculation of classifier entry parameters for each potential palm tree shadow and  
236 selection of the 5 closest shadow objects (Euclidian distance computation) within  
237 the training set.

238           iii) Score calculation, according to the class of the closest shadow objects, enabling  
239           appropriate classification of each shadow.

240           To characterize the palm tree shadows, we worked with the shape characteristics and  
241           invariant described in Torres-Méndez et al. (2000). For each shadow image, we first compute  
242           its moment of inertia (1 parameter). Then, using 12 concentric circles centered on the shadow  
243           centroid we count for each circle the number of intensity changes that occur (shadow/no-  
244           shadow) and the normalized difference of the two largest arcs that are not part of the shadows  
245           (12x2 parameters).

246           The result is a list of points in image or cartographic coordinates that can be compared  
247           with data obtained using image photo-interpretation. The steps by which the LCC palm tree  
248           detection algorithm proceeds are shown in Fig. 3.

249



250

251 Fig. 3. Representation of the steps of the LCC palm trees automatic detection  
252 algorithm (adapted from Demagistri et al., 2014)

253

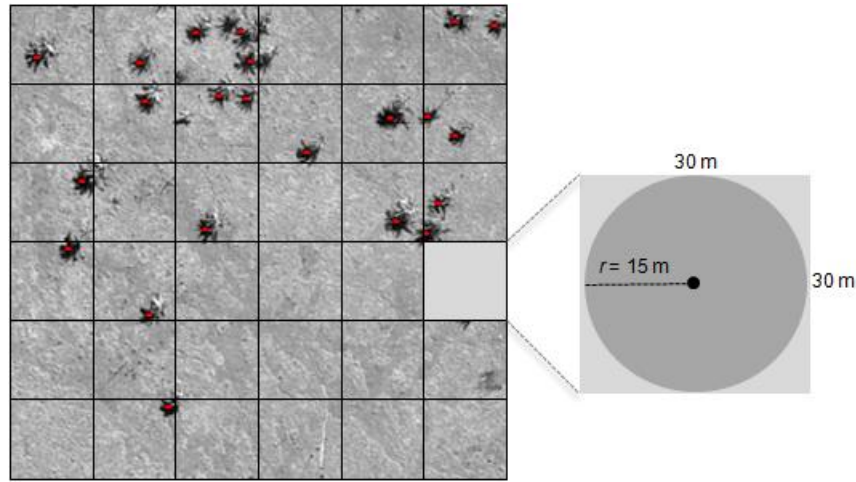
254 The algorithm was validated using image photo interpretation via a sample of 334  
255 points observed over 16 cells of 1-ha, distributed in pastures of low and average babassu  
256 density in the study area.

257 To evaluate the precision and quality of the algorithm used, were considered the  
258 factors adopted by Shufelt (1999) and Luo et al. (2014); these factors can be based on image  
259 pixel classifications or on object shape and consider the numbers of true positives (TP), false  
260 positives (FP), and false negatives (FN). The first factor is the extraction percentage, given by  
261 the expression  $100*TP/(TP+FN)$ , which can be understood as a measure of shadow extraction  
262 performance. The second factor is the branching factor, given by  $FP/TP$ , which measures  
263 delineation performance. The third factor is the quality percentage, given by  
264  $100*TP/(TP+FP+FN)$ , a general measure of method performance. According to Shufelt  
265 (1999), the use of these three measures completely evaluates model performance.

266

## 267 2.5. Density map and calculation of the babassu resource estimate

268 The palm tree location map produced by applying the algorithm to open environments  
269 on the GeoEye-1 2013 image was processed using ArcGis 10.2.2 with the Point Density tool  
270 to obtain the palm tree density map. The parameters used were the size of the raster cells (30-  
271 m) and the size and shape of the point search neighborhood (a 15 m radius circle, Fig. 4). The  
272 number of individuals per ha was used to calculate palm density.



273

274 Fig. 4. Representation of the parameters used to elaborate the density map

275

276 The number of LCC palms actually present ( $B$ ) was defined as:

277  $B=A-(A \times FP)/100+(A \times FN)/100$ ; where:  $A$  = number of points indicated by the

278 algorithm as corresponding to LCC palm trees;  $FP$  = False Positive;  $FN$  = False Negative.

279 Then, based on information from Santos and Mitja (2011) was calculated the number of

280 babassu as 93.6% of the total number of palm trees.

