Seeing the Forest Beyond the Trees

Response to Mitchard et al., GEB 2014.

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Abstract

In a recent paper, Mitchard *et al.* (2014) presented a new map of forest biomass based on a geostatistical model of field data for the Amazon (and surrounding forests) and contrasted the map with two maps based on remote-sensing data: Saatchi *et al.* (2011; RS1) and Baccini *et al.* (2012; RS2). Mitchard *et al.* concluded that each of the remote-sensing based maps is incorrect because they do not conform to their interpretation of the field-based results. In making their case, however, they misrepresented the fundamental nature of primary field and remote sensing data and committed critical errors in their assumptions about accuracy of research plots, the interpolation methodology, and the statistical analysis. Because of these misrepresentations and erroneous methods, we find their critique of the satellite-derived maps invalid.

Introduction

Estimation of carbon stocks in tropical forests is challenging for several reasons: 1) diversity in structure, wood density, and dynamics of tropical forests lead to complex and variable allometry (Chave et al., 2004); 2) natural and anthropogenic disturbances at various spatial and temporal scales add to forest heterogeneity (Esprito-Santo et al. 2014); and 3) lack of strong predictive relationship between climate and soil variables and forest biomass. Ground and remote sensing observations together, have been combined to provide estimates of biomass distribution in tropics at regional to continental scales (Saatchi et al., 2007; 2011; Asner et al., 2010; Mascaro et al. 2011; Baccini et al., 2012). On a per-hectare basis, the ground data (generally consisting of all tree diameters above a threshold, a sampling of tree heights, and species identification that permits inference of wood densities) are more comprehensive than remote sensing data that generally measure aggregate canopy height. In contrast airborne or satellite remote

sensing data are far more extensive including millions of measurements over regional or continental scales compared to hundreds for research plots. Both are measures of physical properties that are not forest biomass (Clark and Kellner 2012). Both efforts rely on statistical techniques to estimate biomass, using single-tree allometry in the case of field plots and plot-aggregate allometry in the case of satellite data.

Here, we show that Mitchard *et al.* misrepresented what they measured in the plots and committed significant errors in their methodology to extrapolate biomass estimates from plots to the entire Amazonia and to compare their results with satellite derived maps.

The Fallacy of Ground Truth

Mitchard et al. used 413 plots covering a total of 404.6 ha to sample more than 650 million ha of forests of Amazonia and the Choco region, west of the Andes. The census data ranged from 1956 to 2013 with more than 1/3 of the plots last censused before 1995. The quality of measurements of structure and botanical information of more than half of the plots outside the RAINFOR (Malhi et al. 2002) and TEAM network (http://www.teamnetwork.org/) is unknown. Mitchard *et al.* argued that their biomass estimation from research plots and derived maps are more accurate. The reader is left with the tacit impression that the Mitchard data must be correct because they come from the ground, while RS1 and RS2 data come from satellites. This argument is unsurprisingly compelling because the human brain is hard-wired to accept results from physical contact rather than results from distant measurement. Liberman and Trope (2008) note that for the human brain, "Remote locations should bring to mind the distant rather than the near future, other people rather than oneself, and unlikely rather than likely events." In other words, "to see the forest we need to step back, whereas to see the trees we need to get closer" (Lieberman and Trope (2008).

Are the primary Mitchard et al. data superior because they are closer to forests? No.

Most local and regional tropical forest biomass allometry before 2005 were based on tree diameter (D) measurements only (Brown, 1997; Chambers et al., 2001; Chave et al., 2004) and in most cases did not include wood density (ρ) or height-diameter (H-D) relations. Following the work of Chave et al. (2005) Mitchard et al. considered the effects

diameter, height, and wood density as did the estimates of biomass using satellite data in RS1 and RS2. The analyses of RS1 and RS2 use similar and sometimes overlapping data to Mitchard et al. There is no clear evidence that one set of data is superior to another. Therefore, the main difference between the Mitchard et al. and the satellite analyses is in the extrapolation approach. We note that the ground-based biomass estimates for all three studies have been challenged recently by the publication of a new another tropical forest allometry (Chave et al., 2014).

Mitchard et al. provided 6 estimates of biomass using the Chave et al. moist forest allometry (2005) with three or two parameters (D, H, and ρ) to allow for variations in biomass estimation but do not include these differences as uncertainty in their analysis. Moreover, each allometric estimate may have additional 10-20% error (smaller plots have larger uncertainty) if one uses error propagation from basic measurements to model implementation (Chave et al., 2004). Including these errors (e.g. 10%) along with estimates from different allometry provides a realistic variation around the mean biomass for each plot location (Figure S1a).

Mitchard et al claimed that the four regional height-diameter models introduced by Feldpausch et al. (2012) improve ground estimates of biomass by "greatly reducing the error in the prediction of H from D compared to a Pan-Amazonian model." The models are implemented by casually assigning the plots to four manually delineated regions of Amazonia without any systematic method of stratification. The western Amazon model, for example, covers areas from highly seasonal rainfall in the south to areas with no dry season in the north, with soils varying from infertile on the east to fertile by the Andes foothills, and vegetation types varying as in floodplains, bamboo dominated, and terrains with widely different geomorphology and topography. The H-D allometry by Feldpausch et al. (2012) has proven to introduce large bias (> 20%) (Chave et al., 2014) in estimates of biomass when compared with local relations (Figure S1b) (see other examples: Kearsley et al. 2013; Hunter et al., 2013) and probably are simplistic approximations of height diameter variations (Figure S1c).

