Height and biomass of mangroves in Africa from ICEsat/GLAS and SRTM

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Abstract

The accurate quantification of forest 3-D structure is of great importance for studies of the global carbon cycle and biodiversity. These studies are especially relevant in Africa, where deforestation rates are high and the lack of background data is great. Mangrove forests are ecologically significant and it is important to measure mangrove canopy heights and biomass. The objectives of this study are to estimate: 1. The total area, 2. Canopy height distributions and 3. Aboveground biomass of mangrove forests in Africa. To derive mangrove 3-D structure and biomass maps, we used a combination of mangrove maps derived from Landsat ETM+, LiDAR canopy height estimates from ICEsat/GLAS (Ice, Cloud, and land Elevation Satellite/Geoscience Laser Altimeter System) and elevation data from SRTM (Shuttle Radar Topography Mission) for the African continent. More specifically, we extracted mangrove forest areas on the SRTM DEM using Landsat based landcover maps. The LiDAR (Light Detection and Ranging) measurements from the large footprint GLAS sensor were used to derive local estimates of canopy height and calibrate the Interferometric Synthetic Aperture Radar (InSAR) data from SRTM. We then applied allometric equations relating canopy height to biomass in order to estimate above ground biomass (AGB) from the canopy height product. The total mangrove area of Africa was estimated to be 25 960 km^2 with 83 % accuracy. The largest mangrove areas and greatest total biomass was found in Nigeria covering 8 573 km^2 with 132 x10^6 Mg AGB. Canopy height across Africa was estimated with an overall root mean square error of 3.55 m. This error also includes the impact of using sensors with different resolutions and geolocation error which make comparison between measurements sensitive to canopy heterogeneities. This study provides the first systematic estimates of mangrove area, height and biomass in Africa. Our results showed that the combination of ICEsat/GLAS and SRTM data is well suited for vegetation 3-D mapping on a continental scale.

1. Introduction

The measurement of forest biomass is crucial for carbon cycle and climate change studies. However, the amount and distribution of forest biomass is still poorly understood. Global estimates of terrestrial biomass range from 385 x 10^9 Mg, to 650 x 10^9 Mg and forests alone hold about 70-90% of the terrestrial biomass (Houghton *et al.* 2009). Mangrove forests only cover about 1% of the Earth's terrestrial surface, but they are amongst the highest carbon storing and exporting ecosystems globally (Dittmar *et al.* 2006, Donato *et al.* 2011).

Estimating distribution and biomass of mangrove forests is challenging due to the difficult physical environment of these forests. They are constantly inundated by diurnal

tides and the characteristic aboveground roots often hinder *in situ* measurements. Large-scale field measurements of mangroves are therefore rare to inexistent. The measurements that do exist are usually tailored towards a particular study, and the sampling and measurement methodologies vary. In Africa, studies of mangroves have focused on forest composition and zonation (Adams 2004; Dahdouh-Guebas 2004a; De Boer 2002; Ukpong 1995), management and utilization of mangrove products (Traynor and Hill 2008; Crona *et al.* 2009), the degradation of mangroves (Kruitwagen *et al.* 2008), and the ecology of mangrove-associated fauna (Faunce and Serafy, 2006). Recent assessments of mangrove cover in Africa mostly cover small areas, which makes the comparison with countrywide statistics difficult (Dahdouh-Guebas *et al.* 2004b). With the emergence of new remote sensing methodologies, it is now possible to systematically map mangrove spatial distribution and 3-D structure (Simard *et al.* 2006, 2008; Fatoyinbo *et al.* 2008; Lucas *et al.* 2007).

Optical Remote Sensing techniques have proven a reliable tool for the estimation of mangrove forest area globally, as shown by the large number of studies (Aschbacher *et al.* 1995; Smith *et al.* 1998; Dahdouh-Guebas *et al.* 2000; Kovacs *et al.* 2001; Satyanarayana *et al.* 2001; Dahdouh-Guebas *et al.* 2002; Sulong *et al.* 2002; Cohen and Lara, 2003; Gesche *et al.* 2004; Wang *et al.* 2003). The most comprehensive database of global mangrove cover is maintained by the UNEP World Conservation Monitoring Center, which published the World Mangrove Atlas (Spalding, 1997). This database is based on a review of the mangrove literature and mangrove cover estimated from multiple studies, datasets and methodologies.