281 Therefore, we can calculate the number of babassu palm trees ( $C$ ) from the total LCC

282 palm trees ( $B$ ).

283 
$$C=(B \times 93.6)/100$$

284 To obtain the proportion of stage 5 and 6 individuals in the pastures we use a total

285 density of palm trees in of 17 transects, with 46.51% of stage 5 and 53.49% of stage 6.

286 Therefore, we calculated the total numbers of babassu palm trees (detected and undetected) in

287 stage 5 ( $V$ ) and stage 6 ( $W$ ) present in open areas in Benfica.

288 Adult palm trees (stage 6):

289 
$$\left\{ \begin{array}{l} C=V+W \\ \text{With } V=(46.51\% \text{ of } C), \text{ and} \\ W=(53.49\% \text{ of } C) \end{array} \right.$$

290

291

292 Finally, despite the high variation in the amount of oil extracted according to the used  
293 method, we estimated the annual potential productivity of almond oil of Benfica, using (i) the  
294 estimated density of adults at Benfica and (ii) literature data on fruit production (24 kg of  
295 fruits / palm / year on average - Anderson, 1983), seed production (1 kg of seeds from 13 kg  
296 of fruits – Gonsalves, 1955), and oil production (1 kg of crude oil from 1.68 kg of almonds -  
297 Frazão, 2001).

298

## 299 2.6. Statistical analyses

300 A principal components analysis (PCA) was used to verify differences in the structural  
301 characteristics of LCC palm trees species. The significance of the PCA was determined using  
302 the Monte Carlo permutation test at  $p < 0.05$ .

303 The structural characteristics of babassu palm trees at stages 5 and 6 were compared  
304 using the non-parametric Wilcoxon test, as were the structural characteristics of the  
305 individuals at each stage based on whether they were detected or not, using the algorithm. All  
306 statistical analyses were performed using the software R 3.1.2 (R Core Team, 2014) with the  
307 packages ADE-4 (Dray and Dufour, 2007; Dray et al., 2007).

308

## 309 **3. Results**

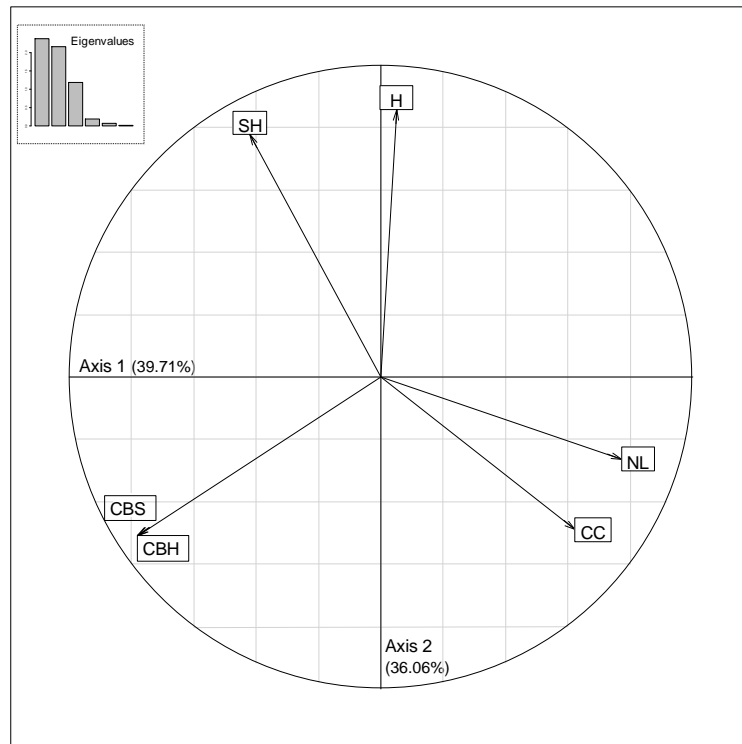
### 310 3.1. Structural characteristics of the LCC palm trees

311 The use of the shadow-detection algorithm detected the babassu palm trees and also  
312 other palm tree, especially those dominant in Benfica, such as inajá and tucumã.

313 In contrast, the PCA of the structures of the babassu, inajá and tucumã palm trees (all  
314 belonging to stage 6, i.e., adults) showed that the LCC palm trees differed structurally. The  
315 first two PCA axes explained 75.77% of the variance in the scatterplot. Axis 1 explained



316 39.71% of the variance, and the structural variables that contributed the most to this axis were  
317 circumference at breast height, circumference at the base of the stipe, number of leaves. The  
318 second axis explained 36.06% of the variance, and its most important variables were total  
319 height, stipe height (Fig. 5).