Wood Specific Gravity, the Achilles Heel of Biomass Estimation

In allometric models, biomass at tree level or at aggregate plot level varies linearly with wood density (Chave et al., 2005; Asner and Mascaro, 2013). However, wood density is not directly measured in the field and estimates are often extracted from tabulated published data with large uncertainty due to variations in measurement techniques, in sample size, geographic concentration of samples, and identification of species (Muller-Landau, 2004). The spatial variation of average wood density over Amazonia is unknown, but it is expected to be large because of geographic variations in taxonomy and phylogenetic characteristics (Chave et al., 2009), as well as interspecific and inter-site variations in both soil fertility and complex processes of tree mortality (Muller-Landau, 2004). Field observations suggest that there is a significant pattern in wood density related to soil characteristics with higher wood density trees in infertile soils of eastern Amazonia and lower wood density in more fertile soils of western Amazonia near Andes foothills (Quesada et al.,2012; ter Steege et al., 2006). However, without a systematic spatial sampling from ground or remote sensing observations of wood traits, we will not be able to prove but only suggest a regional and large-scale pattern.

We challenge the Mitchard et al claim that research plots provide accurate estimates of wood density variations over Amazonia. To demonstrate this, we use a larger dataset (n=3616) compiled over Amazonia using both plots provided by Mitchard et al. and additional data from other sources (Nougeira et al., 2005; Saatchi et al., 2011; Sandra Brown, personal communication). Dividing the data over the same four regions suggested by Mitchard et al., we show that the intra-region variations of wood density are larger than inter-region variations and regional mean values less divergent (Figure S2). Our data, although not based on a systematic sampling of Amazonia, suggest that the wood density may have larger variations at the landscape rather than regional scales because of variations in composition, soil characteristics, geomorphology, size dependent tree mortality, and disturbance regimes, all functioning at small scales (meters to hectares). .

Research Plots and the Curse of Sampling

The Mitchard *et al.* data may be more comprehensive within individual plots, yet they are several orders of magnitude less extensive across space. In other words, they are missing

the forest for 0.00001% of the trees.

By referring to their plot network as an "inventory", Mitchard et al. conflate measurement protocol in the field (i.e., wherein all trees are inventoried) with strategic planning to sample biomass and other forest properties as conducted by national forest inventories (e.g. McRoberts et al. 2005). Their research plot network, although designed and used for ecological studies, are not suitable for biomass inventory because: (i) more than half of the plots are inherited from different groups, increasing the likelihood of measurement errors, (ii) are spatially clustered near roads, rivers, and research stations for easy access, and (iii) the plots are haphazardly located on the map to convey a widespread distribution over Amazonia. The coordinates have large uncertainty (~ 10-50 km) (Mitchard et al supplementary material), because of lack of GPS recordings particularly in older plots. Locations provided in the paper do not always match with data provided in RAINFOR publications or websites (Malhi et al., 2006; Baker et al., 2004; http://www.rainfor.org/). The comparison of the biomass estimates from the opportunistic plot collection that is only broadly constrained in space (at times as poorly as ~10 – 50 km) and time (1956 to 2013) leads to uncertainties ignored by Mitchard et al. when comparing to the satellite estimates that are tightly constrained (2005 ±3 year and < 100 m for GLAS lidar observations; Lefsky, 2010)

To compensate for the sparse sampling of their plot collection, Mitchard et al. opted to average "field plots within 20 km X 20 km boxes and compared the mean biomass values for these boxes to the mean AGB of RS1 and RS2." In the process, however, they committed several methodological errors.

First, they found 107 unique points (20 km X 20 km) with an average of 3.9 (1-14) plots for each box. We could not reproduce the same number of unique points with their data. We found 109 unique points at 80 km x 80 km (with a similar average of 3.8 plots per box) or 189 unique points for 5 km x 5 km boxes (with an average of 2.1 plots). This difference has large implications for trend analysis and map comparison as 80 km boxes are one degree of magnitude larger than typical landscape scales (< 10 km).

Second, Mitchard et al. ignored the sampling problem and treated these average biomass

values as the true mean for each box. Large spatial variability of AGB suggest that an average of at least 9-15 1-ha plots randomly located in the 20 km box areas are required to estimate the mean biomass at each point with 20% error (Chave et al., 2003) (Figure S3 shows examples of biomass spatial heterogeneity using airborne lidar data). Unlike Mitchard et al., we addressed the sampling problem in our map (RS1) and provided the uncertainty of using 5 GLAS lidar shots (> 0.25 ha each) systematically sampling the 1 km map units in developing the RS biomass map (Saatchi et al., 2011).

Third, we followed their approach and performed the trend analysis with unique points (109 or 189) derived from their research plots along the three directions (N-S, E-W, and NE-SW) using the Ordinary Least Squares regression (OLS) model ($y = \alpha + X\beta + \varepsilon$; with X being the explanatory variable as latitude or longitude or diagonal distance, y being AGB, ε representing a geometric error term). The reproduced results show similar significance levels of β to Fig. 2 in Mitchard et al (Table S1). However, if AGB can be fully explained by X using OLS, the residual of OLS regression should be white noise, otherwise any significance test based upon OLS is erroneous (Lennon et al. 2000). Our analysis show that the OLS residual error is spatially correlated (Moran's *I* test in Table 1), confirming the existence of spatial autocorrelation (Fig S4a), even after accounting for the changes in the proposed explanatory variable (Fig S4b). Such spatial autocorrelation can be modeled as the non-zero covariance in regression residual, under the assumption of covariance stationarity (which is the same assumption underlying the ordinary or universal kriging). The so-called Geostatiscal Regression (GR) (Johnson and Hoeting, 2011) utilizing the Generalized Least Squares (GLS) method shows that none of the trends provided by Mitchard et al is significant under this approach (Seber and Lee, 2012). The transformed residuals in GR method are no longer dependent on distance, suggesting the results of our GLS approach is valid (Figure S4b).