For Africa in particular, the data, methodologies and timeframe used to generate the mangrove maps vary greatly, and a systematic methodology is needed to derive mangrove cover estimates. An updated version of global maps has recently been published (Giri *et al.* 2011). However, to obtain 3D structure and biomass, in addition to spatial distribution, active remote sensing from LiDAR and InSAR (Interferometric Synthetic Aperture Radar), are the best measurement tools available.

The only global InSAR and LiDAR datasets currently available are from the spaceborne SRTM (Shuttle Radar Topography Mission), and ICEsat/GLAS (Ice, Cloud and land Elevation Satellite/Geosciences Laser Altimetry System). The Shuttle Radar Topography Mission (SRTM), (Farr *et al.* 2007), was flown aboard the Space Shuttle Endeavor in February 2000 (Rodriguez, 2006). The SRTM measured terrain topography using dual antennae C-band Interferometric Synthetic Aperture Radar (InSAR), covering areas from 56 ° S' and 60º N'. SRTM data is freely available at 1-arcsecond (30m) resolution for the United States and 3-arcsecond (90m), resolution globally. The SRTM DEM (Digital Elevation Model) is the most accurate, globally consistent elevation dataset covering 80% of the earth's landmasses. The SRTM height measurement is in fact biased by vegetation structure and can therefore be used to estimate canopy height (Kellndorfer *et al.* 2004). The GLAS instrument recorded full waveform altimetry using a 1064nm laser that operated from 2003 to 2009. The LiDAR footprint has an approximate diameter of 70 m, which is separated by 172 m along track (Schutz, 2005). In tropical regions, sampling is greatly hindered by consistent cloud cover. Although it was primarily a mission designed for the measurement of icesheet dynamics, it has been used to measure vegetation structure (Lefsky *et al.* 2005, 2007; Rosette et al. 2010). Previous work in the Santa Marta region of Colombia (Simard *et al.* 2008) has shown the possibility of using

95 spaceborne InSAR (Interferometric SAR) and LiDAR data integration, to measure 3-D
96 vegetation structure and biomass in mangroves.
97   The objectives of this study are to: 1) estimate mangrove heights on a continental
98 scale from InSAR and LiDAR integration; 2) estimate the total AGB of mangrove forest
99 in Africa and 3) estimate the associated errors in our measurements. In this study, we
100 produce the first continental scale maps of mangrove spatial distribution, 3-D structure
101 and above ground biomass (AGB), for Africa. We address new challenges introduced by
102 large-scale mapping that are related to the variety of the biogeographical setting as well
103 as the accuracy and sampling of data.
104
105 **2. MATERIALS AND METHODS**
106
107   *2.1. Study areas*
108
109 In continental Africa, mangroves grow in coastal areas ranging from Mauritania (19º
110 N'), in the North West to Angola (10º S'), in the South West, and from South Africa (29º
111 S'), in the South East to Egypt (28º N'), in the North East, including Madagascar. On the
112 Atlantic Coast of Western Africa there are a total of 7 indigenous species plus one
113 introduced mangrove palm, *Nypa fruticans*, which are also found on the Atlantic and
114 Pacific coasts of the Americas (Spalding et al. 1997). The indigenous species are:
115 *Acrostichum aureum, Avicennia germinans, Conocarpus erectus, Laguncularia*
116 *racemosa, Rhizophora harrisonii, Rhizophora mangle* and *Rhizophora racemosa.* The
117 distribution limit of mangroves coincides with arid regions with rainfall below 30
118 mm/year (Saenger and Bellan, 1995).
119 On the Indian Ocean and Red Sea coastlines, the mangrove area is relatively small
120 compared to the total length of the coastline, due to very arid conditions in areas North of
121 the equator. There are fourteen species of mangrove present in this area, which differ
122 from the west coast species. They are: *Acrostichum aureum, Avicenna marina, Bruguiera*
123 *cylindrical, Bruguiera gymnorrhiza, Ceriops tagal, Excoecaria agallocha, Heritiera*
124 *littoralis, Lumnitzera racemosa, Pemphis acidula, Rhizophora mucronata, Rhizophora*
125 *racemosa, Sonneratia alba, Sonneratia caseolaris* and *Xylocarpus granatum.* The largest
126 diversity on the continent is found in Mozambique, where ten of the species are present
127 (Spalding *et al.* 1997).
128
129   *2.2. Mangrove extent from Landsat*
130
131 LANDSAT TM GeoCover data was acquired from the University of Maryland
132 Global Land Cover Facility (http://glcf.umd.edu). The GeoCover dataset consists of
133 Landsat data that has near global coverage and is available for three time periods ranging
134 from 1973 to 2001. The Landsat ETM data used in this study had been orthorectified and
135 georeferenced (Tucker *et al.* 2004).
136 A total of 117 Landsat ETM+ scenes from 1999 to 2002 were subset to include only
137 low elevation coastal areas where mangroves may be present. All areas with elevations
138 lower than 40 m were identified using the SRTM DEM. An unsupervised ISODATA
139 classification was then applied to each Landsat image subset to discriminate mangroves
140 from other types of vegetation (Green *et al.* 1998; Fatoyinbo *et al.* 2008). The
141 classification was filtered using previously published maps, the World Mangrove Atlas

