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# **An integrated pan-tropical biomass map using multiple reference datasets**

(PAN-TROPICAL FUSED BIOMASS MAP)

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26 **Abstract**

27 We combined two existing vegetation biomass datasets (Saatchi et al., 2011; Baccini et al.,  
28 2012) into a pan-tropical aboveground biomass map at 1-km resolution using an independent  
29 reference dataset of field observations and locally-calibrated high-resolution biomass maps,  
30 harmonized and upscaled to 14,477 1-km biomass estimates. Our data fusion approach uses  
31 bias removal and weighted linear averaging that incorporates and spatializes the biomass  
32 patterns indicated by the reference data. The method was applied independently in areas  
33 (strata) with homogeneous error patterns of the input (Saatchi and Baccini) maps, which were  
34 estimated from the reference data and additional covariates. Based on the fused map, we  
35 estimated biomass stocks for the tropics (23.4 N – 23.4 S) of 375 Pg dry mass, 9% - 18%  
36 lower than the Saatchi and Baccini estimates. The fused map also showed differing spatial  
37 patterns of biomass density over large areas, with higher biomass density in the dense forest  
38 areas in the Congo basin, Eastern Amazon and South-East Asia, and lower values in Central  
39 America and in most dry vegetation areas of Africa than either of the input maps. The  
40 validation exercise, based on 2,118 estimates from the reference dataset not used in the fusion  
41 process, showed that the fused map had a RMSE 15 – 21% lower than that of the input maps  
42 and, most importantly, nearly unbiased estimates (mean bias 5 Mg dry mass ha<sup>-1</sup> vs. 21 and 28  
43 Mg ha<sup>-1</sup> for the input maps). The fusion method can be applied at any scale including the  
44 policy-relevant national level, where it can provide improved biomass estimates by  
45 integrating existing regional biomass maps as input maps and additional, country-specific  
46 reference datasets.

47

48

## 49 **Introduction**

50 Recently, considerable efforts have been made to better quantify the amounts and spatial  
51 distribution of aboveground biomass, a key parameter for estimating carbon emissions and  
52 removals due to land-use change, and related impacts on climate (Saatchi et al., 2011; Baccini  
53 et al., 2012; Harris et al., 2012; Houghton et al., 2012; Mitchard et al., 2014; Achard et al.,  
54 2014). Particular attention has been given to the tropical regions, where uncertainties are  
55 higher (Pan et al., 2011; Ziegler et al., 2012; Grace et al., 2014). In addition to ground  
56 observations acquired by research networks or for forest inventory purposes, several biomass  
57 maps have been recently produced at different scales, using a variety of empirical modelling  
58 approaches based on remote sensing data calibrated by field observations (e.g., Goetz et al.,  
59 2011; Birdsey et al., 2013). Biomass maps at moderate resolution have been produced for the  
60 entire tropical belt by integrating various satellite observations (Saatchi et al., 2011; Baccini et  
61 al., 2012), while higher resolution datasets have been produced at local or national level using  
62 medium-high resolution satellite data (e.g., Avitabile et al., 2012; Cartus et al., 2014),  
63 sometimes in combination with airborne Light Detection and Ranging (LiDAR) data (Asner  
64 et al., 2012a, 2012b, 2013, 2014a). The various datasets often have different purposes:  
65 research plots provide a detailed and accurate estimation of biomass (and other ecological  
66 parameters or processes) at the local level, forest inventory networks use a sampling approach  
67 to obtain statistics of biomass stocks (or growing stock volume) per forest type at the sub-  
68 national or national level, while high-resolution biomass maps can provide detailed and  
69 spatially explicit estimates of biomass density to assist natural resource management, and  
70 large scale datasets depict biomass distribution for global-scale carbon accounting and  
71 modelling.

72

73 In the context of the United Nations mechanism for Reducing Emissions from Deforestation  
74 and forest Degradation (REDD+), emission estimates obtained from spatially explicit biomass  
75 datasets may be favoured compared to those based on mean values derived from plot  
76 networks. This preference stems from the fact that plot networks are not designed to represent  
77 land cover change events, which usually do not occur randomly and may affect forests with  
78 biomass density systematically different from the mean value (Baccini and Asner, 2013).  
79 With very few tropical countries having national biomass maps or reliable statistics on forest  
80 carbon stocks, regional maps may provide advantages compared to the use of default mean  
81 values (e.g., IPCC (2006) Tier 1 values) to assess emissions from deforestation, if their  
82 accuracy is reasonable and their estimates are not affected by systematic errors (Avitabile et  
83 al., 2011). However, these conditions are difficult to assess since proper validation of regional  
84 biomass maps remains problematic, given their large area coverage and large mapping unit  
85 (Mitchard et al., 2013), while ground observations are only available for a limited number of  
86 small sample areas.

87  
88 The comparison of two recent pan-tropical biomass maps (Saatchi et al., 2011; Baccini et al.,  
89 2012) reveals substantial differences between the two products (Mitchard et al., 2013).  
90 Further comparison with ground observations and high-resolution maps indicated  
91 substantially different biomass patterns at regional scales (Baccini and Asner, 2013; Hills et  
92 al., 2013; Mitchard et al., 2014). Such comparisons have stimulated a debate over the use and  
93 capabilities of different types of biomass products (Saatchi et al., 2014; Langner et al., 2014)  
94 and have highlighted both the importance and sometimes the lack of integration of different  
95 datasets. On one hand, the two pan-tropical maps are consistent in terms of methodology  
96 because both use the same primary data source (GLAS LiDAR) alongside a similar modelling  
97 approach to upscale the LiDAR data to larger scales. Moreover, they have the advantage of

98 being calibrated using hundreds of thousands of biomass estimates derived from height  
99 metrics computed by a spaceborne LiDAR sensor distributed over the tropics. However, such  
100 maps are based on remotely sensed variables that do not directly measure biomass, but are  
101 sensitive to canopy cover and canopy height parameters that do not fully capture the biomass  
102 variability of complex tropical forests. Furthermore, both products assume global or  
103 continental allometric relationships in which biomass varies only with stand height, and  
104 further errors are introduced by upscaling the calibration data to the coarser satellite data. On  
105 the other hand, ground plots use allometric equations to estimate biomass at individual tree  
106 level using directly measurable parameters such as diameter, height and species identity  
107 (hence wood density). However, they have limited coverage, are not error-free, and compiling  
108 various datasets over large areas is made more complex due to differing sampling strategies  
109 (e.g., stratification (or not) of landscapes, plot size, minimum diameter of trees measured).  
110 Considering the rapid increase of biomass observations at different scales and the different  
111 capabilities and limitations of the various datasets, it is becoming more and more important to  
112 identify strategies that are capable of making best use of existing information and optimally  
113 integrate various data sources for improved large area biomass assessment (e.g., see Willcock  
114 et al., 2012).

115

116 In the present study, we compiled existing ground observations and locally-calibrated high-  
117 resolution biomass maps to obtain a high-quality reference dataset of aboveground biomass  
118 for the tropical region (objective 1). This reference dataset was used to assess two existing  
119 pan-tropical biomass maps (objective 2) and to combine them in a fused map that optimally  
120 integrates the two maps, based on the method presented by Ge et al. (2014) (objective 3).  
121 Lastly, the fused map was assessed and compared to known biomass patterns and stocks  
122 across the tropics (objective 4).