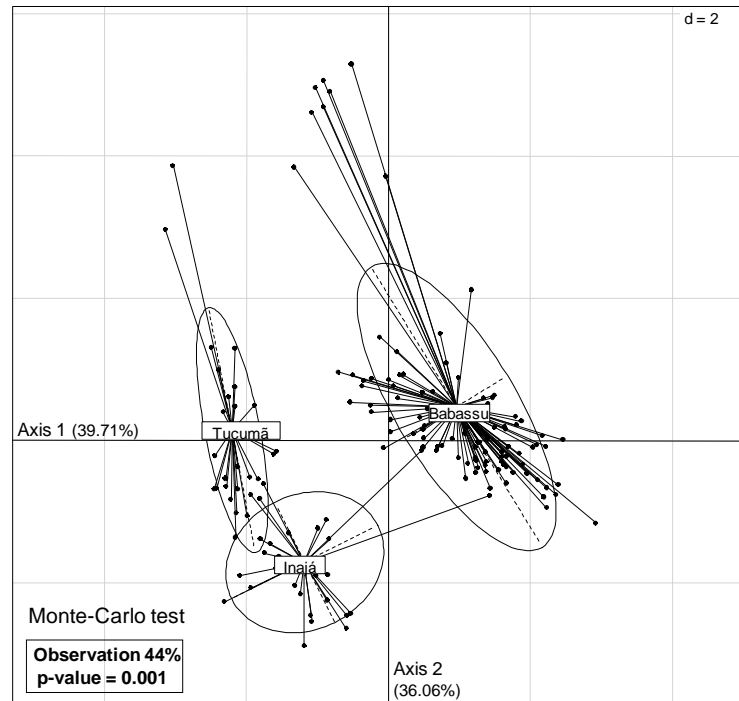
320

321 Fig. 5. The PCA using the structural variables of three palm tree species in Benfica.  
322 Circumference at breast height (CBH), circumference at the base of the stipe (CBS),  
323 number of leaves (NL), total height (H), stipe height (SH), and crown circumference (CC).

324

325 In the PCA formed by the first and second axes, the structural variables were grouped  
326 according to palm tree type: babassu, injá, and tucumã. According to a Monte Carlo test with  
327 999 permutations, 44% of the data variance was explained by palm tree species, and this value  
328 was significant ( $p=0.001$ ; Fig. 6).

329



330

331 Fig. 6. The first and second axes of the PCA regarding the structural variables of the species  
 332 *Attalea speciosa* (Babassu), *Attalea maripa* (Inajá) and *Astrocaryum aculeatum* (Tucumã) in  
 333 Benfica.