Fourth, Mitchard et al. rely on interpolating 412 research plots over 650 million ha forests of Amazonia with large stretches (> 100 million ha) without a single plot. The performance of their interpolation is strongly dependent on the noise in the data, the spatial autocorrelation, the sampling pattern, and the method of interpolations. By using a log-log axis of semivariogram analysis, Mitchard et al. misinterpreted the autocorrelation

among plots. Using a linear axis, our analysis shows that the spatial autocorrelation does exist and extends to more than 2000 km with large variations at local scales (presence of a non-zero nugget) (Figure S4a). Mitchard et al. consequently ignored any statistically rigorous kriging analysis and simply applied an inverse distance-based kernel function for spatial interpolation (Isaaks and Srivastava, 1989). In the presence of spatial autocorrelation the use of inverse distance approach that ignores the uncertainty in the data has no sound statistical basis and can provide misleading interpolated surfaces (Zimmerman et al., 1999). In addition, the performance of the interpolation also deteriorates significantly when sampling patterns are clustered instead of random unless the sampling is designed initially to minimize the maximum or average kriging prediction-error variance (Brus and Heuvelink, 2007), which is not the case with the research plots. Without any optimized spatial sampling used in the forest inventory techniques (Mandallaz, 2008) the interpolated surfaces of the AGB offered by Mitchard et al. are erroneous and do not provide any additional information than the original plots.

Misleading Assessment of Biomass Maps

Mitchard et al. claim to have documented a gradient in biomass from the south-west to the north-east in Amazonia. However, not only they fail to rigorously prove this point as demonstrated above but they present a false narrative of the Amazon biomass distribution and what the maps present.

The literature on the spatial pattern of forest biomass in Amazonia is extremely diverse and sometimes with contradictory results (DeWalt and Chave, 2004; Clark and Clark, 2000; Quesada et al., 2012; Slik et al., 2010). Forest biomass is a synthesis of several ecological and biological processes modulated with climate, soil, and disturbance. If there is some non-randomness in these processes, then what are the controlling factors and at what scale they operate? We showed research plots, without any statistically sampling design, are not suitable to provide reliable answers to these important questions.

In the absence of rigourously designed (and expensive) ground-based forest inventories, remote sensing techniques with spatially resolved, systematic, and repeated measurements of forest structure are the best alternative to inventory sampling (Neigh et al., 2013; Asner et al., 2013). The GLAS lidar measurements taken along the ICESAT

orbital tracks provide systematic samples of forest structure that are three orders of magnitude denser than the opportunistic research plots (Figure S5). Using a simple statistical aggregation of the GLAS lidar measured height samples at 50 km x 50 km grids (with > 1000 samples), we provide spatial patterns of forest structure over Amazonia (Figure S5), showing the distribution of tall trees, potential gradients, and large spatial variability.

We converted the GLAS lidar samples to biomass from a single equation derived from plots scattered in Amazonia close to lidar measurements with the knowledge of uncertainty of using a single allometry or average wood density (Saatchi et al., 2011). However, using a single model based on canopy height over Amazonia had the advantage of not introducing any additional artificial and spatially correlated errors in the biomass map from unknown wood density variations (Chave et al., 2009). Nevertheless, contrary to Mitchard et al claims, the biomass map (RS1), with its regional bias, preserves the potential known patterns in Amazonia,. To show this, we used a soil map of Amazonia (Figure S6) as the basic stratification of forest types, and calculated the mean forest height and biomass for each strata, and colored the map to highlight regional patterns (Figure S7).

In Conclusion

Mitchard et al. have conducted an analysis with many technical flaws pointed out above. Ultimately, they rely on human psychology. They misleadingly imply that measures by touch (i.e., in the field), are superior to measures from space. We know this is a flawed argument. Yet, it is innately compelling because the human brain is wired to accept it. These instincts and arguments impacted their methodology to erroneously use few plots for inferences about distant forests in time and place and comparison with satellite observations, extensive in space and constrained in time. By doing this, they made "predictions, evaluations, and choices with respect to [their] construal of objects rather than the objects themselves." (Lieberman and Trope, 2008).

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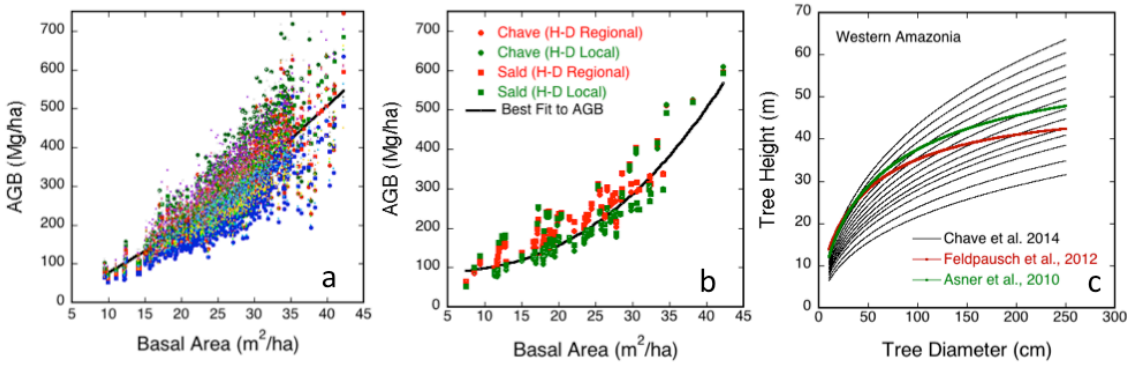

Figure S1. Uncertainty in ground estimates of biomass from regional vs local height-diameter allometry: a) variations in estimates of aboveground forest biomass in research plots (n=413) from six estimates (represented by 6 different colors) by Mitchard et al. plus 10% error in each estimate from the use of allometry at 1-ha. b) Variation of biomass estimates using regional H-D allometry for the western Amazonia (Feldpausch et al. 2012) compared with the local H-D allometry derived from plot data and two biomass allometry from Chave et al. (2005) and Saldarriaga et al. (1988) in Colombian Amazon, c) differences between recently published H-D allometry using weights from environmental variables in western Amazonia by Chave et al. (2014), and Feldpausch et al., (2012), and local allometry in Peru (Asner et al., 2010).