141 (Spalding *et al.* 1997), visual inspection and high-resolution imagery from Google Earth
142 software. The resulting classes were manually combined into a final classification with 4
143 landcover types (mangrove, other vegetation, bare ground and water). In mangrove
144 forests in Central Africa, in particular Gabon and the Democratic Republic of Congo, no
145 cloudless Landsat scenes were available. In these areas with persistent cloud cover, we
146 had to use cloud free Landsat data from 1989.
147   There are no local maps with known accuracy or sufficient field data available to
148 assess relative accuracy. Therefore, we based our estimation of classification accuracy on
149 an independent and systematic method for selecting validation points. We used points
150 separated by 900 m (10 pixels), along a North-South running transect. The points were
151 also spaced by 0.5 degrees longitude for the coast running from Senegal to Nigeria. For
152 the remaining areas, we used points separated by 900 m along an East-West running
153 transect, and spaced by 0.5 degrees latitude. We assessed mapping accuracy by visual
154 interpretation of high-resolution images in Google Earth software. We only used points
155 that were classified or identified as mangroves on the landcover map or in Google earth.
156
157 ### *2.3. Measurement of tree height from LiDAR-InSAR fusion*
158
159   ICESat/GLAS waveforms were acquired from the National Snow and Ice Data Center
160 (NSIDC) website (http://nsidc.org/data/icesat). We used the GLA14 (Global land
161 altimetry) data product to estimate canopy height. A total of 327 waveforms were used to
162 estimate tree height in this study, as GLAS footprints were not available in all mangrove
163 areas. GLAS data was available for sites in Senegal, Gambia, Guinea Bissau, Guinea,
164 Nigeria, Cameroon, Gabon, Congo, Angola, Mozambique, Tanzania, Kenya, Eritrea and
165 Madagascar.
166   The GLA14 product was produced by fitting up to six Gaussian distributions to the
167 GLAS LiDAR waveform (Zwally *et al.* 2003). The shape and position of the Gaussians
168 distributions describe the canopy vertical structure within the LiDAR footprint. It is
169 generally assumed that the Gaussian peak furthest from the sensor is the ground return
170 and the beginning of the waveform signal (i.e. first return with voltage above the noise
171 level) is the return from the top of the canopy (Harding and Carabajal, 2005). The
172 cumulative distribution (i.e. percentile) of the energy within the waveform is generally
173 used to describe the vertical distribution of scatterers (e.g. leaves and branches) within
174 the canopy. The percentile is computed from the beginning of the waveform (i.e. last
175 return above the noise level). A relative height (rh_x) is defined as the distance between
176 the point where the percentile energy reaches x and the location of the ground peak
177 defined as rh_0 (Lefsky *et al.* 2005, Lefsky *et al.* 2007). Figure 1 shows an example of a
178 waveform and the location of GLAS footprints used.
179   We only used data from cloud-free profiles and excluded all waveforms that did not
180 have suitable data for determining tree heights. We excluded waveforms with a single
181 Gaussian peak, which generally meant the footprint measured water or bare soil areas.
182 We also excluded waveforms with low signal to noise ratio (i.e. below 50), which may
183 have been reflected from clouds, or where Gaussians fits may include noise peaks. We
184 found high signal to noise ratios up to 300 in the GLAS data.
185   SRTM version 4 data were downloaded from the Consultative Group for Agricultural
186 Research (CGIAR). We used 30 SRTM scenes to build a single SRTM DEM covering