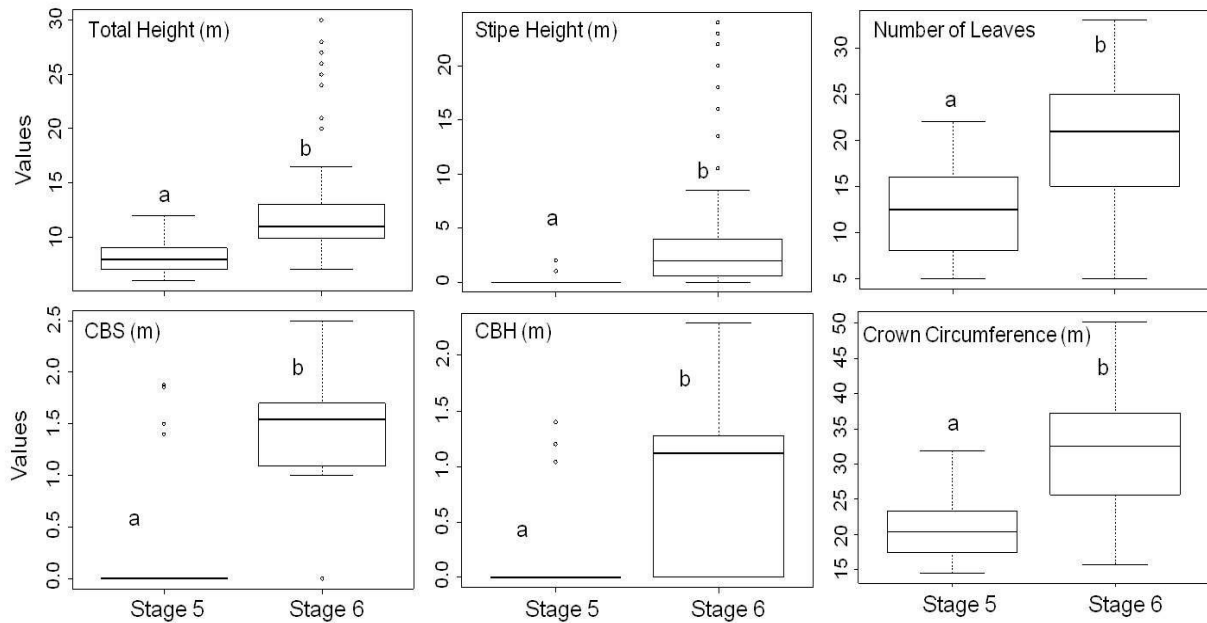
334

335 3.2. The structural characteristics of the individuals detected/undetected by the algorithm

336 The algorithm did not detect any of the stage 4 babassu palm trees identified in the  
 337 field.

338 When comparing the morphological characteristics of the stage 5 and 6 palm trees  
 339 using a boxplot (Fig. 7), we observed that the stage 6 palm trees had higher values and  
 340 significantly differed from those in stage 5 (Wilcoxon test,  $p < 0.0001$ ) for all the structural  
 341 characteristics analyzed.

342



343

344 Fig. 7. A comparison of the morphological characteristics of stage 5 (n=30) and stage 6  
 345 (n=105) *Attalea speciosa* palm trees. Each box of the plot extends from the data of quartiles 1  
 346 and 3; the horizontal lines within each box represent the median; and the circles at the  
 347 extremities represent the values close to the box. The different letters indicate that the means  
 348 are significantly different (Wilcoxon test,  $p < 0.0001$ ). CBH, circumference at breast height;  
 349 CBS, circumference at the base of the Stipe.

350

351 Approximately 96% of the stage 6 palm trees identified in the field were detected  
 352 using the algorithm based on their shadows; only 4% remained undetected. The comparison  
 353 between the mean structural characteristics of the detected and undetected individuals  
 354 revealed a significant difference (Wilcoxon test,  $p < 0.05$ ) only for the mean stipe height,  
 355 which was greater for detected palm trees than undetected palm trees (Table 1).

356

357 Approximately 60% of the stage 5 babassu palm trees identified in the field were  
 358 detected using the algorithm, and 40% were not detected (Table 1). The total height and the  
 number of leaves values of the detected and undetected individuals significantly differed

359 (Wilcoxon test,  $p < 0.05$ ), with detected individuals having larger morphological characteristic  
 360 values than their undetected counterparts.

361

362 Table 1. The morphological characteristics of stage 5 and 6 babassu palm trees, regardless of  
 363 detection using the algorithm in open areas. The means were compared using the non-  
 364 parametric Wilcoxon test. Ns: not significant; \*:  $p < 0.05$

<b>Stage 5</b> (n=30)	% Individuals	Total Height (m)	Stipe Height (m)	Number of Leaves	Circumference at the Base of the Stipe (m)	Circumference at Breast Height (m)	Crown Circumference (m)
Undetected	40	7.33	0.00	9.33	0.00	0.00	20.37
Detected	60	8.25	0.38	14.61	1.66	1.21	21.32
		*	Ns	*	Ns	Ns	Ns

<b>Stage 6</b> (n=105)	% Individuals	Total Height (m)	Stipe Height (m)	Number of Leaves	Circumference at the Base of the Stipe (m)	Circumference at Breast Height (m)	Crown Circumference (m)
Undetected	4	11.25	0.50	15.75	1.68	1.54	28.63
Detected	96	12.38	3.94	19.76	1.60	1.26	31.87
		Ns	*	Ns	Ns	Ns	Ns