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Overall, the approach consisted of pre-processing, screening and harmonizing the pan-tropical biomass maps (called ‘input maps’), the high-resolution biomass maps (called ‘reference maps’) and the field plots (called ‘reference plots’; ‘reference dataset’ refers to the maps and plots combined) to a common spatial resolution and geospatial reference system (Figure 1). The input maps were combined using bias removal and weighted linear averaging (‘fusion’). The fusion model was applied independently in areas representing different error patterns of the input maps (called ‘error strata’), which were estimated from the reference data and additional covariates (called ‘covariate maps’). The reference dataset included only a subset of the reference maps (i.e., the cells with highest confidence) and if a stratum was lacking reference data (‘reference data gaps’), additional data were extracted from the reference maps (‘consolidation’). The fused map was validated using independent data and its uncertainty quantified using model parameters. In this study, the term biomass refers to aboveground live woody biomass and is reported in units of Mg dry mass ha<sup>-1</sup>. The fused map and the corresponding reference dataset ~~will be publicly available~~[can be freely downloaded from http://www.wageningenur.nl/forestbiomass](http://www.wageningenur.nl/forestbiomass).

## 148 **Materials and methods**

### 149 **Input maps**

150 The input maps used for this study were the two pan-tropical datasets published by Saatchi et  
151 al. (2011) and Baccini et al. (2012), hereafter referred to as the Saatchi and Baccini maps  
152 individually, or collectively as input maps. The Baccini map was provided in MODIS  
153 sinusoidal projection with a spatial resolution of 463 m while the Saatchi map is in a  
154 geographic projection (WGS-84) at 0.00833 degrees (c. 1 km) pixel size. The two datasets  
155 were harmonized by first projecting the Baccini map to the coordinate system of the Saatchi  
156 map using the Geospatial Data Abstraction Library ([www.gdal.org](http://www.gdal.org)) and then aggregating it to  
157 match the spatial resolution and grid of the Saatchi map. Spatial aggregation was performed  
158 by computing the mean value of the pixels whose centre was located within each 1-km cell of  
159 the Saatchi map. Resampling was then undertaken using the nearest neighbor method.

160

### 161 **Reference dataset**

162 The reference dataset comprised individual tree-based field data and high-resolution biomass  
163 maps [independent from the input maps](#). The field data included biomass estimates derived  
164 from field measurement of tree parameters and allometric equations. The biomass maps  
165 included high-resolution ( $\leq 100$  m) datasets derived from satellite data using empirical models  
166 calibrated and validated using local ground observations and, in some cases, airborne LiDAR  
167 measurements. Given the variability of procedures used to acquire and produce the various  
168 datasets, they were first screened according to a set of quality criteria to select only the most  
169 reliable biomass estimates, and then pre-processed to be harmonized with the pan-tropical  
170 biomass maps in terms of spatial resolution and variable observed. Field and map datasets  
171 providing aboveground carbon density were converted to biomass units using the same  
172 coefficients used for their original conversion from biomass to carbon. The sources and



173 characteristics of the reference data are listed in the Supplementary Information (Tables S8 -  
174 S11).

175

## 176 **Data screening and pre-processing**

### 177 Reference field data

178 The reference field data included ground observations in forest inventory plots, for which  
179 accurate geolocation and biomass estimates were available. The pre-processing of the data  
180 consisted of a 2-step screening and a harmonization procedure. A preliminary screening  
181 selected only the ground data that estimated aboveground biomass of all living trees with  
182 diameter at breast height  $\geq 5$ -10 cm, acquired on or after the year 2000, [not used to calibrate](#)  
183 [the LiDAR-biomass relationships of the input maps](#), and where plot coordinates were  
184 measured using a GPS. Since the taxonomic identities of trees strongly indicate wood density  
185 and hence stand-level biomass (e.g., Baker et al., 2004; Mitchard et al. 2014), plots were only  
186 selected if tree biomass was estimated using at least tree diameter and wood density as input  
187 parameters. All datasets not conforming to these requirements or not providing clear  
188 information on the biomass pool measured, the tree parameters measured in the field, the  
189 allometric model applied, the year of measurement and the plot geolocation and extent were  
190 excluded. Next, the plot data were projected to the geographic reference system WGS-84 and  
191 harmonized with the input maps by averaging the biomass values located within the same 1-  
192 km pixel [if there was more than one plot per pixel, or by directly attributing the plot biomass](#)  
193 [to the respective pixel if there was only one plot per pixel](#). The field plots not fully located  
194 within one pixel were attributed to the map cell where the majority of the plot area (i.e., the  
195 plot centroid) was located.

196

197 Lastly, the representativeness of the plot over the 1-km pixels was considered, and the ground  
198 data were further screened to discard plots not representative of the map cells in terms of  
199 biomass density. More specifically, since the two input maps [in their native reference systems](#)  
200 are not aligned and therefore their pixels do not correspond to the same geographic area, the  
201 plot representativeness was assessed on the area of both pixels (identified before the map  
202 resampling). The representativeness was evaluated on the basis of the homogeneity of the tree  
203 cover and crown size within the pixel, and it was assessed using visual interpretation of high-  
204 resolution images provided on the Google Earth platform. If the tree cover and tree crowns  
205 were not homogeneous over at least 90% of the pixel area, the plots located within the pixel  
206 were discarded (Fig. S1). [In addition, if subsequent Google Earth images indicated that forest](#)  
207 [change processes \(e.g., deforestation or regrowth\) occurred in the period between the field](#)  
208 [measurement and the reference years of the input maps, the corresponding plots were also](#)  
209 [discarded.](#)~~More details on the selection procedure are provided in the Supplementary~~  
210 [Information.](#)

## 212 Reference biomass maps

213 The reference biomass maps consisted of high-~~resolution~~[quality](#) local or national maps  
214 published in the scientific literature. Maps providing biomass estimates grouped in classes  
215 (e.g., Willcock et al., 2012) were not used since the class values represent the mean biomass  
216 over large areas, usually spanning multiple strata used in the present study (see ‘Stratification  
217 approach’). The reference biomass maps were first pre-processed to match the input maps  
218 through re-projection, aggregation and resampling using the same procedures described for  
219 the pre-processing of the Baccini map. Then, only the cells with largest confidence (i.e.,  
220 lowest uncertainty) were selected from the maps. Since uncertainty maps were usually not  
221 available, and considering that the reference maps were based on empirical models, the map

222 cells with greatest confidence were assumed to be those in correspondence of the training data  
223 (field plots and/or LiDAR data). When the locations of the training data were not available,  
224 random pixels were extracted from the maps. [For maps based only on radar or optical data,](#)  
225 [whose signals saturate above a certain biomass density value, only pixels below such a](#)  
226 [threshold were considered.](#) In order to compile a reference database that was representative of  
227 the area of interest and well-balanced among the various input datasets (as defined in  
228 ‘Consolidation of the reference dataset’), the amount of reference data extracted from the  
229 biomass maps was proportional to their area and not greater than the amount of samples  
230 provided by the field datasets representing a similar area. In the case where maps with  
231 extensive training areas provided a disproportionate number of reference pixels, a further  
232 screening selected only the areas underpinned by the largest amount of training data.

233

#### 234 **Consolidation of the reference dataset**

235 Considering that the modelling approach used in this study is applied independently by  
236 stratum ([which represent areas with homogeneous error structure in both input maps,](#) see  
237 ‘Stratification approach’) and is sensitive to the characteristics of the reference data (see  
238 ‘Modelling approach’), each stratum requires that calibration data are relatively well-balanced  
239 between the various reference datasets. Specifically, if a stratum contains few calibration data,  
240 the model becomes more sensitive to outliers, while if a reference dataset is much larger than  
241 the others, the model is more strongly determined by the dominant dataset. For these reasons,  
242 [for the strata](#) where the reference dataset was under-represented or un-balanced, it was  
243 consolidated by additional reference data taken from the reference biomass maps, if available.  
244 The reference data were considered insufficient if a stratum had less than half of the average  
245 reference data per stratum, and were considered un-balanced if a single dataset provided more  
246 than 75% of the reference data of the whole stratum and it was not representative of more than

247 75% of its area. In such cases, additional reference data were randomly extracted from the  
248 reference biomass maps that did not provide more than 75% of the reference data. The  
249 amount of data to be extracted from each map was computed in a way to obtain a reference  
250 dataset with an average number of reference data per stratum and not dominated by a single  
251 dataset. If necessary, additional training data representing areas with no biomass (e.g., bare  
252 soil) were included, using visual analysis of Google Earth images to identify locations without  
253 vegetation.

