#1 Response to : Interactive comment on "An analysis of forest biomass sampling strategies across scales" by Hetzer et al.

The paper by Hetzer et al. aims at assessing the effect of sampling strategy for estimating tropical forest aboveground biomass at different spatial scales. While this topic is of importance, it has already been well covered in the litterature. However, the simulated approach developped here have some originality (e.g. the point pattern reconstruction) but, in my opinion, some rather surprising or context-dependent results are due to methodological artefacts as described below. These artefacts are rather difficult to overcome but they should be at the minimum discussed or acknowledged before consideration for publication.

Thank you for your very helpful comments. We will prepare a revision of our manuscript that will follow your recommendations closely. The main changes will be:

a) Consideration of the biome for the biomass sampling

We conducted an additional analysis where sampling was carried out only in tropical forest biomes. This could reduce the number of plots required for continental biomass estimates. A further stratification into single biomes did not decrease this number significantly. We plan to add and discuss these findings in the revised manuscript.

b) Renaming the sampling method

We propose to rename the 'remote sensing sampling' method to 'transect sampling' and consider the implications for remote sensing in the discussion section (e.g., airplane tracks from LiDAR campaigns).

c) Impact of more variation in high biomass values

The current analysis leads to conservative estimations of necessary sample plots. We agree that the tested biomass maps have limitations due to saturation effects. We will conduct additional analyses with higher variation in high biomass values and discuss the results.

We have added our responses to your comments in blue following each comment.

##Major comments

Globally, many statements (see my specific comments) are very basic and already well known in the litterature (e.g. many sentences in the conclusion section). The author C1 should refer more to previous works and concepts, including those developped for temperate forests where a huge research effort on sampling strategy has been done in the past.

Thank you for this helpful comment. We will improve our introduction by including a paragraph discussing some state of the art sampling methods for temperate forests (e.g., national forest inventories in Europe and North America), where systematic sampling designs were established and evaluated (e.g., Keith et al., (2009).

Furthermore, we will discuss why these sampling approaches are more difficult to establish in tropical regions. One main challenge is that tropical forests are often more dense than temperate forests (about twice as many trees per km^2 (Crowther et al., 2015)), so measurements are more labor intensive. Another issue is that access to tropical forest regions is often restricted due to topographic, logistic or political reasons (Houghton et al., 2009; Mitchard et al., 2014). This limits a comprehensive sampling as applied for temperate forests.

Investigating the effect of spatial scales (local, regional and continental) on sampling strategy is very appealing. However, I am very skeptikal about the use of remote sensing products as reference data. Both Asner and Baccini used passive optical data to extrapolate AGB at large scale and these products are well known to saturate for large AGB (>100-200 t/ha) values leading to a strong underestimation of AGB variability. This effect is well illustrated by the Fig. S2 where the SD of AGB first increase with AGB and then decrease. Theoretically the SD of AGB should continuously increase with the mean AGB (this is why people generally use CV instead of SD for comparison purpose). Thus, the decrease of SD with AGB in Fig. S2 is simply an illustration of the saturation problem so that using these maps, or dowscaling them using such SD pattern, result in a strong underestimation of AGB variation in high biomass areas, which, in my opinion, bring a strong bias in the final results presented here. This is probably the reason why some results are very counter-intuitive, such that plot size does not matter at large scale or that a large number of large plots provide less accurate AGB estimate than a small number of small plots (Lines 157-159).

Thank you for that important remark. It is true that the biomass maps used in our study have their limitations. However, these maps represent currently the only possibility to analyze continent-wide biomass distributions. To overcome specific biomass map artifacts we analyzed different biomass maps (Baccini et al., (2012) and Saatchi et al., (2011); see supplements, table S1).

We agree that the saturation effect has not been considered yet. Therefore we analyzed a second downscaling method, where we assume, as an extreme case, a strongly increasing trend between mean aboveground biomass and its standard deviation (see attached figure 1). In this case we found that about 150 one-ha plots (instead of 88 one-ha plots derived by the currently used approach) would be necessary for mean biomass estimations of the South America tropical forest (see attached figure 2). Thus, saturation will increase the number of sampling plots needed. We plan to add and discuss these results in the revised manuscript.

I had two problems with the simulation of RS sampling. First, RS was simulated as discrete measurements, may be to simulate satellite LiDAR measurements such as those produced by GLASS or GEDI, but there is no justification for that (most satellites produce continuous measurements). This is surprising given that the authors used continuous RS-based maps to validate such RS sampling strategy, which look like a bit skizophrenic.