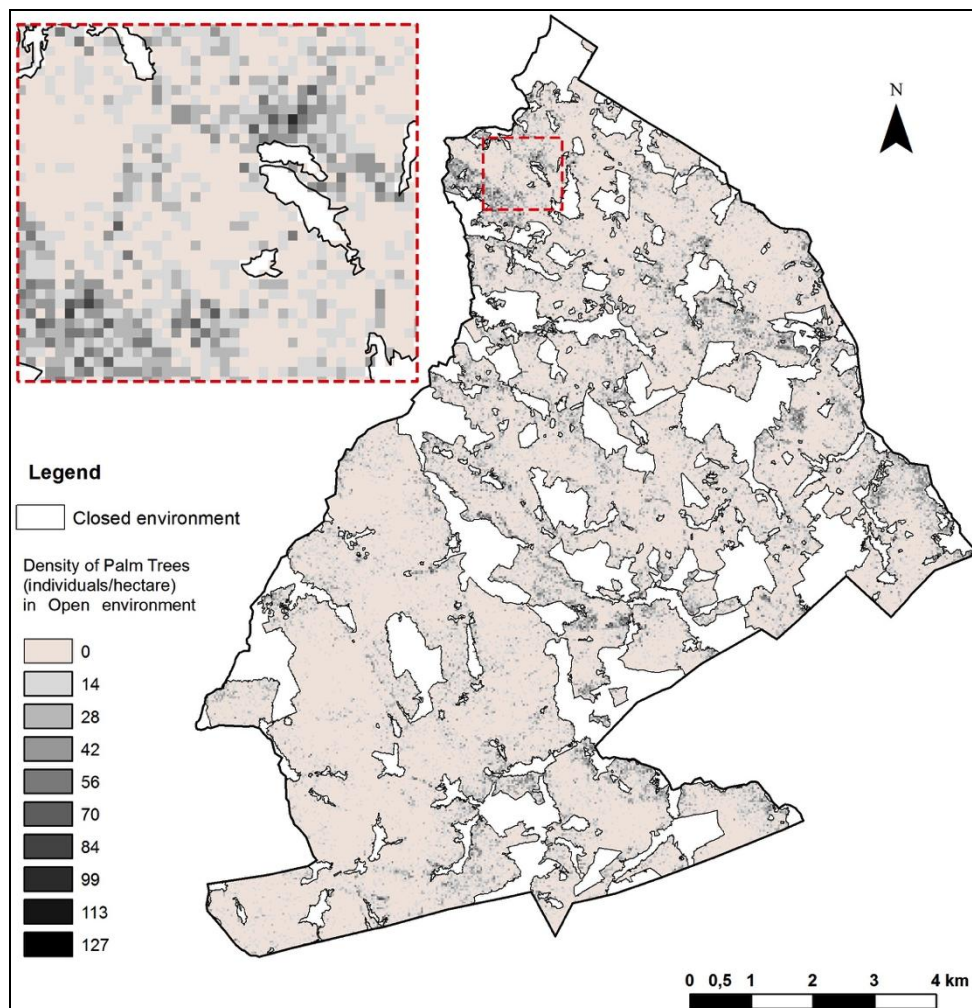
365

366

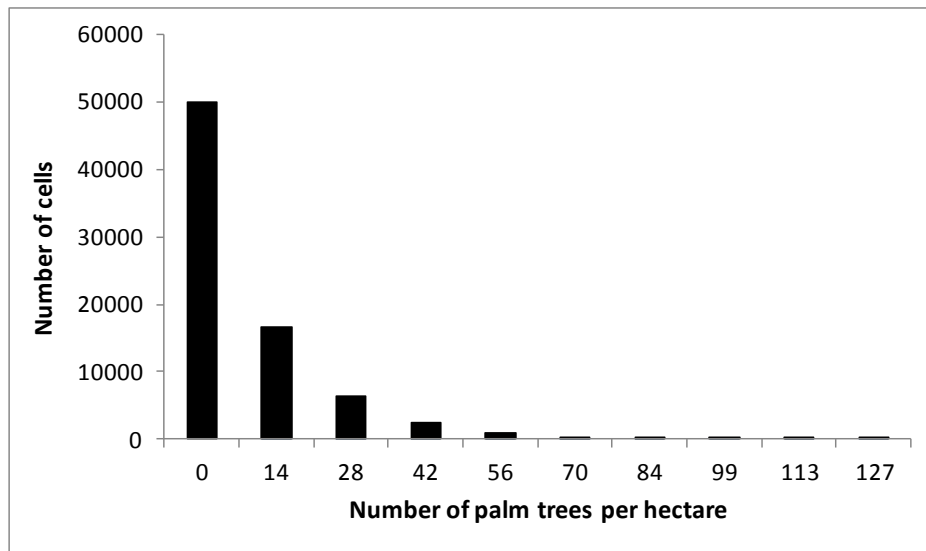
### 367 3.2. Algorithm quality and LCC palm tree density

368 When evaluating the performance of the algorithm used to automatically detect the  
 369 LCC palm trees, we considered 334 points, in which 252 (75.45%) had been correctly  
 370 identified by the algorithm (true positives), 55 (16.47%) points indicated by the algorithm that  
 371 did not correspond to palm trees (false positives), and 27 (8.08%) points corresponding to  
 372 palm trees that were not identified by the algorithm (false negatives). This analysis resulted in  
 373 90.32% of Extraction, 0.218 of Branching factor, and 75.45% of Quality.