254

### 255 **Selected reference data**

256 The biomass reference dataset compiled for this study consists of 14,477 1-km reference  
257 pixels, distributed as follows: 953 in Africa, 449 in South America, 7,675 in Central America,  
258 400 in Asia and 5,000 in Australia (Fig. 2, Table 1). The reference data were relatively  
259 uniformly distributed among the strata (Table S6) but their amount varied considerably by  
260 continent. The average amount of reference data per stratum ranged from 50 (Asia) to 958  
261 (Central America) 1-km reference pixels and their variability (computed as standard deviation  
262 relative to the mean) ranged from 25% (South America) to 52% (Central America). The  
263 uneven distribution of reference data across the continents is mostly caused by the availability  
264 of ground observations: as indicated above, in order to have a balanced reference dataset for  
265 each stratum the reference data extracted from biomass maps were limited to the (smaller)  
266 amount of direct field observations. When biomass maps were the only source of data this  
267 constrain was not occurring and larger datasets could be derived from the maps (i.e., Central  
268 America, Australia).

269

270 The reference data were selected from 18 ground datasets and from 9 high-resolution biomass  
271 maps calibrated by field observations and, in 4 cases, airborne LiDAR data (Table 1). The

272 field plots used for the calibration of the maps are not included in this section because they  
273 were only used to select the reference pixels from the maps. The visual screening of the field  
274 plots removed 35% of the input data (from 6,627 to 4,283) and their aggregation to 1-km  
275 resolution further removed 70% of the reference units derived from field plots (from 4,283 to  
276 1,274), while 10,741 reference pixels were extracted from the high-resolution biomass maps.  
277 The criteria used to select the reference pixels for each map are reported in Table S2. The  
278 consolidation procedure was necessary only for Central America where it added 2,415  
279 reference data, while 47 pixels representing areas with no biomass were identified in Asia  
280 (Table S1). In general, ground observations were mostly discarded in areas characterized by  
281 fragmented or heterogeneous vegetation cover and high biomass spatial variability. In such  
282 contexts, reference data were often acquired from the biomass maps.

283

### 284 **Stratification approach**

285 Preliminary comparison of the reference data with the input maps showed that the error  
286 variances and biases of the input maps were not spatially homogeneous but varied  
287 considerably in different regions. Since the fusion model used in this study (see ‘Modelling  
288 approach’) is based on bias removal and weighted combination of the input maps, the more  
289 homogeneous the error characteristics in the input maps are, the better they can be reduced by  
290 the model. For this reason, the stratification approach aimed at identifying areas with  
291 homogeneous error structure (hereafter named ‘error strata’) in both input maps. A first  
292 stratification was done by geographic location (namely Central America, South America,  
293 Africa, Asia and Australia) to reflect the regional allometric relationships between biomass  
294 and tree diameter and height (Feldpausch et al., 2011, 2012). Then, the error strata were  
295 identified for each continent, using a two-step process. Firstly, the error maps of the Saatchi  
296 and Baccini maps were predicted separately. [Since the biomass estimates of the input maps](#)

297 were mostly based on optical and LiDAR data that are sensitive to tree cover and tree height,  
298 it was assumed that their uncertainties were related to the spatial variability of these  
299 parameters. In addition, the errors of the input maps resulted to be linearly correlated with the  
300 respective biomass estimates. For these reasons, the biomass maps themselves as well as  
301 global datasets of ~~on the basis of their biomass estimates and~~ land cover (ESA, 2014a), tree  
302 cover (Di Miceli et al., 2014) and tree height (Simard et al., 2011) ~~parameters by~~ were used to  
303 predict the map errors using a Random Forest model (Breiman, 2001), calibrated on the basis  
304 of the reference dataset. Secondly, the error maps of the Saatchi and Baccini datasets were  
305 clustered using the K-Means approach. Eight clusters (hence, eight error strata) was  
306 considered as a sensible trade-off between homogeneity of the errors of the input maps and  
307 number of reference observations available per stratum, with a larger number of clusters  
308 providing only a marginal increase in homogeneity but leading to a small number of reference  
309 data in some strata (Fig. S2). In areas where the predictors presented no data (i.e., outside the  
310 coverage of the Baccini map) or for classes of the categorical predictor without reference data  
311 (i.e., land cover) the error strata (instead of the error maps) were predicted using an additional  
312 Random Forest model based on the predictors without missing values (i.e., Saatchi map, tree  
313 cover and tree height) and 10,000 training data randomly extracted from the stratification map.

314

315 This method produced a stratification map that identifies eight strata for each continent with  
316 homogeneous error patterns in the input maps (Fig. S3). The root mean square error (RMSE)  
317 computed on the Out-Of-Bag data (i.e., data not used for training) of the Random Forest  
318 models that predicted the errors of the input maps ranged between  $22.8 \pm 0.3 \text{ Mg ha}^{-1}$  (Central  
319 America) to  $83.7 \pm 2.5 \text{ Mg ha}^{-1}$  (Africa), with the two models (one for each input map)  
320 achieving similar accuracies in each continent (Table S4, Fig. S4). In most cases the main  
321 predictors of the errors of the input maps were the biomass values of the maps themselves,

322 followed by tree cover and tree height, while land cover was always the least important  
323 predictor (Table S5). Further details on ~~error modelling and the~~ processing of the input data  
324 are provided in the Supplementary Information.

325

326 The use of a stratification based on the errors of the input maps was compared with a  
327 stratification based on an alternative variable, ~~such as~~ namely land cover (used by Ge et al.,  
328 2014), tree cover ~~or and~~ tree height. A separate stratification map was obtained for each of  
329 these alternative variables by aggregating them ~~Each of these variables was aggregated~~ into  
330 eight ~~classes~~ strata (to maintain comparability with the number of clusters used in the error  
331 strata), and each stratification map was used to develop a specific fused map. The  
332 performance of alternative stratification approaches was assessed by validating the respective  
333 fused maps (see Supplementary Information – Alternative stratification approaches). The  
334 results demonstrated that the stratification based on error modelling and clustering (i.e., the  
335 error strata) produced a fused map with higher accuracy than that of the maps based on other  
336 stratification approaches, and therefore was used in this study (Fig. S5).

337

## 338 **Modelling approach**

### 339 **The fusion model**

340 The integration of the two input maps was performed with a fusion model based on the  
341 concept presented by Ge et al. (2014) and further developed for this study. The fusion model  
342 consists of bias removal and weighted linear averaging of the input maps to produce an output  
343 with greater accuracy than each of the input maps. The reference biomass dataset described  
344 above was used to calibrate the model and to assess the accuracy of the input and fused maps.  
345 A specific model was developed for each stratum.