187 the coast of Africa mosaic. Using the mangrove landcover map, we masked all non-
188 mangrove areas on the SRTM DEM. This resulted in an uncalibrated height map of the
189 mangrove areas. In forests, the C-band Radar signal penetrates into the canopy to scatter
190 with all forest components and the ground. Thus, the radar height estimate (i.e. radar
191 phase center) lies somewhere within the canopy volume, which can be used to estimate
192 canopy height (Kellndorfer *et al.* 2004; Gillespie *et al.* 2006). Based on the reasonable
193 assumption that mangroves are located at sea level, the elevation measured by SRTM (i.e
194 phase center) is directly related to canopy height and can be calibrated to estimate the
195 canopy height of mangrove forests (Simard *et al.* 2006).
196   The SRTM pixel corresponding to the GLAS shots were extracted (Figure 1).
197 Assuming that represents the canopy height, we derived linear regressions between the
198 GLAS point's rh_{75} values (relative height of the canopy at the 75th percentile minus rh_0),
199 and DEM height (H_{SRTM}) values to determine the regression equation of the form:
200
201                          $$rh_{75} = a * H_{SRTM} + b \quad (1)$$
202
203   Studies of forest biomass worldwide have shown that there is a strong correlation
204 between tree size, in terms of diameter and height, and tree biomass. In general, the
205 Diameter at Breast Height (DBH), of a tree is the strongest predictor of aboveground
206 biomass (Chave *et al.* 2005). For mangrove forests, a global stand height-biomass
207 allometric equation was calculated by Saenger and Snedaker (1993):
208
209              $$\text{Biomass (Mg ha}^{-1}), = 10.8 * Height\ (m) + 35 (2)$$
210
211   This equation was obtained from 43 field datasets distributed globally ($r^2 = 0.59$ and
212 RMSE= 43.8). To compute total aboveground biomass and aboveground biomass
213 distribution of mangroves on the continental scale, we used rh_{75} and equation (2) to
214 derive the biomass values as this equation was computed for a large range of tree heights
215 and was derived to be applicable globally. **[Insert figure 1 here]**
216
3. Results and Discussion
218
219   All of the results were calculated and mapped on a per country basis to facilitate
220 comparison with previously published results and data distribution. The maps are freely
221 available for Google earth software at http://www-radar.jpl.nasa.gov/coastal.
222
3.1. Mangrove landcover map
224
225   The total area of mangrove cover in Africa was found to be 25 960 km^2 with 83 %
226 accuracy. The five largest mangrove areas were - in decreasing order - in: 1) Nigeria, 2)
227 Mozambique, 3) Guinea Bissau, 4) Madagascar and 5) Guinea. The smallest area of
228 mangroves is found in Mauritania at 0.4 km^2. With 8 573 km^2, Nigeria has the fourth
229 largest mangrove area in the world, after Indonesia, Brazil and Australia. The overall
230 accuracy of the land cover map was of 83 % considering 10% omissions and 7%
231 commissions, based on a total of 540 points (Table 1). The main sources of error in the
232 landcover map were due to difficulties distinguishing between mangrove forests and