374 A palm tree density map (Fig. 8) was created after applying the open area algorithm to  
375 the GeoEye1 2013 image. A total of 54,540 palm trees were detected in open vegetation in  
376 Benfica communities (6,870 ha). In the study area, 65% of the cells had a null density, less  
377 than 35% of the cells had a low LCC palm tree density (1 to 3 palm trees in a circle with a 15  
378 m-radius, corresponding to 14 to 42 palm trees per ha), and less than 2% of the cells had an  
379 average LCC palm tree density (4 to 9 palm trees in a circle with a 15 m-radius,  
380 corresponding to 56 to 127 palm trees per ha) (Fig. 9). The average-density areas were  
381 localized and dispersed, whereas the low-density and null-density areas occupied a large  
382 surface characterized by continuous areas.



383  
384 Fig. 8. The LCC palm tree density map in Benfica based on the application of automatic  
385 detection using the open areas algorithm with regard to the GeoEye1 2013 image



386

387 Fig. 9. A histogram of the number of cells as a function of palm tree density per ha in the  
 388 density map obtained from the GeoEye1 2013 image

389

### 390 3.3. Babassu resource density productivity estimate

391 The 54,540 LCC palm tree points detected using the GeoEye1 2013 image of Benfica  
 392 were corrected with regard to the algorithm's errors, resulting in 49,964 LCC palm trees  
 393 actually present. By applying the 93.6% rate, we obtained 46,766 babassu palm tree based on  
 394 the total number of LCC palm trees. Based on the field data of the proportion of stage 5  
 395 (46.51%) and 6 (53.49%) palm trees in the study areas, we calculated 25,015 of babassu  
 396 individuals in stage 6 (adults). Finally, we estimated that the adults in the open areas of  
 397 Benfica have an annual potential productivity of 27.4 t of almond oil.

398

## 399 Discussion

400

### 401 4.1. The contribution of the field methods to validate the remote-sensing data

402 The local densities obtained via automatic detection are accurate; however, this  
 403 information becomes much more efficient when combined with the data obtained via field

404 measurements (Zhou et al., 2013). In the present study, the measurements of the  
405 morphological characteristics of palm trees and their cartographic coordinates were essential  
406 to validate the remote-sensing data obtained using automatic detection.

407 As expected, it was not possible to differentiate between the LCC palm tree species in  
408 images with a resolution of 0.50 m. However, these species have different structures. As Kahn  
409 (1986) reported, the genera *Astrocaryum* and *Attalea* have a variety of forms: the species  
410 *Astrocaryum aculeatum* has well-developed stipes (15 to 20 cm in diameter and 15 to 25 m in  
411 height), and its leaflets are always placed on different planes (Kahn, 1986). Conversely,  
412 *Attalea speciosa* has leaflets along the same plane (Kahn, 1986). *Attalea speciosa* can reach a  
413 height of 10 to 30 m and have a stipe diameter of 30 to 60 cm (May et al., 1985; Lorenzi et  
414 al., 2010), whereas *Attalea maripa* can reach a height of 7 to 24 m, have a stipe diameter of 20  
415 to 40 cm, and leaves that are disposed in five directions (Lorenzi et al., 2010).

416 All of these forest palm trees grow in pastures and secondary vegetation (May et al.,  
417 1985; Anderson and Anderson, 1985; Kahn, 1986) where they usually reach sexual maturity  
418 earlier and grow to a smaller height than their counterparts in forests (Kahn, 1986). As palm  
419 trees increase in height, their crowns become relatively narrower (Rich et al., 1986).

420 The PCA of the structure of the LCC palm trees (*Attalea speciosa*, *Attalea maripa* and  
421 *Astrocaryum aculeatum*) present in the study area reinforces the differences in the architecture  
422 among the species and suggests that stipe circumference (axis 1) and height (axis 2) are the  
423 most important variables. Wang and Augspurger (2006) investigated the influence of palm  
424 tree crown architecture on seedling recruitment on Barro Colorado Island in Panama and La  
425 Selva forest in Costa Rica; based on a PCA, they concluded that the four palm tree species  
426 studied at each site had different growth forms and crown architectures, with the number of  
427 leaves and leaf area having the greatest influence on one axis and crown area influencing the  
428 other two axes.