346

347 Following Ge et al. (2014), the  $p$  input maps for locations  $s \in D$ , where  $D$  is the geographical  
348 domain of interest common to the input maps, were combined using a weighted linear average:

$$349 \quad (1) \quad f(s) = \sum_{i=1}^p w_i(s) \cdot (z_i(s) - v_i(s))$$

350 where  $f$  is the fused map, the  $w_i(s)$  are weights,  $z_i$  the estimate of the  $i$ -th input map and  $v_i(s)$  is  
351 the bias estimate. The bias term was computed as the average difference between the input  
352 map and the reference data [for each stratum](#). The weights were obtained from a statistical  
353 model that assumes the map estimates  $z_i$  to be the sum of the true biomass  $b_i$  with a bias term  
354  $v_i$  and a random noise term  $\varepsilon_i$  with zero mean for each location  $s \in D$ . We further assumed that  
355 the  $\varepsilon_i$  of the input maps are jointly normally distributed with variance-covariance matrix  $C(s)$ .  
356 Differently from Ge et al. (2014),  $C(s)$  was estimated using a robust covariance estimator as  
357 implemented by the ‘robust’ package in R (Wang et al., 2014), which uses the Stahel-Donoho  
358 estimator for strata with fewer than 5,000 observations and the Fast Minimum Covariance  
359 Determinant estimator for larger strata. Under these assumptions, the variance of the  
360 estimation error of the fused map  $f(s)$  is minimized by calculating the weights  $w(s)$  as Searle  
361 (1971, p. 89):

$$362 \quad (2) \quad w(s)^T = (\mathbf{1}^T C(s)^{-1} \mathbf{1})^{-1} \mathbf{1}^T C(s)^{-1}$$

363 where  $\mathbf{1} = [1, \dots, 1]^T$  is the  $p$ -dimensional unit vector and where  $T$  means transpose. [The sum of](#)  
364 [the weights computed for each stratum is equal to 1 and their value is inversely proportional](#)  
365 [to the error variance of the map](#). Larger weights were assigned to the map with lower error  
366 variance, [i.e. to the map able to provide more accurate estimates after its bias has been](#)  
367 [removed](#). The fusion model assured that the variance of the error in the fused map was smaller  
368 than that of the input maps (Bates and Granger, 1969), especially if the errors associated with  
369 these maps were not strongly positively correlated and their error variances were close to the  
370 smallest error variance. The fusion model can be applied to any number of input maps. Where



371 there is only one input map, the model estimates and removes its bias and the weights are set  
372 equal to 1.

373

#### 374 **The model parameters**

375 The fusion model computed a set of bias and weight parameters for each stratum and  
376 continent on the basis of the respective reference data, and used these for the linear weighted  
377 combination of the input maps (Table S6). Since the stratification approach grouped together  
378 data with similar error patterns, the biases varied considerably among the strata and could  
379 reach values up to  $\pm 200 \text{ Mg ha}^{-1}$ . However, considering the area of the strata, the biases of  
380 both input maps were smaller than  $\pm 45 \text{ Mg ha}^{-1}$  for at least 50% of the area of all continents  
381 and smaller than  $\pm 100 \text{ Mg ha}^{-1}$  for 81% - 98% of the area of all continents.

382

#### 383 **Post-processing**

##### 384 **Predictions outside the coverage of the Baccini map**

385 The Baccini map covers the tropical belt between 23.4 degree north latitude and 23.4 degree  
386 south latitude while the Saatchi map presents a larger latitudinal coverage (Fig. 2). The fusion  
387 model was firstly applied to the area common to both input maps (Baccini extent) and then  
388 extended to the area where only the Saatchi map is available. In the latter area, the model  
389 focused only on removing the bias of the Saatchi map using the values estimated for the  
390 Baccini extent. The model predictions for the Saatchi extent were mosaicked to those for the  
391 Baccini extent using a smoothing function (inverse distance weight) on an overlapping area of  
392 1 degree within the Baccini extent between the two maps. Water bodies were masked over the  
393 whole study area using the ESA CCI Water Bodies map (ESA, 2014**b**). The resulting fused  
394 map was projected to an equal area reference system (MODIS Sinusoidal) before computing

395 the total biomass stocks for each continent, which were obtained by summing the products of  
396 the biomass density of each pixel with their area.

397

### 398 **Assessing biomass in intact and non-intact forest**

399 The biomass estimates of the fused and input maps in forest areas were further investigated  
400 regarding their distribution in ecozones and between intact and non-intact landscapes. Forest  
401 areas were defined as areas dominated by tree cover according to the GLC2000 map ([Mayaux](#)  
402 [Bartholomé and Belward, 2005](#)~~et al., 2004~~). Ecozones were defined according to the Global  
403 Ecological Zone (GEZ) map for the year 2000 (FAO, 2000). The intact landscapes were  
404 defined according to the Intact Forest Landscape (IFL) map for the year 2000 (Potapov et al.,  
405 2008). On the basis of these datasets the mean forest biomass density of the fused and input  
406 maps were computed for intact and non-intact landscapes for each continent and major  
407 ecozone. To allow direct comparison of the results among the maps, the analysis was  
408 performed only for the area common to all maps (Baccini extent). In addition, to reduce the  
409 impact of spatial inaccuracies in the maps, only ecozones with [IFL](#) intact forest areas larger  
410 than 1,000 km<sup>2</sup> were considered. The mean biomass density of intact and non-intact forests  
411 per continent was computed as the area-weighted mean of the contributing ecozones.

412

### 413 **Validation and uncertainty**

414 Validation [of the fused and input maps](#) was performed by randomly splitting the reference  
415 data into a calibration set (70% of the data) and a validation set (remaining 30%). The ‘final’  
416 fused map presented in Fig. 3 used 100% of the reference data ~~and while~~ for validation  
417 purposes a ‘test’ fused map was produced using only the calibration data and its estimates, as  
418 well as those of the input maps, were compared with the validation data. [Thus, the validation](#)  
419 [results refer to the ‘test’ fused map based only on the calibration set and are expected to be](#)

420 [representative \(if not conservative\) of the accuracy of the ‘final’ fused map based on all the](#)  
421 [reference data.](#) To maintain full independence, validation data were not used for any step  
422 related to the development of the ‘test’ fused map, including production of the stratification  
423 map. To account for any potential impacts of the random selection of validation data, the  
424 procedure was repeated 100 times, computing each time a new random selection of the  
425 calibration and validation datasets. This procedure allowed computing the mean RMSE and  
426 assessing its standard deviation for ~~each~~[the fused and input maps.](#)

427  
428 The uncertainty of the fused map was computed with respect to model uncertainty, not  
429 including the error sources in the input data (see ‘Discussion’). The model uncertainty  
430 consisted of the expected variance of the error of the fused map (which is assumed bias-free)  
431 and was derived for each stratum from  $C(s)$ , [hence the uncertainty was estimated by strata and](#)  
432 [not at pixel level.](#) The error variance was converted to an uncertainty map by reclassifying the  
433 stratification map, [where the stratum value was converted to the respective error variance](#)  
434 [computed for each stratum and continent.](#)

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## 451 **Results**

### 452 **Biomass map**

453 The fusion model produced a biomass map at 1-km resolution for the tropical region, with an  
454 extent equal to that of the Saatchi map (Fig. 3). In terms of aboveground stocks, the fused  
455 map gave biomass estimates lower than both input maps at continental level. The total stock  
456 for the tropical belt covered by the Baccini map (23.4 N – 23.4 S, see Fig. 2) was 375 Pg dry  
457 mass, 9% and 18% lower than the Saatchi (413 Pg) and Baccini (457 Pg) estimates,  
458 respectively. Considering the larger extent of the Saatchi map, the fused map estimate was  
459 462 Pg, 15% lower than the estimate of the Saatchi map (545 Pg) (Table S7).

460

461 Moreover, the fused map presented spatial patterns substantially different from both input  
462 maps (Fig. 4): the biomass estimates were higher than the Saatchi and Baccini maps in the  
463 dense forest areas in the Congo basin, in West Africa, in the north-eastern part of the Amazon  
464 basin (Guyana shield) and in South-East Asia, and lower in Central America and in most dry  
465 vegetation areas of Africa. In the central part of the Amazon basin the fused map showed  
466 lower estimates than the Baccini map and higher estimates than the Saatchi map, while in the  
467 southern part of the Amazon basin these differences were inverted. Similar trends emerged  
468 when comparing the maps separately for intact and non-intact forest ecozones (Supporting  
469 Information). In addition, the average difference between intact and non-intact forests was

470 larger than that derived from the input maps in Africa and Asia, similar or slightly larger in  
471 South America, and smaller in Central America (Fig. S6).