233 other forest types, such as coastal forests or rainforests and the presence of clouds,
234 especially in the equatorial regions. In Central Africa the map accuracy was much lower,
235 at 68%, due to the high cloud cover. The landcover maps for Nigeria, Cameroon,
236 Tanzania and Kenya are presented in figure 2 and the breakdown of mangrove area by
237 state is presented in table 2. [**Insert table 1**]

238   Although it is not our objective to assess changes in the spatial extent of mangroves
239 over time, it is important to compare our results with previous studies. Overall, the
240 landcover maps show that the mangrove area of Africa is smaller than the previously
241 estimated 30 000 km^2 (Spalding *et al.* 1997, FAO 2007). However the exact estimate of
242 mangrove area change due to natural and anthropogenic disturbances cannot be
243 calculated because of the differences in data collection methodologies, the variations in
244 the definition of mangrove forests and the differences in resolution of the datasets used in
245 the previous estimates. The large decreases in mangrove area estimates are in part due to
246 degradation in mangrove area but also due to different definitions of "mangrove areas".

247   In many studies, mangrove area was overestimated because it was difficult to
248 differentiate between mangrove forests and adjacent mudflats, salt marshes, swamp
249 forests and bare areas using low-resolution data (1 km x1 km). The consistent cloud
250 cover in many tropical areas and poor coverage of optical data. This is the case in many
251 of the tropical regions, with extreme discrepancies in Congo and Côte d'Ivoire for
252 example. Furthermore, certain studies include the "mangrove palm" *Nypa fruticans* as a
253 mangrove species, whereas other studies do not. In this study we did not include bare
254 ground and mudflats and also did not count uniform *Nypa* stands as mangrove areas as
255 much as was possible. Other very large differences in area measurement such as in Egypt,
256 Côte d'Ivoire, Sudan, are probably due to a lack of up-to-date studies and remotely
257 sensed data leading to poor mapping capabilities at the time of the study.

258   A direct comparison or estimation of the amount and rate of decrease or degradation
259 in mangrove area throughout Africa is difficult, but we know that mangrove areas have
260 decreased on the continent due to anthropogenic influences. Over 60% of Nigeria's
261 mangrove stands are found in the Niger Delta region, yet studies in the Niger Delta have
262 shown that mangroves have greatly suffered from the development and rapid increase in
263 oil and gas exploitation in the area and the resulting pollution by oil spills, rapid
264 urbanization and dredging of canals, as well as the introduction of the invasive mangrove
265 palm *Nypa fruticans* (James, G. K. *et al.* 2007). In general, decreases in mangrove area in
266 West Africa are primarily attributed to anthropogenic pressures in coastal regions leading
267 to conversion of land use for the production of salt and rice, urban and tourism
268 development, pollution, lack of sustainable resource management and recently, the
269 development of shrimp aquaculture (FAO, 2007). In eastern Africa, large decreases in
270 mangrove areas are primarily due to felling for household products and conversion to
271 urban, agricultural and touristic areas and diversion of freshwater from damming. These
272 measurement inconsistencies justify the need for a systematic approach to mangrove
273 mapping as presented in this study.

274
275
276   ***3.2. Height and biomass measurements***
277

The GLAS-SRTM calibration regression is shown in Figure 2. The resulting linear fit between the height estimates from rh_{75} and the SRTM DEM is:

$$rh_{75} = 1.07 * H_{SRTM} + 1.70$$

The RMSE (Root Mean Square Error) is of 3.55 m. Calibrated canopy height maps for West and East Africa are presented in Figure 3. In previous studies comparing SRTM derived canopy height with field and airborne LiDAR data, resulted in RMS errors of 1.6 m and 2.0 m respectively (Fatoyinbo *et al*. 2008; Simard *et al*. 2006). Our results are very similar to these studies. These are the lowest errors that can be achieved using data fusion of these LiDAR and radar sensors without the incorporation of field validation. **[insert figure 2]**

Based on our results, the equatorial areas of Africa are the best suited for the growth of tall mangroves but not for their expansion, since the actual mangrove area is small in these countries. Average biomasses per country ranged from 76 Mg ha^{-1} in the Republic of Benin to 178 Mg ha^{-1} in Congo. The greatest total biomass values were found in Nigeria and Guinea Bissau, the lowest in Mauritania.