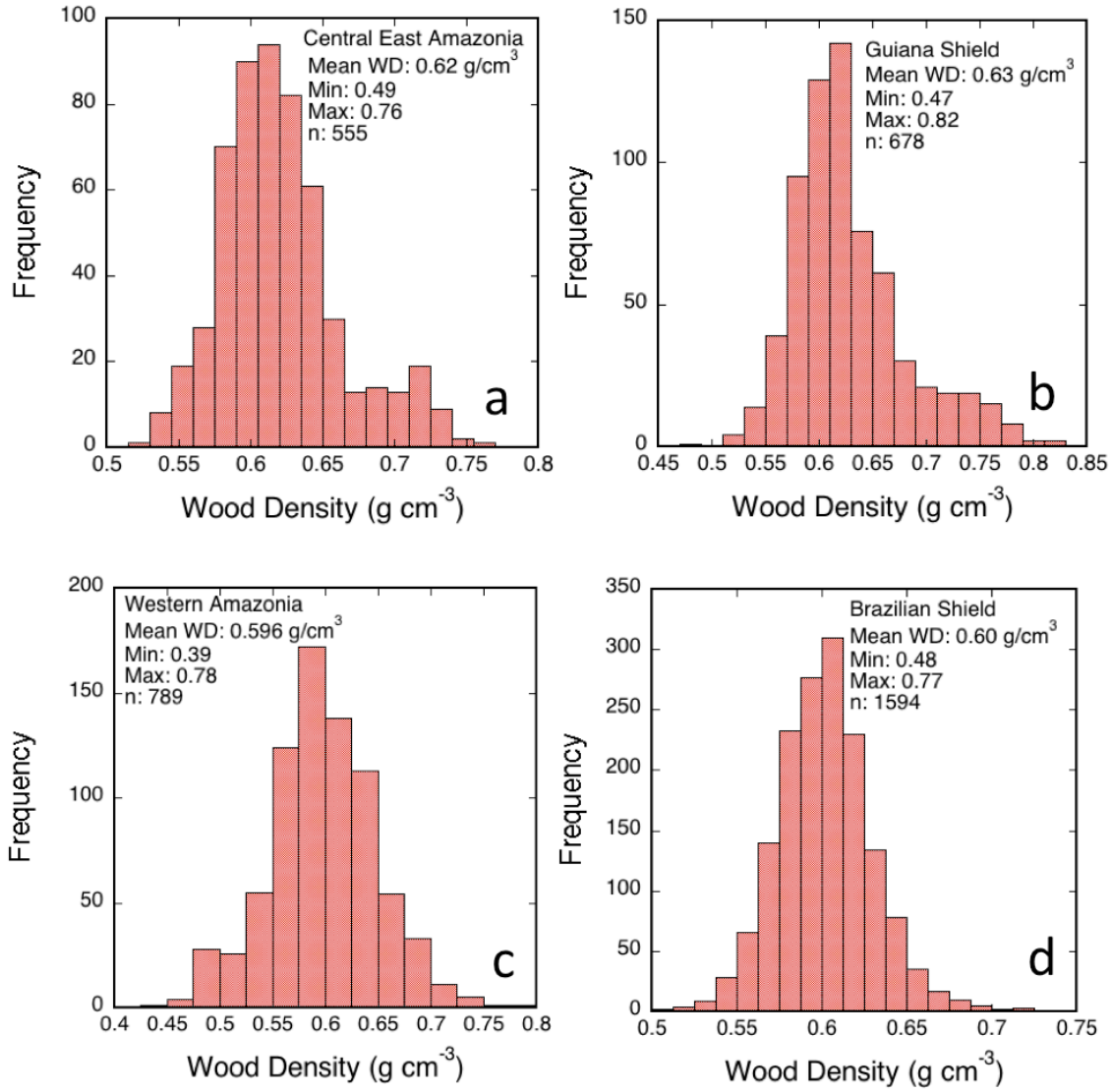

Figure S2. Distribution of wood density over four regions in Amazonia derived from a large plot level data complied from different sources including plots used in Mitchard et al. 2014. The distribution from larger plot network shows: a) average of central and east Amazonia is 0.62 compared to 0.68 from EM plots, b) average of the Guiana shield is 0.63 compared to 0.69 from EM plots, c) over western Amazonia the average of larger plot set is 0.59 slightly larger than 0.58 from EM data, and d) the average of wood density in Brazilian shield is 0.6 similar to the value provided by EM plots.