472

473 The fused map records the highest biomass density ( $> 400 \text{ Mg ha}^{-1}$ ) in the Guyana shield, in  
474 the Central and Western part of the Congo basin and in the intact forest areas of Borneo and  
475 Papua New Guinea. The analysis of the distribution of forest biomass in intact and non-intact  
476 ecozones showed that, according to the fused map, the mean biomass density was greatest in  
477 intact African ( $360 \text{ Mg ha}^{-1}$ ) and Asian ( $335 \text{ Mg ha}^{-1}$ ) forests, followed by intact forests in  
478 South America ( $266 \text{ Mg ha}^{-1}$ ) and Central America ( $146 \text{ Mg ha}^{-1}$ ) (Fig. S6). Biomass in non-  
479 intact forests was much lower in all regions (Africa,  $78 \text{ Mg ha}^{-1}$ ; Asia,  $211 \text{ Mg ha}^{-1}$ ; South  
480 America,  $149 \text{ Mg ha}^{-1}$ ; and Central America,  $57 \text{ Mg ha}^{-1}$ ) (Fig. S6).

481

## 482 **Validation**

483 The validation exercise showed that the fused map achieved a lower RMSE (a decrease of 5 –  
484 74%) and bias (a decrease of 90 – 153%) than the input maps for all continents (Fig. 5). While  
485 the RMSE of the fused map was consistently lower than that of the input maps but still  
486 substantial ( $87 - 98 \text{ Mg ha}^{-1}$ ) in the largest continents (Africa, South America and Asia), the  
487 mean error (bias) of the fused map was almost null in most cases. Moreover, in the three main  
488 continents the bias of the input maps tended to vary with biomass, with overestimation at low  
489 values and underestimation at high values, while the errors of the fused map were more  
490 consistently distributed (Fig. 6). When computing the error statistics for the pan-tropics  
491 (Baccini extent) as average of the regional validation results weighted by the respective area  
492 coverage, the mean bias (in absolute terms) for the fused, Saatchi and Baccini maps was 5, 21  
493 and  $28 \text{ Mg ha}^{-1}$  and the mean RMSE was 89, 104 and  $112 \text{ Mg ha}^{-1}$ , respectively (Fig. 5). The  
494 accuracy of the input maps reported above was computed using the validation dataset (30% of

495 the reference dataset) to be consistent with the accuracy of the fused map. The accuracy of the  
496 input maps was also computed using all reference data and the results (Table S3) were similar  
497 to those based on the validation dataset.

498

### 499 **Uncertainty map**

500 | The uncertainty of the model predictions ~~at 1 km resolution~~ indicated that the standard  
501 deviation of the error of the fused map for each stratum was in the range 11 - 108 Mg ha<sup>-1</sup>,  
502 with largest uncertainties in areas with largest biomass estimates (Congo basin, Eastern  
503 Amazon basin and Borneo). When computed in relative terms (as percentage of the biomass  
504 estimate) the model uncertainties presented opposite patterns, with uncertainties larger than  
505 the estimates (> 100%) in low biomass areas (< 20 Mg ha<sup>-1</sup> on average) of Africa, South  
506 America and Central America, while high biomass forests (> 210 Mg ha<sup>-1</sup> on average) had  
507 uncertainties lower than 25% (Fig. 7). The uncertainty measure derived from C(s) is  
508 computed only when two or more input maps are available. Hence it could not be calculated  
509 for Australia because the model for this continent was based on only one input map (Saatchi  
510 map).

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## **Discussion**

### **Biomass patterns and stocks emerging from the reference data**

The biomass map produced with the fusion approach is largely driven by the reference dataset and essentially the method is aimed at spatializing the biomass patterns indicated by the reference data using the support of the input maps. For this reason, great care was taken in the pre-processing of the reference data, which included a two-step quality screening based on metadata analysis and visual interpretation, and their consolidation after stratification. As a result, the reference dataset provides an unprecedented compilation of biomass estimates at 1-km resolution for the tropical region, covering a wide range of vegetation types, biomass ranges and ecological regions across the tropics. It includes the most comprehensive and accurate tropical field plot networks and high-quality maps calibrated with airborne LiDAR, which provide more accurate estimates compared to those obtained from other sensors (Zolkos et al., 2013). The main trends present in the fused map emerged from the combination of different and independent reference datasets and are in agreement with the estimates derived from long-term research plot networks (Malhi et al., 2006; Phillips et al., 2009; Lewis et al., 2009; Slik et al., 2010, 2013; Lewis et al., 2013) and high-resolution maps (Asner et al., 2012a, 2012b, 2013, 2014a). Specifically, the biomass patterns in South America represent spatial trends described by research plot networks in the dense intact and non-intact forests in the Amazon basin, forest inventory plots collected in the dense forests of Guyana and samples extracted from biomass maps for Colombia and Peru representing a wide range of vegetation types, from arid grasslands to humid forests. Similarly, biomass patterns depicted in Africa

545 were derived from a combination of various research plots in dense undisturbed forest (Gabon,  
546 Cameroon, Democratic Republic of Congo, Ghana, Liberia), inventory plots in forest  
547 concessions (Democratic Republic of Congo), biomass maps in woodland and savannah  
548 ecosystems (Uganda, Mozambique) and research plots and maps in montane forests (Ethiopia,  
549 Madagascar). Most vegetation types in Central America, Asia and Australia were also well-  
550 represented by the extensive forest inventory plots (Indonesia, Vietnam and Laos) and high-  
551 resolution maps (Mexico, Panama, Australia).

552

553 In spite of the extensive coverage, the current database is far from being representative of the  
554 biomass variability across the tropics. As a consequence, the model estimates are expected to  
555 be less accurate in contexts not adequately represented. In the case of the fusion approach, this  
556 corresponds to the areas where the input maps present error patterns different than those  
557 identified in areas with reference data: in such areas the model parameters used to correct the  
558 input maps (bias and weight) may not adequately reflect the errors of the input maps and  
559 hence cannot optimally correct them. In particular, deciduous vegetation and heavily  
560 disturbed forest of Africa and South America, and large parts of Asia were lacking quality  
561 reference data. Moreover, even though plot data were spatially distributed over the central  
562 Amazon and the Congo basin, large extents of these two main blocks of tropical forest have  
563 never been measured (cf. maps in Lewis et al., 2013; Mitchard et al., 2014). Considering the  
564 evidence of significant local differences in forest structure and biomass density within the  
565 same forest ecosystems (Kearsley et al., 2013), additional data are needed to strengthen the  
566 confidence of the fused map as well as that of any other biomass map covering the tropical  
567 region. Moreover, a dedicated gap analysis to assess the main regions lacking biomass  
568 reference data and identify priority areas for new field sampling and LiDAR campaigns would  
569 be very valuable for future improved biomass mapping.



570

571 Regarding the biomass stocks, a previous study showed that despite their often very strong  
572 local differences the two input maps tended to provide similar estimates of total stocks at  
573 national and biome scales and presented an overall net difference of 10% for the pan-tropics  
574 (Mitchard et al., 2013). However, such convergence is mostly due to compensation of  
575 contrasting estimates when averaging over large areas. The larger differences with the  
576 estimates of the present study (9% and 18%) suggest an overestimation of the total stocks by  
577 the input maps. This is in agreement with the results of two previous studies that, on the basis  
578 of reference maps obtained by field-calibrated airborne LiDAR data, identified an  
579 overestimation of 23% - 42% of total stocks in the Saatchi and Baccini maps in the  
580 Colombian Amazon (Mitchard et al., 2013) and a mean overestimation of about 100 Mg ha<sup>-1</sup>  
581 for the Baccini map in the Colombian and Peruvian Amazon (Baccini and Asner, 2013).

