Reply to Comment on ‘A first map of tropical Africa’s above-ground biomass derived from satellite imagery’

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Abstract

Biomass mapping using satellite imagery is a rapidly evolving field that has been greatly facilitated in recent years by the advent of LiDAR remote sensing coupled with co-located field measurements. The biomass map of Africa that we published in 2008 did not take direct advantage of coincident field and LiDAR measurements, as our more recent efforts have. The criticisms of our earlier map by Mitchard et al (2011 Environ. Res. Lett. 6 049001) are duly noted and worthwhile, although they are also limited in several respects that we describe. Most notably, they assess our map with field data sets that are only representative of a subset of conditions across the study domain, thus they not only inadequately characterize undisturbed tropical forest regions but also the diverse disturbance dynamics that are captured in satellite imagery. We point out the limitations of their assessment and focus on a way forward, moving beyond both inadequate field sampling and remote sensing to an approach that captures the full range of dynamics by directly coupling field and satellite measurements.

Keywords: biomass, carbon, MODIS, LiDAR, GLAS

We welcome the opportunity to respond to the comment by Mitchard et al (2011) on our 2008 letter in Environ. Res. Lett. (Baccini et al 2008). They make specific criticisms of our letter, which was (as our title indicated) a first attempt to map tropical Africa’s aboveground biomass directly using satellite imagery and existing field inventories. Their criticisms are based on comparisons of our map of aboveground biomass (AGB) using field data and satellite LiDAR observations (Geoscience Laser Altimetry System), a variation of which we also used in our 2008 letter as part of a comparison of LiDAR heights to our AGB estimates.

Mitchard et al (2011) conclude with three ‘lessons’ to be learned to ‘avoid these types of errors in the future’: (1) care must be taken to use good quality, unbiased field data; (2) field data must be drawn from across the spatial extent and ecological variability of the prediction area; and (3) accuracy assessments should be done using truly independent data sets. We would certainly not disagree with any of these fundamental observations (or ‘lessons’) and, in fact, we made similar points in Goetz et al (2009) regarding the extension of field measurements to larger spatial domains using satellite imagery directly, as opposed to using a ‘stratify and multiply’ or a ‘combine and assign’ approach with land cover type classifications. While we appreciate the effort at clarifying issues with analyses that estimate biomass using limited field data sets, we feel that Mitchard et al (2011) may have fallen victim to some of the same issues that they call out in relation to our work. Notably, they rely on field data sets that vary in plot size and in the timing of data collection relative to the satellite observations, and they make assumptions about the representativeness of their field plot data sets relative to the extensive variability that the satellite observations that we relied upon were sensitive to. Aside from failing to provide information on how their field plots were selected and whether they were designed to be representative of field conditions, or collected on the basis of appropriate probability
sampling design, the field data set that they present is clearly proportional neither to the spatial extent of vegetation types nor to 'ecological conditions' across Africa (note the spatial distribution of their sites shown in their figure 1(a)). For example, on the basis of their table 1, they have a sample size of 29 in closed evergreen lowland forest (which covers 8.6% of the mapped region that we focused on), 11 in submontane forest (0.8% of the region) and 138 in deciduous woodland and shrubland (25.7% of the region). We note that 85% of their field data are located outside high biomass lowland forest.

They also fail to note that their plot measurements capture a small range of the variability that exists in aboveground biomass across a broad range of natural and human-modified conditions (e.g. degraded areas) that are captured in the satellite observations, and thus may tend to overestimate AGB in forest and woodland areas (as has been well documented; see e.g. Asner et al 2011). Finally, although it is probably obvious to anyone who has worked with such data sets, the satellite data that we used were based on 1 km$^2$ (100 ha) pixels whereas the plot data of Mitchard et al always covered a smaller proportion of the MODIS pixels (as did, we note, the field data that we calibrated our initial model on). Mitchard et al (2011) also fail to address the importance of scaling field data to the resolution of remotely sensed data, a fundamental step for assuring that field measurements are actually representative of the area covered by the field of view of the satellite (Baccini et al 2007). We will not comment further on their lessons learned other than to note that 'avoiding such errors in the future' applies to the judicious use of field data no matter what the source.

In addition to these basic points as regards representative field data, we feel that it is worthwhile correcting and clarifying other aspects of the analysis conducted by Mitchard et al (2011). We acknowledge that the field data that we used were far from perfect, and rather represented the best available data sets at the time (some five years ago). We would be perfectly willing to incorporate their field data into the development of an updated model of AGB, although it is not clear from their analysis the extent to which doing so would produce a more accurate map—presumably it would do so on the basis of the increased sample size alone. Regardless of this, we have moved on to even more appropriate data sets and an integrated model—the data fusion approach (Baccini et al 2011), as noted below—and seek to refine our past work, as we expect Mitchard et al (2011) will do as well. That said, we take issue with several of their criticisms of the field data that we used, including their assumption that the forest inventory plots from the Republic of Congo were biased. While we agree that forest inventory designed for forestry purposes (i.e. selective harvest) may not be representative of broader ecological conditions reflected in AGB, and may not be selected in a strictly random fashion, we have no evidence that the inventories were biased in a manner that would lead us to underestimate the AGB of tropical evergreen lowland forest. Foresters in the Congo tend to focus on selective harvesting of large trees with high commercial value (e.g. African mahoganies), so presumably any bias would be towards AGB overestimation rather than underestimation. Rather, the mismatch between our map and the limited field plots of Mitchard et al in tropical evergreen lowland forest is much more likely to be related to the spatial averaging inherent in the nominal 1 km$^2$ pixels that comprise the basis of our map (i.e. their limited plot measurements very likely miss the variability within the MODIS pixel and captured—and averaged—in the larger area satellite observations). Second, we consider it unlikely that the screening approach that we used to avoid plots that may have changed state in Cameroon (between the times at which the field measurements were conducted and the MODIS satellite data were acquired) would not be captured in Landsat TM imagery. Because TM data have ~30 m spatial resolution and are acquired frequently, we believe that they adequately captured areas of change, and we were intentionally conservative in screening with this in mind. Third, as regards the field data set from Uganda that we used, Mitchard et al indicate that because these data were spatially extended using Landsat TM imagery there may be some circularity in our use of MODIS imagery, which is also an optical sensor. This strikes us as a somewhat inappropriate criticism in that Landsat TM imagery is widely used for land cover type classification, and just because we used another optical sensor (MODIS) for our AGB mapping this does not mean that our results would somehow be invalid or biased towards greater accuracy than would otherwise be the case. In brief, we acknowledge the limitations in the field data sets that we used, but we have doubts that the Mitchard et al field data are a greater 'truth' against which our map or other field data sets can or should be dismissed as being grossly in error.