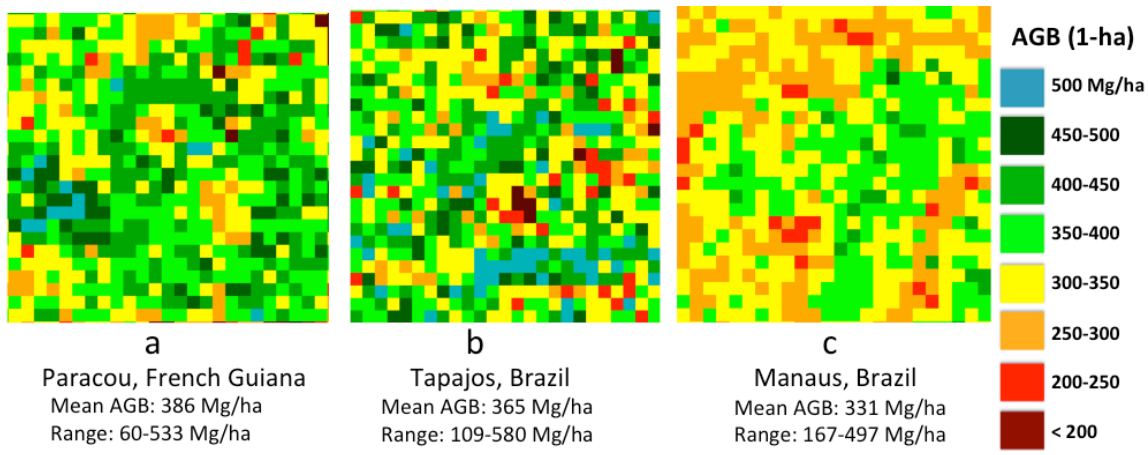

Figure S3. Spatial heterogeneity of forest biomass at landscape scale represented by three sites of approximately 2.5 km x 2.5 km in size: a) Paracou, French Guiana site over a topographically complex terrain with maximum height limited to approximately 50 m, mean wood density of approximately 0.68 g cm^{-3}, landscape biomass of 386± 72 Mg ha^{-1}, and range between 60-533 62 Mg ha^{-1} (14 randomly distributed 1-ha plots are required to estimate the biomass of the 1100 ha area with 10% accuracy and 95% confidence interval), b) Tapajos, Brazil, with trees reaching 60 m in height, average wood density of about 0.68 g cm^{-3}, with biomass of 365± 84 Mg ha^{-1}, and range between 109-580 Mg ha^{-1} (20 randomly distributed 1-ha plots are required to estimate the biomass of the site with 10% accuracy and 95% confidence interval), and c) Manaus, Brazil, covering the Ducke forest site, with maximum height rarely reaching 50 m, mean wood density of about 0.69, and landscape scale biomass of 331± 32 Mg ha^{-1}, and range between 67-497 Mg ha^{-1} (about 7 randomly distributed 1-ha plots are required to estimate the biomass of the site with 10% accuracy and 95% confidence interval). Over larger areas such as 20 or 80 km grid cells, the heterogeneity increases and the number of random plots to estimate the mean will also increase.

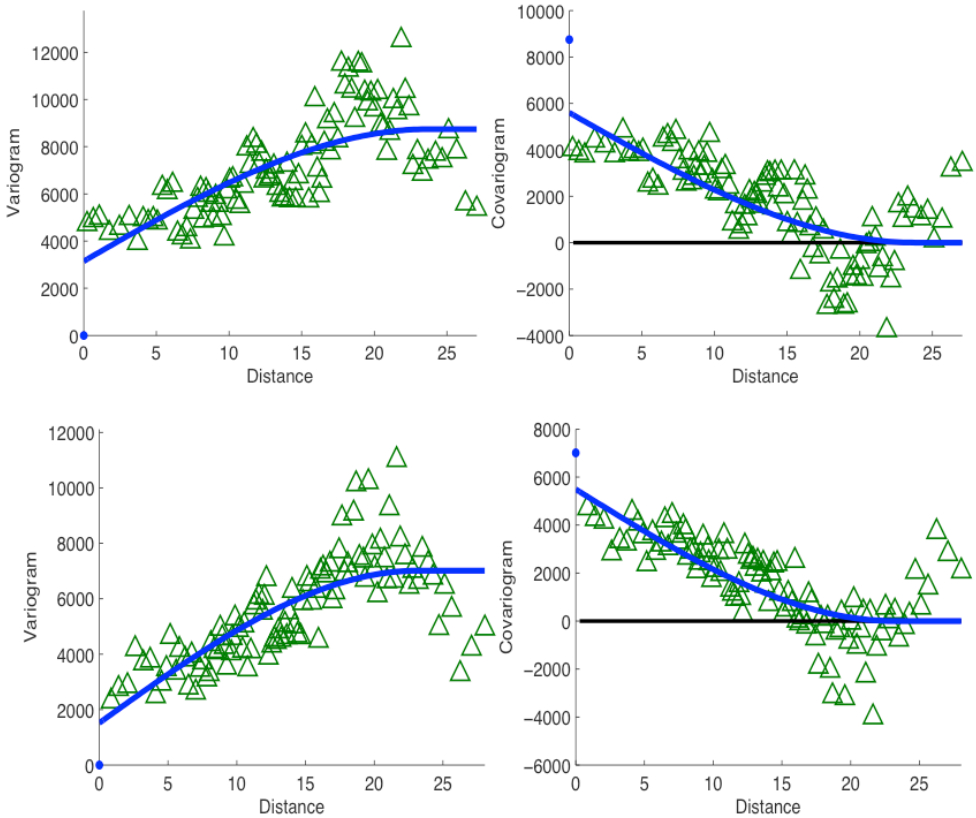

Figure S4a. Empirical semivariogram of average AGB derived from 189 unique observations by averaging the plot biomass estimates within an approximately 5 km x 5km (0.05 degrees) grid cells (top panel) and 109 available observations by averaging the measurements of each 0.8° grid box (bottom panel). *Left panel:* Semivariogram $[\gamma(h)]$ of average AGB; *Right panel:* Corresponding covariogram $[C(h) = \sigma^2 - \gamma(h)]$ of average AGB. Spatial autocorrelation analysis shows that the log-log axis of semivariogram analysis shown by EM in Fig. S. of their paper leads to erroneous interpretation. Our results show that the range of spatial autocorrelation extends to more than 2×10^3 kilometers. Although the local variation does exist (nugget effect), one cannot ignore the residual spatial autocorrelation at a longer distance. The existence of spatial autocorrelation at large distances means that the measurement at one location can be correlated with nearby measurements, suggesting that the OLS regression model can be inefficient and resulting in erroneous statistical significance tests.