Previous studies of mangrove canopy height, biomass and distribution have shown that geographical setting is more important in determining mangrove structure and distribution than the latitudinal distribution (Fatoyinbo *et al.* 2008). This is particularly evident on the African continent, and particularly in West Africa, where a great proportion of mangroves grow within a small range of latitudes, but the forest area and structure vary greatly. In Nigeria mangroves are extensive and canopy height can be very tall, but in adjacent Benin and Togo, their distribution is very limited and canopy height is short. In Senegal, Gambia, Guinea Bissau and Guinea, mangroves extend very far inland, up to 160 km in Gambia, but at the same latitudes in East Africa, in Somalia, Djibouti and Eritrea, mangrove forests are sparse. Estuaries and deltas with extensive freshwater supply are the most advantageous for mangrove growth, both in terms of height and extent, and have a much greater influence than latitude. Indeed, all of the mangrove forests with large areas, tall trees and/or high biomass grow either in estuaries or in deltas. **[Insert figure 3 and table 2]**

3.3. Error Analysis

The fact that we used 3 different data sets in this study also increases the incidence of error in our calculations. In the landcover classification, we observed 83% accuracy, with 17% errors from commissions and omissions from the classification. The systematic error (i.e. bias) from the calibration equation was low at 1%.

Cloud cover was a major source of error, especially in central African nations, where cloud cover is persistent. Some systematic but localized errors in the SRTM DEM resulted in overestimation of tree height and biomass, but also in the omission of mangrove areas. For example on an island in the Niger Delta, the DEM indicated that canopy height was 363 m. This is a common error with the SRTM DEM on islands that may have been caused by difficult SRTM interferometric phase unwrapping (i.e. the method to retrieve elevation from radar interferometric phase). Because this measurement

323 was too high for mangroves this area was omitted from the height and biomass
324 estimation.
325   The geolocation error of the GLAS instrument ranges from 4.6 m to 53.4 m
326 (according to NSIDC), which greatly influences the accuracy of the height measurement,
327 particularly if the canopy is heterogeneous. The actual height derived from the GLAS
328 waveform may therefore not correspond to the mean canopy height of the SRTM pixel
329 that is measured. The height estimated from the LiDAR waveform is affected by forest
330 composition and heterogeneity as canopy shape, reflective properties and the associated
331 photon interactions all influence the structure of the waveform (Rosette *et al.* 2010, North
332 *et al.* 2010). In addition, the waveform is most sensitive to the footprint center since laser
333 gain decreases with distance from the center of the footprint. Mangrove forests are
334 characterized by distinct "zones" that are dependent on the location relative to the coast
335 or river and that show great heterogeneity in forest structure, type and composition
336 (Tomlinson, 1994). When the GLAS footprint is close to the border of two zones, this can
337 result in large discrepancies in height measurement (Figure 4). Although low in species
338 composition, mangrove forests are very heterogeneous, ranging from tall, dense forests to
339 very short, sparse and shrubby areas within a few hundred meters. The 70 m GLAS
340 footprint is not always able to characterize this heterogeneity, resulting in discrepancies
341 with SRTM measurements. For example when looking at the variance within a seemingly
342 homogeneous forest in Cameroon, we found that within a single 1 km^2 patch, the canopy
343 height standard deviation was 5 m, showing that the height within a forest can vary
344 greatly within a small area (Figure 4). Therefore, since the trees measured by SRTM and
345 GLAS are not exactly the same, the differences between the height measurements and
346 what we state as the error of the measurement are inflated. The differences in physical
347 parameters measured by radar and LiDAR, in addition to differences in resolution also
348 increase the height and biomass estimation error. These combinations of sources of error
349 are illustrated in figure 5. **[Insert figure 4]**
350   The identification of the ground location within the waveform influences the
351 estimate of the canopy height and therefore also of the biomass. In tidal forests, such as
352 mangroves, the height of the ground, or of the water level may vary depending on the
353 tidal level. This may influence the GLAS ground and therefore the relative height
354 estimates. On the other hand, microtopographic features will most likely average out by
355 selecting the furthest Gaussian peak as the ground. In this study we chose to use rh_{75} as
356 the height of the canopy as this measurement resulted in the lowest error when comparing
357 to the SRTM measurement.
358   The RMS error of equation (3) is of 65.4 Mg ha^{-1}. This error is high due to large
359 variability in the measurements taken and the natural variability of the data set. Since this
360 is a global equation, it does not take into account local variability in height and biomass.
361 There is generally a great amount of uncertainty when working with height-biomass
362 allometric equations. Because height is not the most direct indicator of tree biomass
363 (Chave *et al.* 2005), some error is always introduced into the estimate when deriving
364 biomass from height. To obtain more accurate measurements of biomass from radar and
365 LiDAR, it is crucial that more reliable allometric equations be developed as a
366 function of vertical structure parameters. **[Insert figure 5]**
367
368 **4. Conclusions**