429 All of the structural variables analyzed in the present study influenced the shape of the  
430 shadow of each species because different architectures can have more or less impact on the  
431 way light propagates through vegetation (Wang and Augspurger, 2006). Because we used a  
432 shadow-detection algorithm that also considers the shape of the shadow, differentiating  
433 among LCC palm tree species might be possible if an image with a better spatial resolution  
434 (i.e., less than 0.50 m) is used, given that these species have different structures. Moreover, it  
435 might be possible to create a density map specific for the babassu palm tree (*Attalea speciosa*)  
436 by extracting only the shadows that correspond to this species.

437 The validation of the information concerning stage 4, 5, and 6 of babassu palm tree,  
438 with the aid of field methods (i.e., structural census and georeferencing) regardless of the  
439 detection algorithm, enabled us to report which structural characteristics have a stronger  
440 influence on their detection using a high spatial resolution image.

441 Almost all (96%) of the stage 6 babassu palm tree were detected using the high spatial  
442 resolution satellite images, and only 4% did not have visible shadows and were not  
443 automatically detected. The numbers of leaves and the crown widths of these individuals did  
444 not significantly differ from those detected; however, their stipes were significantly smaller.

445 In turn, the stage 5 babassu palm tree were partially detected (60%). The 40% that  
446 were not detected were shorter and had fewer leaves than those detected. However, it is  
447 difficult to individually characterize the undetectable palm trees that belong to this stage  
448 based on their morphological characteristics, as was done for stage 6. Some individuals with  
449 similar morphological characteristics might not be detected because unmeasured factors might  
450 also influence shadow formation. These factors might include i) the orientation of the palm  
451 trees in relation to the sun when the image was captured by the sensor, ii) the leaf area (i.e.,  
452 leaf width by blade length) of each individual (Wang and Augspurger, 2006), and iii) the  
453 average distance between leaflets (Wang and Augspurger, 2006).



454           The algorithm most likely failed to detect stage 4 babassu palm trees because of the  
455 spatial resolution of the image used (0.50 m), given that the shadow of these individuals is  
456 nearly imperceptible or nonexistent under this resolution.

457           The babassu palm trees were divided into developmental stages to monitor the plant  
458 growth over time across different environments (i.e., forests, pastures, and secondary forests).  
459 Although this organization is biologically artificial, a continuum in babassu growth exists  
460 from the seedling to adult stages. The significant difference in the structure of individuals  
461 between stages 5 and 6 indicates that the separation of individuals into these life stages was  
462 well established. Although certain stage 5 individuals were similar to those in stage 6, stage 6  
463 palm tree usually have higher morphological characteristic values that explain their  
464 predominance among the detected plants. Because this species is native, non-cultivated, and  
465 non-domesticated where no selection is yet practiced, significant between-plant variability  
466 exists in the babassu population (Danielle Mitja, Personal communication).

467

#### 468 4.2. Algorithm performance for the automatic detection of LCC palm trees

469           The result of the detection via the algorithm (75.45% quality) was promising given  
470 that it was applied to natural, non-planted areas. In commercial plantations of the African oil  
471 palm tree, organized along lines and without other species besides the cultivated one, the  
472 detection precision reaches 90% (Srestasathiern and Rakwatin, 2014); when high spatial  
473 resolution satellite images are used, this rate is approximately 95% (Shafri et al., 2011). Even  
474 in homogeneous commercial plantations, however, issues might exist with the methods used  
475 because of the presence of objects other than the cultivated species, which are often detected  
476 as false positives (Srestasathiern and Rakwatin, 2014). Future studies should use texture  
477 information to suppress the presence of objects other than the species of interest  
478 (Srestasathiern and Rakwatin, 2014).

479 In the present study, 75.45% of the LCC palm trees were successfully detected.  
480 However, this rate might be improved by decreasing the number of false positives (as reported  
481 above) and that of false negatives (for groups composed of 2 or 3 palm trees, only 1 palm tree  
482 is detected). In the case of a false negatives, the palm tree crowns might overlap, resulting in a  
483 single shape that differs from that of an isolated palm tree. Zhou et al. (2013) also faced the  
484 challenge of crown overlap; these authors were unable to detect the canopies of closely  
485 spaced trees on a Eucalyptus plantation. Moreover, Shari et al. (2011) noted that the crown-  
486 detection method applied worked well only for isolated African oil palm trees. All these  
487 studies used a spatial resolution of 0.50 m or greater. Better resolutions (0.10 – 0.30 m) for  
488 example using drones, and the improvement of the algorithm should decrease this error.