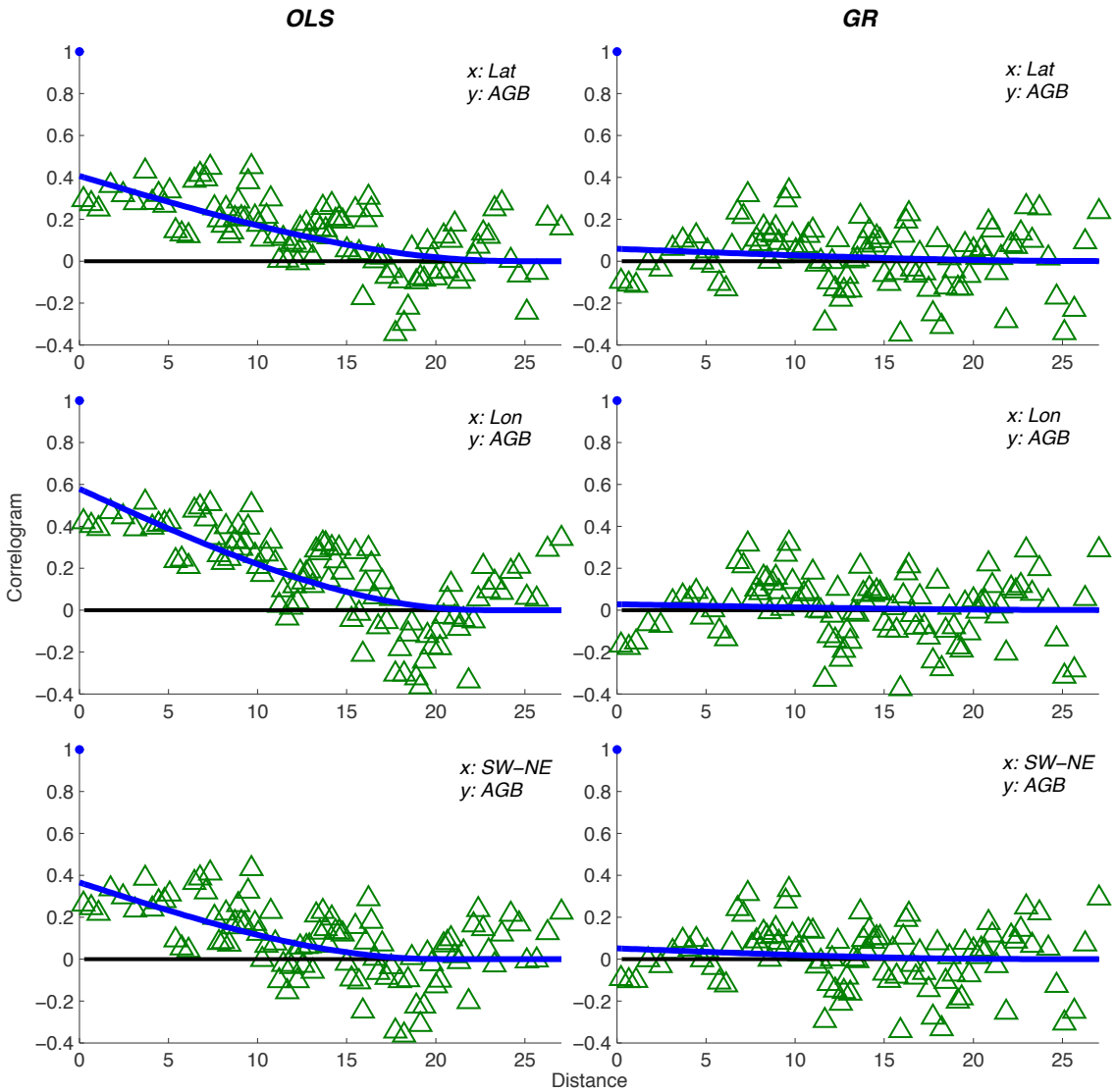

Figure S4b. Comparison of OLS and GLS models showing none of the linear regression results (shown in Fig. 2 of Mitchard et al., 2014) is statistically significant (details are also provided in Table S1). Correlogram (normalized covariogram) of OLS regression residual (*left column*) and transformed residual of GLS (*right column*). Here it shows that the transformed residual of the GR (geostatistical regression) method successfully takes the spatial dependence into account. With the presence of spatial correlations, the results of OLS regression can still be unbiased, but the coefficients' standard errors can be severely underestimated. Assuming covariance stationarity, the covariance matrix of the regression error can be estimated from the empirical variogram (to at least account for the spatial dependence on distance), and the classical OLS can be converted into a problem of Generalized Least Squares (GLS) regression to deal with unequal variance. We show that the statistical significance evaluations simply cannot be performed on OLS regressions because of the strong evidence of the presence of spatial dependence of errors and the results of the trend analysis in Mitchard et al is not valid. Adding spatially correlated uncertainty (bias) in biomass values for each unique point could have increased the spatial dependence of errors reduced the trend even further.

Table S1. Regression tests using OLS (Ordinary least-square) and GR (geostatistic regression) on the 189 unique plots and 109 available unique points aggregated from EM provided plots.

Test		OLS			GR		
		Y - Lat	Y - Lon	Y - Diag	Y - Lat	Y – Lon	Y - Diag
189 observations	β	4.72***	1.79*	3.22***	3.34	0.61	2.54
	R^2	0.17	0.03	0.17	0.13	0.00	0.15
	Moran's I on ε	0.11***	0.22***	0.12***	-0.02	-0.04	-0.02
109 observations	β	4.58***	1.27	2.89***	3.03	0.88	2.53
	R^2	0.16	0.02	0.17	0.14	0.01	0.15
	Moran's I on ε	0.13***	0.20***	0.13***	0.01	-0.02	-0.00

Significance level: $p<0.05$ (*); $p<0.01$ (**); $p<0.001$ (***).