369

370   Mangroves are one of the most important ecosystems in coastal areas in terms of
371 ecology and economy, but they are still being destroyed and degraded at great rates. The
372 lack of field studies and homogeneous historical data has made the calculation of rates of
373 change in mangrove cover difficult. In this paper, we produced the first systematic
374 estimate of mangrove cover, structure and biomass for the entire African continent and
375 Madagascar. This map can now be used as a baseline as the techniques used in this paper
376 allows the recalculation and reproduction with updated estimates of canopy height and
377 allometry in Africa as well as comparison with the rest of the world.

378   The total area of mangrove forest in Africa for the period of 1999 to 2000 based on
379 the classification of Landsat ETM+ images is of 25 960 km^2 with the largest area found
380 in Nigeria at 8 573 km^2 and the smallest area in Mauritania with 0.4 km^2. The overall
381 accuracy of the map was of 83% considering 10% omissions and 7% commissions. This
382 overall estimate is lower than previous estimates of mangrove cover in the World
383 Mangrove Atlas (Spalding, 1997), mostly due to classification errors from high cloud
384 cover and difficulties in distinguishing between mangroves and adjacent forests. We do
385 believe that there is an overall decrease in mangrove cover that can be attributed to
386 deforestation and degradation of mangroves from anthropogenic pressures, however, we
387 cannot accurately quantify the rate and percent decrease in area because of the
388 differences in methodology and datasets used between the various published estimates.

389   Since mangroves are a relatively homogeneous ecosystem that grows on flat terrain at
390 sea level, the results from this study are some of the most accurate we can expect from a
391 Radar/LiDAR integration study. The height maps derived from SRTM and GLAS data
392 confirmed this type of data fusion to measure mangrove canopy height to be appropriate,
393 with an average RMSE of 3.55 m. This value includes the impact of canopy
394 heterogeneity on the remote sensing measurement that is not geolocated. Previous studies
395 using SRTM and LiDAR datasets in Colombia measured canopy height with an accuracy
396 of 2.7 m (Simard *et al.* 2008). When similar methods using LiDAR were combined with
397 field data, the RMSE decreased to 1.6 m in Mozambique (Fatoyinbo *et al.* 2008). To
398 achieve even higher accuracy, or lower error, field validation of mangrove height and
399 biomass calibration should therefore be included in future studies.

400   Overall, only 327 usable GLAS footprints were found for all mangrove areas in
401 Africa. This is a very small sample size covering only 0.02 % of the total mangrove area.
402 This is however, the greatest number of systematic height measurements available.
403 GLAS was not optimized for vegetation measurement, but as the only spaceborne LiDAR
404 it is the only dataset available for continental-scale studies. We look forward to the future
405 LiDAR and InSAR missions, which will provide greater coverage over forested areas.

406

407 **5. Acknowledgements**

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