582

583 In general, the biomass density values of the fused map were calibrated and therefore in  
584 agreement with the existing estimates obtained from plot networks and high-resolution maps.  
585 The comparison of mean biomass values in intact and non-intact forests stratified by ecozone  
586 provided further information on the differences among the maps. The mean biomass values of  
587 the fused map in non-intact forests were mostly lower than those of the input maps,  
588 suggesting that in disturbed forests the biomass estimates derived from stand height  
589 parameters retrieved by spaceborne LiDAR (as in the input maps) tend to be higher compared  
590 to those based on tree parameters or very high-resolution airborne LiDAR measurements (as  
591 in the fused map and reference data). This difference occurred especially in Africa, Asia and  
592 Central America while it was less evident in South America and Australia. By contrast, the  
593 differences among the maps for intact forests varied by continent, with the fused map having,  
594 on average, higher mean biomass values in Africa, Asia and Australia, lower values in Central

595 America, and variable trends within South America, reflecting the different allometric  
596 relationships used by the various datasets in different continents.

597

598 As mentioned above, a larger amount of reference data, ideally acquired based on a clear  
599 statistical sampling design, instead of an opportunistic one, will be required to confirm such  
600 conclusions. While dense sampling of tropical forests using field observations is often  
601 impractical, new approaches combining sufficient ground observations of individual trees at  
602 calibration plots with airborne LiDAR measurements for larger sampling transects would  
603 allow a major increase in the quantity of calibration data. In combination with wall-to-wall  
604 medium resolution satellite data (e.g., Landsat) these may be capable of achieving high  
605 accuracy over large areas (10% - 20% uncertainty at 1-ha scale) while being cost-effective  
606 (e.g., Asner et al., 2013, 2014b). In addition, new technologies, such as terrestrial LiDAR  
607 scanning, allows for better estimates at ground level (Calders et al., 2015; [Gonzalez de](#)  
608 [Tanago et al., 2015](#)), reducing considerably the uncertainties of field estimates based on  
609 generalized allometric equations without employing destructive sampling. Nevertheless, since  
610 floristic composition influences biomass at multiple scales (e.g., the strong pan-Amazon  
611 gradient in wood density shown by ter Steege et al., 2006) such techniques benefit from  
612 extensive and precise measurements of tree identity in order to determine wood density  
613 patterns and to account for variations in hollow stems and rottenness (Nogueira et al., 2006).  
614 [Moreover, we note that the reference data do not include lianas, which may constitute a](#)  
615 [substantial amount of woody stems, and their inclusion would allow to obtain more correct](#)  
616 [estimates of total aboveground biomass of vegetation \(Phillips et al., 2002; Schnitzer &](#)  
617 [Bongers, 2011; Durán & Gianoli, 2013\).](#)

618

619 **Additional error sources**

620 Apart from the uncertainty of the fusion model described above (see ‘Uncertainty’), three  
621 other sources of error were identified and assessed in the present approach: i) errors in the  
622 reference dataset; ii) errors due to temporal mismatch between the reference data and the  
623 input maps; iii) errors in the stratification map.

624

### 625 **Errors in the reference dataset**

626 The reference dataset is not error-free but it inherits the errors present in the field data and  
627 local maps. In addition, additional uncertainties are introduced during the pre-processing of  
628 the data by resampling the maps and by upscaling the plot data to 1-km resolution. In  
629 particular, while the geolocation error of the original datasets was considered relatively small  
630 (< 50 m) since plot coordinates were collected using GPS measurements and the biomass  
631 maps were based on satellite data with accurate geolocation (i.e., Landsat, ALOS, MODIS),  
632 larger errors (up to 500 m, half a pixel) could have been introduced with the resampling of the  
633 1-km input maps. All these error sources were minimized by selecting only the datasets that  
634 fulfilled certain quality criteria and by further screening them by visual analysis of high-  
635 resolution images available on the Google Earth platform, discarding the data not  
636 representative of the respective map pixels. In case of reference data that clearly did not  
637 match with the high-resolution images and/or with the input maps (e.g., reporting no biomass  
638 in dense forest areas or high biomass on bare land), the data were considered as an error in the  
639 reference dataset, a geolocation error in the plots or maps, or it was assumed that a land  
640 change process occurred between the plot measurement and the image acquisition time (see  
641 next paragraph).

642

### 643 **Errors due to temporal mismatch**

644 The temporal difference of input and reference data introduced some uncertainty in the fusion  
645 model. The input maps refer to the years 2000 – 2001 (Saatchi) and 2007 – 2008 (Baccini)  
646 while the reference data mostly spanned the period 2000 – 2013. Therefore, the differences  
647 between the input maps and the reference data may also be due to a temporal mismatch of the  
648 datasets. However, changes due to deforestation were most likely excluded during the visual  
649 selection of the reference data, when high-resolution images showed clear land changes (e.g.,  
650 bare land or agriculture) in areas where the input maps provided biomass estimates relative to  
651 forest areas (or vice-versa, depending on the timing of acquisition of the datasets). However,  
652 changes due to forest regrowth and forest degradation events that did not affect the forest  
653 canopy could not be considered with the visual analysis and may have affected the mismatch  
654 observed between the reference data and the input maps ( $< 58 - 80 \text{ Mg ha}^{-1}$  for 50% of the  
655 cases of the Saatchi and Baccini maps, respectively). Part of the mismatch was in the range of  
656 biomass changes due to regrowth ( $1 - 13 \text{ Mg ha}^{-1} \text{ year}^{-1}$ ) (IPCC, 2003) or low-intensity  
657 degradation ( $14 - 100 \text{ Mg ha}^{-1}$ , or 3 – 15% of total stock) (Asner et al., 2010; Pearson et al.,  
658 2014). On the other hand, considering the limited area affected by degradation (about 20% in  
659 the humid tropics) (Asner et al., 2009), the temporal mismatch could be responsible only for a  
660 correspondent part of the differences observed between the reference data and the input maps.  
661 Small additional offsets may also be caused by the documented secular changes in biomass  
662 density within intact tropical forests, which has been increasing by 0.2 – 0.5% per year  
663 (Phillips et al., 1998, Chave et al., 2008, Phillips and Lewis, 2014). It should also be noted  
664 that the reference data were used to optimally integrate the input maps, and in the case of a  
665 temporal difference the fused map was ‘actualized’ to the state of the vegetation when the  
666 reference data were acquired. [The reference data were acquired between 2000 and 2013, and  
667 their mean acquisition year weighted by their contribution to the fusion model \(by continent\)  
668 corresponds to the period 2007 – 2010 \(2007 in Africa, 2008 in Central America, 2009 in](#)

669 | [South America and 2010 in Asia](#)). Therefore the [complete](#) fused map cannot be attributed to a  
670 | specific year and [more generally](#) it represents the first decade of the 2000's.

671

## 672 **Errors in the stratification map**

673 | The errors in the stratification map (i.e., related to the prediction of the errors of the input  
674 | maps) were still substantial in some areas and affected the fused map in two ways. First, the  
675 | reference data that were erroneously attributed to a certain stratum introduced 'noise' in the  
676 | estimation of the model parameters (bias and weight), but the impact of these 'outliers' was  
677 | largely reduced by the use of a robust covariance estimator. Second, erroneous predictions of  
678 | the strata caused the use of incorrect model parameters in the combination of the input maps.  
679 | The latter is considered to be the main source of error of the fused map and indicates that the  
680 | method can achieve improved results if the errors of the input maps can be predicted more  
681 | accurately. However, additional analysis showed that, on average, fused maps based on  
682 | alternative stratification approaches achieved lower accuracy than the map based on an error  
683 | stratification approach (Fig. S5). Therefore, this approach was preferred over a stratification  
684 | based on an individual biophysical variable (e.g., tree cover, tree height, land cover or  
685 | ecozone).