Thank you for this important comment. After some critical reflection, we decided to call this method ‘transect sampling’ as we focus mainly on the establishment of empirical forest plots with this sampling method. We will discuss the relevance of this sampling strategy also for remote sensing applications in the discussion section, as this transect sampling could be interpreted as proxy for airplane flight tracks from lidar campaigns.

Second, I did not fully understand the methodology. I understood that measurements were simulated at different distance along simulated transects but I did not understand how and if the distance between transects varied or not. I am not even sure that the authors simultaneously simulated several transects as would typically be done by a satelitte. I would suggest to simulate a sampling design similar to the one C2 that was or is adopted by GLASS or GEDI to make this simulation more practical even if this is challenging due to the high resolution of LiDAR footprint (~70 and 20 m) and the abovementioned downscaling problem.

As mentioned above, this transect method sampled plots in North-South transects. Within one transect, the plots had regular distances of 0.5km, 1km or 5 km. The spacing between transects was not regular, but randomly chosen. For the South America forest, for example, this method needed typically about 100 randomly chosen North-South transects (considering 1 km distances). We will revise the method section to clarify this approach.

The sampling showed in Fig. 2 illustrates a major problem. Nobody sample at the same time dense humid and dry forests to depict a mean biomass. This is always practically done by forest type using a prior stratification design. The minimum, to have something comparable with the other scales (BCI and Panama) is to focus only on tropical dense humid forests. This may explain why an aggregated sampling design produce such huge errors given that it sample very different forests at the continental scale.

Thank you, this is a good point. In the revised manuscript we will combine the biomass map with a biome map (Dinerstein et al., 2017) to distinguish between different vegetation types. This gives us the possibility to analyze the sampling strategies not only for tropical forest (covering moist broadleaf, dry broadleaf, conifer and mangrove forest) but also for forests of different biomes separately. After merging these two maps, we found that the number of sampling plots decreases if taking only tropical forest into account (from 48,000 to 36,000 plots, see attached figure 2, first two bars). The additional analysis indicated furthermore, that a stratification into biomes does not lead to a significant reduction of the needed sample plots, since the sum of the plots needed for single biomes (34,000 plots) is similar to the plots needed for an overall forest sampling (36,000 plots). However, this stratification helps to better evaluate sampling effort for each biome. We will add the new results (see attached Figure 2) and discuss them in the revised manuscript.

As illustrated in Fig. S3, and by previous studies conducted in BCI, the spatial distribution in AGB do not significantly differs from a random distribution. This explain why, for a given sampled area, using several small or few large plots little impacts your estimates. This should be better explained in the present paper by explicitely mentioning the effect of spatial aggregation on sampling design and by stating that your result would probably not hold at the same scale in many (!) other forests that show strong AGB aggregation patterns (which is the case of most forests).

Thank you for your comment. We will revise the discussion by mentioning the effect of spatial aggregation (e.g., Chave et al., (2003); Marvin et al., (2014)).

Note also that the central limit theorem only applies if observations are independents (i.e., in absence of significant spatial structure), such that this theorem is theoretically valid only for the BCI scale in your study.

Thank you for that note, this is a tricky point. It is true that the large scale biomass maps show spatial autocorrelation, but we choose in our sampling strategy "random sampling" the biomass values from random locations of the map. This secures that each of our biomass observation is randomly generated in a way that does not depend on the values of the other biomass observations.

We would have an autocorrelation problem with the used biomass map if we apply for example clustered sampling (i.e., select always nearby points with higher probability). In our study we compared the outcome of the central limit theory only with the random sampling, not with the other sampling strategies. For all other sampling strategies the spatial autocorrelation of the underlying biomass map is crucial – therefore we simulated these sampling strategies instead of applying the central limit theorem. We will clarify this in the revised manuscript.

The discussion section may discuss the realism of a random sampling design at the continental scale in Amazonia.

We will add a paragraph on the realism of sampling in the discussion section (i.e., current amount of inventory plots in Amazonia, current remote sensing measurements).

The conclusion section should highlight more the originality of the present work.

We will revise the conclusion carefully regarding this comment. Highlights are for example novel methods to investigate non-random sampling strategies (e.g., by using point pattern simulations).