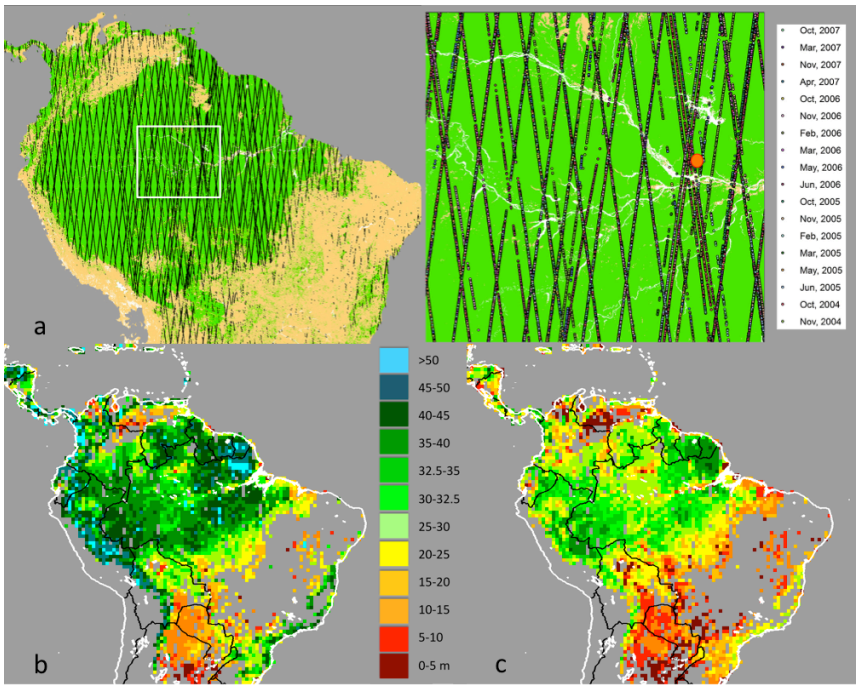

Figure S5. Systematic sampling of more than 1.2 million GLAS lidar shots over Amazonia showing a) the GLAS sampling along the satellite orbits and clusters over time in a selected region of central Amazonia and location of research plots in the red dot, b) top canopy height from GLAS lidar shots gridded at 0.5 x 0.5 degrees showing variations of maximum top canopy height (90 percentile), and c) mean top canopy height over the Amazon basin. Number of GLAS shots in each grid exceeds 1000 points that are systematically acquired along the ICESAT orbits. The figures provide three distinct patterns in the region: 1. The center of the Amazon between the area west of Rio Negro and north of Solemois, extending to borer of Venezuela in northwest of Amazonia, is covered by geomorphological complex terrain of inundated forests, sandy and old alluvial deposits and have significantly lower height than surrounding regions of ancient oxisols on the central eastern part of the Amazon. 2. Southern Amazonia bordering the transitional forests along the arc of deforestation also have significantly lower height than other regions. 3. Areas in northeast and western Amazonia around extending to the foothill of Andes all have significantly taller trees that the other region. However, the tall forests showing up in the 90 percentile map disappears in the mean height map, suggesting the western regions are more diverse in height than the northeastern Amazon where tall trees are dominant on the landscape and on infertile soil. Other regions with average tall trees on the landscape are areas in central eastern Amazon, and scattered lowland areas of less infertile soil of western Amazonia in southern Peru, southern Colombia and eastern Ecuadorian Amazon.