686

## 687 **Application of the method at national scale**

688 | The fusion method presented in this study allows for the optimal integration of any number of  
689 | input maps to match the patterns indicated by the reference data. However, the accuracy of the  
690 | fused map depends on the availability of reference data representative of the error patterns of  
691 | the input maps. While the current reference database does not represent adequately all error  
692 | strata for the tropical region, and the model estimates are expected to have lower confidence  
693 | in under-represented areas, the proposed method may be applied locally and provide

694 improved biomass estimates where additional reference data are available. For example, the  
695 fusion method may be applied at national level using existing forest inventory data, research  
696 plots and local maps that cover only part of the country to calibrate global or regional maps,  
697 which provide national coverage but may not be tailored to the country context. Such country-  
698 calibrated biomass maps may be used to support natural resource management and national  
699 reporting under the REDD+ mechanism, especially for countries that have limited capacities  
700 to map biomass from remote sensing data (Romijn et al., 2012). Considering the increasing  
701 number of global or regional biomass datasets based on different data and methodologies  
702 expected in the coming years, and that likely there will not be a single ‘best map’ but rather  
703 the accuracy of each will vary spatially, the fusion approach may allow to optimally combine  
704 and adjust available datasets to local biomass patterns identified by reference data.

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## References

- Achard F, Beuchle R, Mayaux P et al. (2014) Determination of tropical deforestation rates and related carbon losses from 1990 to 2010. *Global Change Biology*, **20**, 2540–2554.
- Asner GP, Clark JK, Mascaro J et al. (2012a) High-resolution mapping of forest carbon stocks in the Colombian Amazon. *Biogeosciences*, **9**, 2683–2696.
- Asner GP, Clark JK, Mascaro J et al. (2012b) Human and environmental controls over aboveground carbon storage in Madagascar. *Carbon Balance and Management*, **7**, 2.
- Asner GP, Mascaro J, Anderson C et al. (2013) High-fidelity national carbon mapping for resource management and REDD+. *Carbon balance and management*, **8**, 7.
- Asner GP, Knapp DE, Martin RE et al. (2014a) Targeted carbon conservation at national scales with high-resolution monitoring. *Proceedings of the National Academy of Sciences*, **111**, E5016–E5022.
- Asner GP, Mascaro J (2014b) Mapping tropical forest carbon: Calibrating plot estimates to a simple LiDAR metric. *Remote Sensing of Environment*, **140**, 614–624.
- Avitabile V, Herold M, Henry M, Schullius C (2011) Mapping biomass with remote sensing: a comparison of methods for the case study of Uganda. *Carbon Balance and Management*, **6**, 7.
- Avitabile V, Baccini A, Friedl MA, Schullius C (2012) Capabilities and limitations of Landsat and land cover data for aboveground woody biomass estimation of Uganda. *Remote Sensing of Environment*, **117**, 366–380.



768 Baccini A, Goetz SJ, Walker WS et al. (2012) Estimated carbon dioxide emissions from  
769 tropical deforestation improved by carbon-density maps. *Nature Climate Change*, **2**,  
770 182–185.

771 Baccini A, Asner GP (2013) Improving pantropical forest carbon maps with airborne LiDAR  
772 sampling. *Carbon Management*, **4**, 591–600.

773 [Bartholomé E, Belward a. S \(2005\) GLC2000: a new approach to global land cover mapping](#)  
774 [from Earth observation data. \*International Journal of Remote Sensing\*, \*\*26\*\*, 1959–1977.](#)

775 Bates JM, Granger CWJ (1969) The Combination of Forecasts. *Journal of the Operational*  
776 *Research Society*, **20**, 451–468.

777 Birdsey R, Angeles-Perez G, Kurz W a et al. (2013) Approaches to monitoring changes in  
778 carbon stocks for REDD+. *Carbon Management*, **4**, 519–537.

779 Breiman L (2001) Random forests. *Machine Learning*, **45**, 5–23.

780 Calders K, Newnham G, Burt A et al. (2015) Nondestructive estimates of above-ground  
781 biomass using terrestrial laser scanning. *Methods in Ecology and Evolution*, **6**, 198–208.

782 Cartus O, Kellndorfer J, Walker W, Franco C, Bishop J, Santos L, Michel-Fuentes JM (2014)  
783 A National, Detailed Map of Forest Aboveground Carbon Stocks in Mexico. *Remote*  
784 *Sensing*, **6**, 5559–5588.

785 Chave J, Olivier J, Bongers F et al. (2008) Above-ground biomass and productivity in a rain  
786 forest of eastern South America. *Journal of Tropical Ecology*, **24**, 355–366.

787 [DiMiceli CM, Carroll ML, Sohlberg RA et al. \(2011\) Annual Global Automated MODIS](#)  
788 [Vegetation Continuous Fields \(MOD44B\) at 250 m Spatial Resolution for Data Years](#)  
789 [Beginning Day 65, 2000 - 2010, Collection 5 Percent Tree Cover, University of](#)  
790 [Maryland, College Park, MD, USA](#)

791 [ESA \(2014a\) Global land cover map for the epoch 2005. \*http://www.esa-landcover-cci.org/\*](#)

792 [ESA \(2014b\) Global Water Bodies. \*http://www.esa-landcover-cci.org/\*](#)

793 FAO (2000) Global ecological zoning for the global forest resources assessment 2000. FAO  
794 FRA Working Paper Rome, Italy; 2001

795 Feldpausch TR, Banin L, Phillips OL et al. (2011) Height-diameter allometry of tropical  
796 forest trees. *Biogeosciences*, **8**, 1081–1106.

797 Feldpausch TR, Lloyd J, Lewis SL et al. (2012) Tree height integrated into pantropical forest  
798 biomass estimates. *Biogeosciences*, **9**, 3381–3403.

799 Ge Y, Avitabile V, Heuvelink GBM, Wang J, Herold M (2014) Fusion of pan-tropical  
800 biomass maps using weighted averaging and regional calibration data. *International*  
801 *Journal of Applied Earth Observation and Geoinformation*, **31**, 13–24.

802 Goetz S, Dubayah R (2011) Advances in remote sensing technology and implications for  
803 measuring and monitoring forest carbon stocks and change. *Carbon Management*, **2**,  
804 231–244.

805 [Gonzalez de Tanago J, Bartholomeus H, Joseph S et al. \(2015\) Terrestrial LiDAR and 3D tree](#)  
806 [Quantitative Structure Model for quantification of aboveground biomass loss from](#)  
807 [selective logging in a tropical rainforest of Peru. In: Proceedings of Silvilaser 2015](#)  
808 [Conference. La Grande Motte, France. 28-30 September 2015.](#)

809 Grace J, Mitchard E, Gloor E (2014) Perturbations in the carbon budget of the tropics. *Global*  
810 *Change Biology*.

811 Harris NL, Brown S, Hagen SC et al. (2012) Baseline Map of Carbon Emissions from  
812 Deforestation in Tropical Regions. *Science*, **336**, 1573–1576.

813 Hill TC, Williams M, Bloom-a A, Mitchard ET-a, Ryan CM (2013) Are Inventory Based and  
814 Remotely Sensed Above-Ground Biomass Estimates Consistent? *PLoS ONE*, **8**, 1–8.

815 Houghton RA, House JI, Pongratz J et al. (2012) Carbon emissions from land use and land-  
816 cover change. *Biogeosciences*, **9**, 5125–5142.

817 Jiahui W, Zamar R, Marazzi A, et al. (2014) robust: Robust Library. R package version 0.4-  
818 16. <http://CRAN.R-project.org/package=robust>.

819 Kearsley E, de Haulleville T, Hufkens K et al. (2013) Conventional tree height-diameter  
820 relationships significantly overestimate aboveground carbon stocks in the Central Congo  
821 Basin. *Nature communications*, **4**, 2269.

822 IPCC (2003) Good practice guidance for land use, land-use change and forestry. IPCC  
823 National Greenhouse Gas Inventories Programme, Technical Support Unit. Hayama,  
824 Japan: Institute for Global Environmental Strategies.

825 IPCC (2006) 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Prepared by  
826 the National Greenhouse Gas Inventories Programme, Eggleston HS, Buendia L, Miwa  
827 K, Ngara T and Tanabe K (eds). Published: IGES, Japan.