In addition to the field data comparisons and conclusions that Mitchard et al report, we have concerns with the GLAS comparison that they present as well (their figure 2). Their comparison indicates issues with the basal area weighted canopy height data set (Lorey’s height) that they produced from the freely available GLAS data set (www.nsidc.gov). Their figure 2(c) shows biomass bins of 10 Mg ha$^{-1}$ and while the Baccini et al values increase to 350 Mg ha$^{-1}$, the AGB
estimated from Lorey’s height increases to an average within the 350 Mg/bin of about 180 Mg ha$^{-1}$, with a max around 240 Mg ha$^{-1}$. In essence, their figure shows that their derived GLAS biomass is underestimating compared to the biomass map. This contrasts with their claim that, according to their field data, the biomass in the region should have a value of 445 Mg ha$^{-1}$ in closed evergreen lowland forest (table 1 in Mitchard et al). The GLAS-derived Lorey height used by Mitchard et al is based on 484 points, of which 389 are in needleleaf stands within the Tahoe National Forest (California, USA) and the Willamette Forest (Oregon, USA), and 95 stands of broadleaf forest in New Hampshire, USA. Lorey’s height–biomass relationship includes just a few tropical forest stands in Brazil (Lefsky 2010), yet they are applying it to tropical regions of the world.

The data of Mitchard et al show no apparent relationship with our MODIS-derived AGB map, yet a similar comparison using our GLAS canopy height data set, based on the difference between ground return and the first significant LiDAR return (i.e. RH100), as well as the height of median energy (HOME), shows a reasonably good relationship with our AGB values (figure 7 in Baccini et al (2008)). We updated this analysis using additional GLAS height data acquired for the period 2003 and 2005 (see figure 1) and converted those heights into AGB using more than 300 field plots centered within GLAS shot locations across the tropics (Baccini et al 2011). This comparison indicates that our original inventory-based estimates and mapping using MODIS were not as inaccurate as Mitchard et al suggest. Apparently there are discrepancies between the GLAS data processing techniques that we are each using. We refer the reader to Goetz and Dubayah (2011) for specifics on LiDAR data screening and canopy height metrics, but a quick visual assessment of the Mitchard et al GLAS data set, which is reported in Lefsky (2010), reveals apparent underestimation of the canopy height (and thus AGB) across most of the tropical evergreen lowland forest region. This height product is perhaps lacking in tropical forest (which dominates the region that we mapped) because, as noted earlier, it was almost entirely derived from conifer and broadleaf forest plots in the United States. We note that this same height data set forms the basis for the recent tropical AGB maps produced by Saatchi et al (2011).

There are several other issues with the analysis that Mitchard et al present, including their suggestion that the error was even larger when they considered only MODIS pixels that contained more than five ‘scientific’ inventory plots ($N = 70$) as opposed to pixels that contained fewer than five plots ($N = 239$). Surely the smaller sample size of the former influenced the error estimate compared to the latter, larger sample. We also question their poorly described comparison of MODIS to an L-band radar mosaic (presumably the freely available PalSAR mosaic distributed by the Japanese Space Agency), for which they conclude that MODIS bands and PalSAR L-band ‘plots’ differed markedly across the continent and with vegetation type. This finding should not be a surprise as it is widely known that optical and radar imagery are sensitive to different aspects of vegetation structure, and so provide different information, allowing them to be used best in a synergistic manner (often called ‘fusion’). We point out that while undoubtedly radar is useful for biomass estimation, particularly in lower biomass and drier areas, it is also sensitive to a broad range of attenuating factors such as soil and canopy moisture, topography and other environmental variables that may be unrelated to biomass density.

Finally, we note that biomass estimation with direct remote sensing is rapidly advancing, particularly from LiDAR remote sensing (see Goetz and Dubayah (2011)) and we have moved on to improved data sets and methods since the work leading to the Baccini et al (2008) letter was conducted. Importantly, our current approach relies on field measurements spatially located within GLAS LiDAR measurement ‘footprints’, which allows us to extend our field measurements to millions of plot locations around the tropical region. This approach is far more representative of ecological conditions than using randomly located field plots of variable size (scientific or otherwise) that are not coordinated with the specific locations measured by satellite remote sensing (particularly LiDAR) observations. We conclude by noting that a comparison of our original AGB estimates (Baccini et al 2008) with those of Saatchi et al (2011) and Gibbs et al (2007) reveals reasonably good agreement as regards total aboveground biomass for the countries covered by the Baccini et al (2008) map (figure 2). Clearly this aggregation to the national scale ‘averages out’ some of the error that may occur in any given location, and this comparison should be considered with that in mind.

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