489 Using the LCC palm tree density map, we observed that this algorithm might be used  
490 to estimate the occurrence of palm trees present in the open area of interest using a high  
491 spatial resolution image (0.50 m). One of the major advantages of mapping species of interest  
492 via high-resolution images compared with forest censuses is that this information can be  
493 obtained for large areas (Zhou et al., 2013), as it is the case in the present study, especially  
494 because multispectral and hyperspectral images are becoming more accessible.

495

496 4.3. The potential use of this technique for babassu productivity monitoring, planning, and  
497 management

498 Automatic mapping in commercial plantations seeks to identify high-mortality points  
499 (Zhou et al., 2013) and the plants affected by disease (Shari et al., 2011; Johansen et al., 2014)  
500 to define management practices. In turn, the density map of the LCC palm trees over large  
501 areas proposed here, provides a wide view of resource distribution along the entire basin and  
502 enables the identification of areas with greater densities, access and productive potential,  
503 favoring the planning of resource exploitation and management based on the interests of land

504 owners or producer associations. In addition, given the risk of overexploitation and species  
505 extinction, environmental agencies might use this tool to aid in the inspection of areas where  
506 babassu felling is prohibited by law (Porro et al., 2011) or to monitor the variation in resource  
507 density over time, as suggested by Aouragh et al. (2013) and Zhou et al. (2013) with regard to  
508 tree species.

509 Remote sensing, very high spatial resolution images, image processing, and object  
510 detection algorithms have become some of the major technologies in geospatial research,  
511 exploitation and monitoring of biodiversity (Bai et al., 2005; Clark et al., 2005; Schmidtlein et  
512 al., 2012; Engler et al., 2013; Garrity et al., 2013; Lin, 2013; Laurin et al., 2014), and  
513 commercial plantations of forest species of interest (Zhou et al., 2013; Srestasathiern and  
514 Rakwatin, 2014). The present paper seeks to contribute to the use of this technology by  
515 studying the native palm trees naturally and randomly dispersed and mixed with numerous  
516 other species.

517 Because babassu is a native species that is adapted to secondary environments (May et  
518 al., 1985; Anderson and Anderson, 1985), the expansion of the areas occupied by this species  
519 is directly related to the advancement of the agricultural frontier in the Amazon through  
520 deforestation (Teixeira, 2003). For many decades, this species has been the primary source of  
521 income for farmers in North and Northeast Brazil (Teixeira, 2003; Porro et al., 2011; Porro  
522 and Porro, 2014). However, the major hindrances within the production chain of babassu oil  
523 in Brazil are the lack of a regular supply system for quality raw materials and the scarcity of  
524 strategic partnerships with small farmers (Teixeira, 2003). The methods proposed in this study  
525 regarding the density and production capacity estimates based on the results of automatic  
526 detection will provide more precise results that might be used to simulate numerous  
527 exploitation scenarios based on different systems of fruit harvest, adult density management

528 and species regeneration time. These systems might provide farmers with better plans of  
529 action for the constant and sustainable use of the production potential of this palm tree.

530

## 531 **5. Conclusions**

532 The result of the automatic detection using the algorithm on a very high spatial  
533 resolution image (75.45% quality) was promising, given that it was applied to natural, non-  
534 planted areas.

535 The validation of the information concerning stage 4, 5, and 6 *Attalea speciosa*  
536 (babassu) palm trees using field methods (i.e., structural census and georeferencing),  
537 regardless of algorithm detection, provided information regarding which structural  
538 characteristics have a greater influence on their detection in a very high spatial resolution  
539 image. This step is important in the study of automatic detection using remote sensing images  
540 of palm trees.

541 By itself, the use of the algorithm on very high spatial resolution images does not yet  
542 deliver researchers a density map exclusively for babassu for farmers, associations or public  
543 policies. However, the detection of LCC palm trees and the implementation of auxiliary field  
544 methods to estimate the density of the species of interest is an important first step toward the  
545 large-scale monitoring of this important resource, not only by the Brazilian industry and  
546 economy but also by the thousands of families who depend on babassu extraction for  
547 subsistence.

548

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558

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