##Specific comments

Line 27: space lacking: “important(Broich” Will be done.

Line 29: Are those referenced all provided biomass maps? In this study, we compared the biomass maps of Baccini et al., (2012) and Saatchi et al., (2011), but there are more biomass maps available (e.g.,Avitabile et al., (2016)). We will clarify this point.

Line 34: Please replace by “so that the local distribution in biomass”. At least remove C3 “local regions”, which is inapropriate. Will be done.

Lines 34-35: This last sentence is very vague. Will be deleted.

Line 45: This is an old reference, what about most recent works such as Baccini and Saatchi maps? We will adjust the numbers to latest literature.

Line 49: Assume that plots or biomass are. . .. Will be done.

Line 52: I don’t see the logic here. First it is obvious that the representativness of a given number of plots is context-dependent and varies with the total area of interest and second the number of plots fall into the recommendation cited line 48 so that it does not illustrate that the number of plots varies according to the sampling design. We agree that this number does not reflect the differences between sampling strategies. We will delete this example and revise the paragraph.

Figure 1: I would have personally not call the b panel a landscape scale but rather a regional scale. I know that the definition of scale strongly varies in the litterature but I can hardly imagine a landscape of more than 500 km. Thank you. We will rename the term.

Line 73: "determined using allometric relationship" is really vague, unless the methodology is fully described in the Knapp paper. If yes, please add (see Knapp. . .. For details). The methodology is described in the Knapp paper. We will add the reference as proposed.

Lines 77-78: The following sentence is useless and confusing (strange to refer to plots for RS maps, we usually use pixels instead): "For this purpose, between 4 and 25 plots from the original map were averaged." We will revise this sentence.

Lines 79-80: This last sentence is useless. Will be deleted.

Line 81-82: This is not true that the Baccini map mostly derived from LiDAR measurements. The global methodology used was to callibrate GLASS LiDAR footprints with field data and then to calibrate a MODIS product with the calibrated LiDAR measurements. Thus the final product mostly reflect MODIS data, that are very little sensitive to biomass and highly sensitive to cloud cover (e.g. the large area of lower biomass observed on the western coastal area of central Africa, compared to the central basin, C4 is simply due to cloud cover). Thank you for mentioning this important point. We will revise this sentence.

Line 83: Please provide rounded numbers. Will be done.

Line 86-87: Please replace plot by pixel. Will be done.

Fig. 3 legend: "below the bar " should be replaced by "above the bar" Will be done.

Lines 143-144: Very obvious and well-known result. We will add "Likewise to many other studies we show …".

Lines 154-155: First sentence useless. Will be deleted.

Lines 180-181: Please reformulate. Will be done.

Lines 230-232: Very obvious. We will revise this sentence.

Line 235: If forest types are known a better strategy would be to stratify the sampling by forest types. We agree with you and will show that by the expanded results on biomes.

Lines 255-256: As already shown and discussed by previous works. We will add references.

Line 259: What is a regional scale here? Forest sites comparable to BCI. We will revise this sentence.

Line 267: For a given sampled area, plot size should not. . ... Will be done.

Line 270-271: This is what is generally done, remote sensing almost always relies on field data. Please be more explicit. We will revise our conclusions as we proposed above.