828 Langner A, Achard F, Grassi G (2014) Can recent pan-tropical biomass maps be used to  
829 derive alternative Tier 1 values for reporting REDD+ activities under UNFCCC?  
830 *Environmental Research Letters*, **9**, 124008.

831 Lewis SL, Lopez-Gonzalez G, Sonké B et al. (2009) Increasing carbon storage in intact  
832 African tropical forests. *Nature*, **457**, 1003–1006.

833 Lewis SL, Sonké B, Sunderland T et al. (2013) Above-ground biomass and structure of 260  
834 African tropical forests. *Philosophical transactions of the Royal Society of London.*  
835 *Series B, Biological sciences*, **368**, 20120295.

836 Malhi Y, Wood D, Baker TR et al. (2006) The regional variation of aboveground live biomass  
837 in old-growth Amazonian forests. *Global Change Biology*, **12**, 1107–1138.

838 ~~[Mayaux P, Bartholome E, Fritz S, Belward A \(2004\) A New Land Cover Map of Africa for](#)~~  
839 ~~[the Year 2000. \*Journal of Biogeography\*, \*\*31\*\*, 861–877.](#)~~

840 Mitchard ET, Saatchi SS, Baccini A, Asner GP, Goetz SJ, Harris NL, Brown S (2013)  
841       Uncertainty in the spatial distribution of tropical forest biomass: a comparison of pan-  
842       tropical maps. *Carbon balance and management*, **8**, 10.

843 Mitchard ET, Feldpausch TR, Brienen RJW et al. (2014) Markedly divergent estimates of  
844       Amazon forest carbon density from ground plots and satellites. *Global Ecology and*  
845       *Biogeography*, **23**, 935–946.

846 Nogueira MA, Diaz G, Andrioli W, Falconi FA, Stangarlin JR (2006) Secondary metabolites  
847       from *Diplodia maydis* and *Sclerotium rolfsii* with antibiotic activity. *Brazilian Journal of*  
848       *Microbiology*, **37**, 14–16.

849 Pan Y, Birdsey RA, Fang J et al. (2011) A large and persistent carbon sink in the world's  
850       forests. *Science*, **333**, 988–993.

851 Pearson TRH, Brown S, Casarim FM (2014) Carbon emissions from tropical forest  
852       degradation caused by logging. *Environmental Research Letters*, **034017**, 11.

853 Phillips O L, Malhi Y, Higuchi N et al. (1998) Changes in the carbon balance of Tropical  
854       Forests: Evidence from long-term plots. *Science*, **282**, 439–442.

855 Phillips OL, Aragão LEOC, Lewis SL et al. (2009) Drought sensitivity of the Amazon  
856       Rainforest. *Science*, **323**, 1344–1347.

857 Phillips OL, Lewis SL (2014) Evaluating the tropical forest carbon sink. *Global Change*  
858       *Biology*, **20**, 2039–2041.

859 Potapov P, Yaroshenko A, Turubanova S et al. (2008) Mapping the world's intact forest  
860       landscapes by remote sensing. *Ecology and Society*, **13**.

861 Romijn E, Herold M, Kooistra L, Murdiyarso D, Verchot L (2012) Assessing capacities of  
862       non-Annex I countries for national forest monitoring in the context of REDD+.  
863       *Environmental Science and Policy*, **19-20**, 33–48.

864 Saatchi SS, Harris NL, Brown S et al. (2011) Benchmark map of forest carbon stocks in  
865 tropical regions across three continents. *Proceedings of the National Academy of*  
866 *Sciences*, 108, 9899–9904.

867 Saatchi SS, Mascaro J, Xu L et al. (2014) Seeing the forest beyond the trees. *Global Ecology*  
868 *& Biogeography*, **23**, 935 – 946.

869 Searle SR (1971) *Linear Models*, Vol. XXI. WILEY-VCH Verlag, York-London-Sydney-  
870 Toronto, 532 pp.

871 [Simard M, Pinto N, Fisher JB, Baccini A \(2011\) Mapping forest canopy height globally with](#)  
872 [spaceborne lidar. \*Journal of Geophysical Research: Biogeosciences\*, 116, 1–12.](#)

873 Slik JWF, Aiba SI, Brearley FQ et al. (2010) Environmental correlates of tree biomass, basal  
874 area, wood specific gravity and stem density gradients in Borneo’s tropical forests.  
875 *Global Ecology and Biogeography*, **19**, 50–60.

876 Slik JWF, Paoli G, Mcguire K et al. (2013) Large trees drive forest aboveground biomass  
877 variation in moist lowland forests across the tropics. *Global Ecology and Biogeography*,  
878 **22**, 1261–1271.

879 Ter Steege H, Pitman NC a, Phillips OL et al. (2006) Continental-scale patterns of canopy  
880 tree composition and function across Amazonia. *Nature*, **443**, 444–447.

881 Willcock S, Phillips OL, Platts PJ et al. (2012) Towards Regional, Error-Bounded Landscape  
882 Carbon Storage Estimates for Data-Deficient Areas of the World. *PLoS ONE*, **7**, 1–10.

883 Wright JS (2013) The carbon sink in intact tropical forests. *Global Change Biology*, **19**, 337–  
884 339.

885 Ziegler AD, Phelps J, Yuen JQ et al. (2012) Carbon outcomes of major land-cover transitions  
886 in SE Asia: Great uncertainties and REDD+ policy implications. *Global Change*  
887 *Biology*, **18**, 3087–3099.

888 Zolkos SG, Goetz SJ, Dubayah R (2013) A meta-analysis of terrestrial aboveground biomass  
889 estimation using lidar remote sensing. *Remote Sensing of Environment*, **128**, 289–298.

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912 **Supporting Information**

913 **Appendix S1.** Supplementary methods and results

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## 933 **Tables**

934 **Table 1: Number of reference data (plots and 1-km pixels) selected after the screening, upscaling and**  
935 **consolidating procedures, per continent. The reference data selected for each individual dataset are**  
936 **reported in Table S1. The field plots underpinning the reference biomass maps are not included.**

<b>Continent</b>	<b>Available</b>	<b>Selected</b>		<b>Consolidated</b>
	<i>Plots</i>	<i>Plots</i>	<i>Pixels</i>	<i>Pixels</i>
<b>Africa</b>	2,281	1,976	953	953
<b>S. America</b>	648	474	449	449
<b>C. America</b>	-	-	5,260	7,675
<b>Asia</b>	3,698	1,833	353	400
<b>Australia</b>	-	-	5,000	5,000
<b>Total</b>	<b>6,627</b>	<b>4,283</b>	<b>12,015</b>	<b>14,477</b>

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949 **Figure captions**

950 **Figure 1: methodology flowchart**

951 **Figure 2: Biomass reference dataset for the tropics and spatial coverage of the two input maps**

952 **Figure 3: Fused map, representing the distribution of live woody aboveground biomass (AGB) for all land**  
953 **cover types at 1-km resolution for the tropical region.**

954 **Figure 4: Difference maps obtained by subtracting the fused map from the Saatchi map (top) and the**  
955 **Baccini map (bottom).**

956 **Figure 5: RMSE (left) and bias (right) of the fused and input maps per continent obtained using**  
957 **independent reference data not used for model development. The error bars indicate one standard**  
958 **deviation of the 100 simulations. Numbers reported in brackets indicate the number of reference**  
959 **observations used for each continent. The results for the pan-tropics exclude Asutralia, which is not**  
960 **covered by the Baccini map.**

961 **Figure 6: scatterplots of the validation reference data (x-axis) and predictions (y-axis) of the input maps**  
962 **(left plots) and fused map (right plots) by continent.**

963 **Figure 7: Uncertainty of the fused map, in absolute values (top) and relative to the biomass estimates**  
964 **(bottom), representing one standard deviation of the error of the fused map.**

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