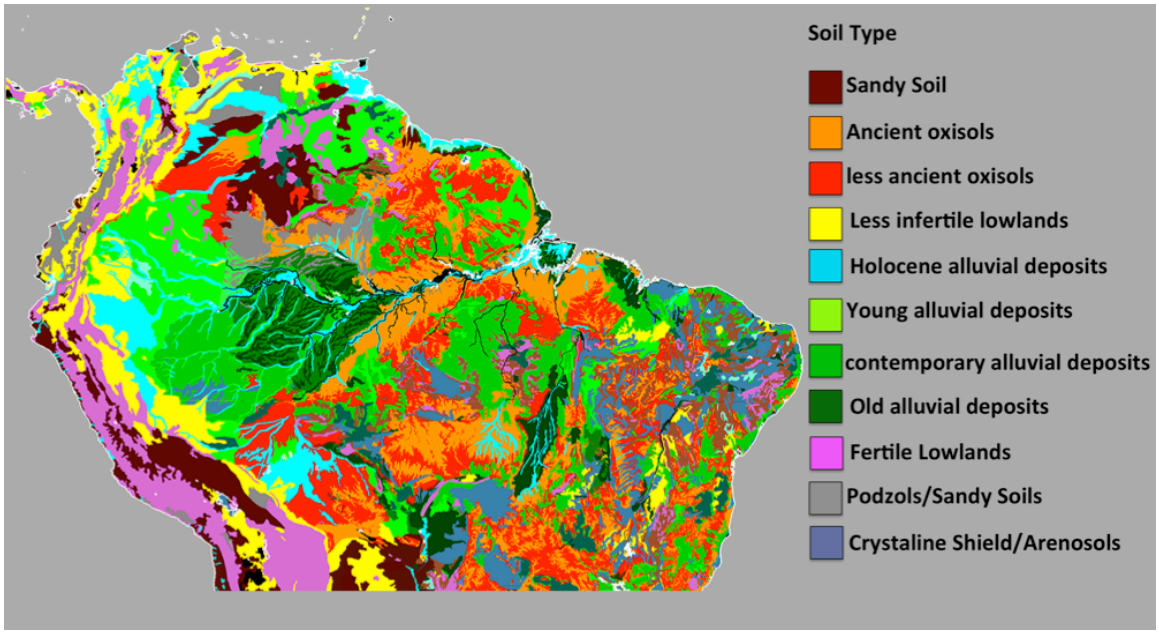

Figure S6. Soil map of Amazonia derived from SOTERLAC of South America and IBGE soil map of Brazil. We developed the soil class/landform map for the entire Amazonia to assist in the interpretation and analysis of forest height and distribution maps. The soil class data for the entire study area have been derived from two data sets: 1. Outside Brazil, the Soil and Terrain Database for Latin America and Caribbean (SOTERLAC, version 2) released in 2005 at 1:5 million scale (Dijkshoorn, et al., 2005); 2. Within Brazil, the RADAMBRAZIL soil classification complied by the Instituto Brasileiro de Geografia e EstatÌstica (IBGE) in 1981 (EMBRAPA, 1981). The assignment of the soil class was based on matching the descriptions of the map units and comparing with the landforms and geographical description provided by Sombroek (2000). The categories are: (1) Heavily leached white sand soils (spodosols and spodic psamments in US Soil Taxonomy, podzols in World Reference Base (WRB) taxonomy), (2) Heavily weathered, ancient oxisols (ferralsols in WRB classification), which predominate in the eastern Amazon lowlands, (3) Less ancient oxisols and other younger soils soils (ferralsols and nitosols in WRB taxonomy, (4) Less infertile lowland soils (ultisols and entisols is USDA taxonomy; cambisols and acrisols in WRB classification), which particularly predominate in the western Amazonian lowlands and some parts of Brazil, (5) Alluvial deposits from the Holocene (less that 11 500 years old), including very recent deposition, including the fluvisols of Brazil, (6) Young alluvial soils in northwestern Amazonia, (7) Contemporary alluvial soils including acrisols with plinthic and gleyic content, gleysols, luvisols, histosols, (8) Old alluvial soils of central Amazonia, (9) Young, lowland and submontane soils, perhaps fertilized by volcano-aeolian deposition, (10) Poorly drained and waterlogged podzols and sandy soils dominated in central Amazonia,(11) Low fertility lowland sites of crystalline shield with mixed entisols and aerosols.

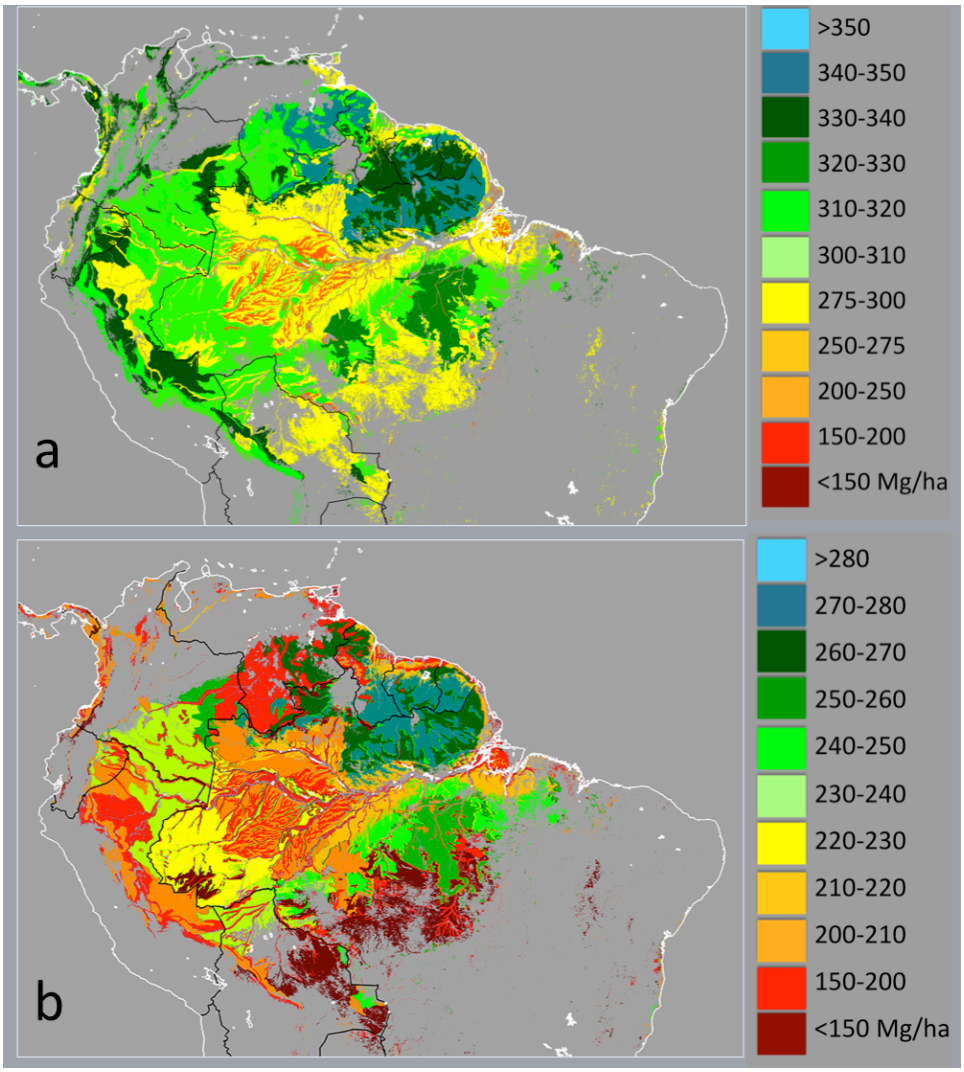

Figure S7. Distribution of 90 percentile and mean biomass in forests aggregated based on soil types of Amazonia provided in Figure S6: a) the 90 percentile biomass distribution for each soil type provides a clear distinction of regional patterns in Amazonia suggesting that areas on the northeast Amazonia on infertile oxisols have higher carbon stocks in forest aboveground biomass than the western forests on fertile soils. The less infertile soils of south western and younger Alluvial soils of northwestern region are also potential regions of relatively high biomass forests, and b) the mean biomass provides a much wider range of biomass distribution in Amazonia separating the fertile soils of western lowland and submontane regions from northeastern infertile soils of Guiana Shields. The central Amazonia covered with sandy, podzols, and old alluvial deposits have relatively lower biomass than the northeastern regions.