Figures

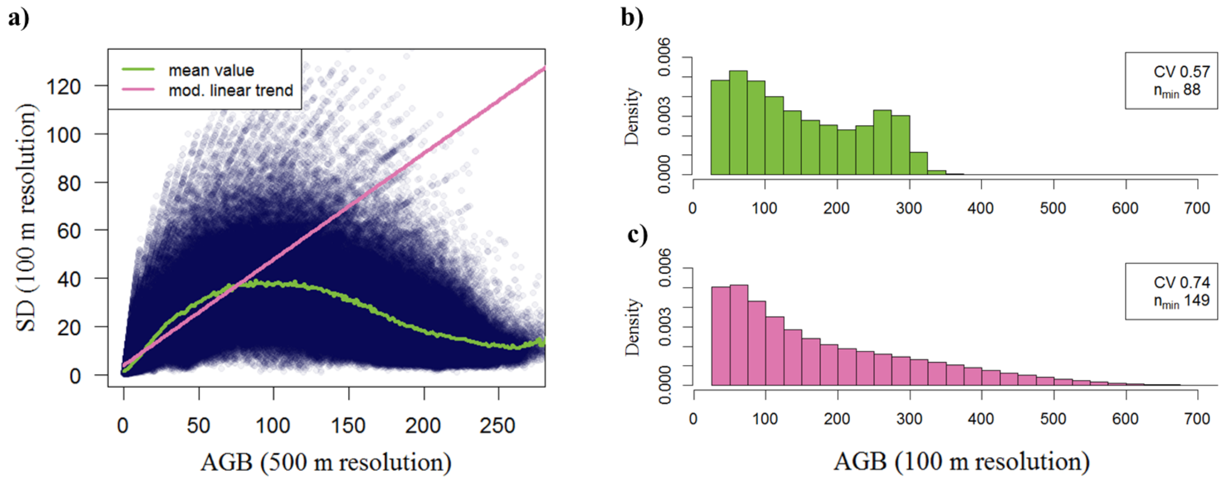

Figure 1: Comparison of downscaling approaches. **a)** Subplot heterogeneity in the Panama biomass map (500 m resolution). Shown is the aboveground biomass (AGB) at a 500 m resolution and the standard deviation (SD) of its associated 25 subplots at a 100 m resolution. Each dot represents one plot from the Panama map (~300,000 plots).The green line shows the 'mean value approach', as it was implemented in the current study. The pink line shows the proposed second downscaling approach. There, the linear trend resulting from AGB values smaller than 100 t/ha is continued for larger biomass values. With this second approach we assume a much higher variation in large biomass values as observed in the map. **b-c)** Aboveground biomass distribution of South America at a 100 m resolution using b) the mean value approach as implemented in the current study (green) and c) the linear trend approach (pink). Coefficient of variation (CV) and the minimum sample size (n_{min}) of randomly chosen 1 ha plots are displayed at the upper right corner for each biomass distribution.

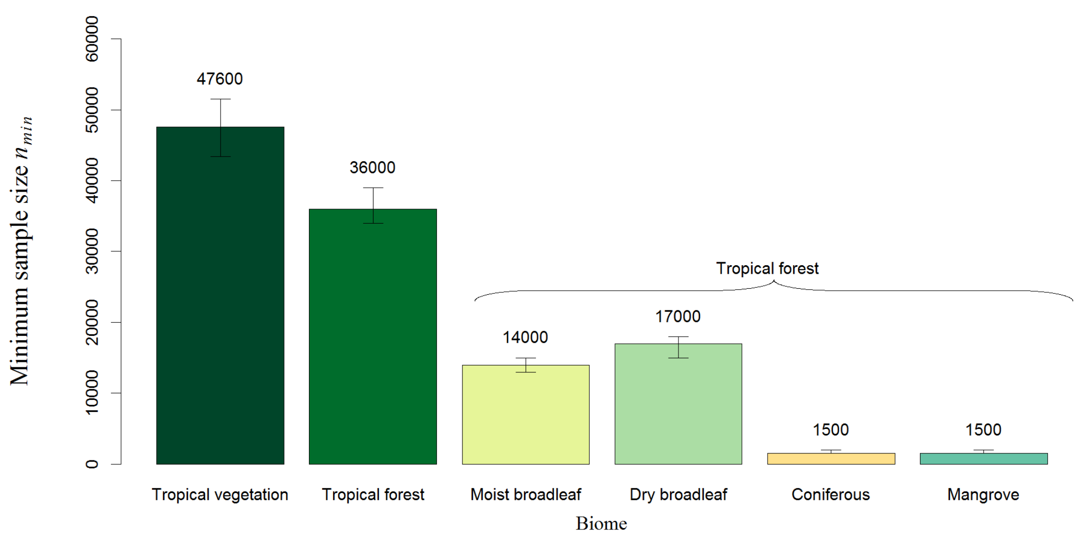

Figure 2: Necessary number of samples to derive accurate mean estimations for different forest biomes of South America by applying the transect sampling (former remote sensing sampling). Samples (25 ha each) were taken with regular distances of 1 km between plots. The first bar shows the results for South America as implemented in the current study (Tropical vegetation). The second bar displays the number of plots when sampling is carried out exclusively in forest biomes. Therefore we merged the biomass map used (Baccini et al., 2012) with a biome map (Dinerstein et al., 2017), restricting sampling to moist broadleaf, dry broadleaf, coniferous and mangrove forest. The last four bars give the minimum sample size if forest biomes are sampled separately. Error bars reflect the range of 10 repetitions.

Literature

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