Response to Referee#2

General Comments:

Referee#2

This paper provides an interesting comparison of biomass stock estimation with different techniques across a broad area of peat swamp forests in Indonesia. Biomass estimates, use of LiDAR and studies on forest degradation are scarce for this region and this paper represent a valuable contribution. However, there are several methodological and sampling design issues that are likely to alter the findings and undermine the conclusions. Despite an interesting error propagation approach, the way LiDAR metrics are then weighed by density remain unclear. More importantly, the uncertainties in both plot-based biomass stocks and LiDAR heights estimates are not accounted for and are not discussed at all throughout the paper. I am afraid the sampling design will embed to answer the points I am raising. I would be happy to read further comments and clarification from the authors in a revised version though.

Authors' response

We would like to thank referee#2 for the constructive comments. We will provide more information on LiDAR data processing, DTM generation, sampling design and uncertainties. Further the language of the manuscript will be proofread with the help of a native English speaker. Below we address the comments point by point.

Major Revision:

Referee#2

p. 11820 – Acquisition and processing The authors provide in this section a very ideal description of their device and I would have preferred a verification of the accuracy of their device in the real conditions.

Authors' response

Indeed a valuable comment:
We will add the following to the manuscript:
We collected 88 dGPS measurements in various locations along and across track. DTM accuracy was 0.4m RMSE with a mean point density of 0.43pt/m2.

Referee#2

The authors don't mention here if they used a multi-echo LiDAR (or first/last return). Depending on the type of LiDAR, the penetration might greatly vary and so do height estimates (see (Gaveau and Hill, 2003)).

Authors' response

On p.11820, L 3 we write that small-footprint full-waveform LiDAR data was used. Processed full-waveform data results in multi-echo LiDAR point clouds.

Referee#2
Furthermore, unpublished results (http://www.kalteng.org/dyn/pdf_files/Silvilaser-Boehm-Lieseberg-Frank-ID-113-20.9.2010.pdf) indicate that tree height might be correlated with peat dome slope (i.e. higher trees on top of the domes) and thus changing the H/DBH relationship locally, and subsequently the AGB/CHM relationship. Did the author have the opportunity to investigate H/DBH relation within and among forest types?

Authors' response

We are aware of this not peer reviewed paper. LiDAR tree height has not been compared to and validated by field measurements in this study as we did it. They present tree heights which are too low. The paper does not tell a single line on how the DTM or the tree crown model was generated. In addition own field data and published literature (Anderson, 1963) shows that either small or tall trees can grow on top of peat domes.

We used full waveform data to avoid problems to determine tree heights as it occurs with first/last pulse data (which was used in the Böhm paper). And we used relative heights and Centroid Height (CH) and the Quadratic Mean Canopy profile Height.

Since both technologies, LiDAR and field measurements, do not allow to accurately determine tree heights in this tropical swamp forest environment, we decided not to use this parameter and subsequently did not investigate H/DBH relation.

Referee#2
p. 11820, L15-19: No reference is given on the algorithm used to filter ground points.

Authors' response
We will provide more detail concerning the LiDAR point cloud filtering and the DTM generation in the manuscript. More details are given in the response to reviewer 1.

Both filtering and interpolation were implemented through the Inpho software package (DTMaster and SCOP++). LiDAR point cloud filtering was the separation between ground and off-ground points. Since within the study area all off-ground points consisted of vegetation no further classification was necessary. The filtering methodology used was the Hierarchic Robust Filtering (Pfeifer *et al.* 2001), followed by a strict quality control.

SCOP++ software package was used for the identification of the terrain surface. It uses linear prediction. The theoretical basis of linear prediction is presented in detail in various publications (e.g. Kraus 1998, Assmus 1975). Linear adaptable prediction corresponds to the statistical estimation method Kriging, often applied in Geo-sciences (Kraus 1998).

Referee#2

p. 11821, L. 1-5: 0.13–ha plots sounds very small to accurately quantify biomass stocks especially when using expansions factors. Do the authors have quantified the variability of their estimates and number of plots required per forest type? (Wagner et al., 2010) showed that plots < 0.1 ha had CV > 20 % in an unmanaged forest in French Guiana. I expect even greater variability in degraded forests. An accurate assessment of this variability should be accounted for in the regression models proposed. For instance, (Mascaro et al., 2010) calibrated LiDAR data with plots of 0.33-ha, a size about 3 times bigger than the values reported here and recommended to be cautious with plot sizes below this threshold.

Authors' response

Mascaro et. al (2011) uses a mixture of plots with sizes of 0.1ha and 0.36ha. He also confirms that these are standard values when modeling AGB. Increasing plot size could mask actual AGB variations. In our Kronseder et al., 2011 paper we investigated plot designs. Best results for PSF were achieved when using this field plot configuration.

Referee#2

p. 11821, L. 26-27: How is Centroid Height computed? This is technique refers generally to large-footprint data. If you were using the distribution of points into vertex of 0.13-ha and removed only the first bin, then why not accounting for trees smaller than 7 cm dbh? I agree that this DBH-class do not account for a large fraction of biomass stocks, but might largely affect the height distribution in your plots.

Authors' response

It is common in forest inventories to only measure trees below a certain DHB (usually 5cm). We used 7cm because in the highly inaccessible peat swamp forests we found this a good tradeoff between the time required for the in in-situ measurements, the number of sample plots which could be measured with the available resources and measuring a sufficient number of trees (Pearson et al. 2005). As the proportion of trees with small diameter on the overall AGB was very small we decided to accept a slightly lesser accuracy in overall AGB estimation order to minimize the invested time per sample plot. In reducing measuring time per sample plot more sample plots could be recorded, which represented more different environmental and ecological peat swamp forest conditions.

Referee#2

Why did you prefer the quadratic mean canopy height (QMCH) to mean canopy height (MCH), as this is a classical LiDAR metric used in several other studies. In the reference you are citing, QMCH does not provide better fit than MCH.

Authors' response

In our study the QMCH performed slightly better than the MCH. In the study where the MCH and QMCH are described in detail (Lefsky, 1999), the QMCH also showed a better performance over the MCH. In (Asner, 2010) both parameters showed the same r2.

Referee#2
Furthermore, in a very similar study (Kronseder et al., 2012) showed that the best predictor of AGB was a tough combination of several metrics (SEM, H65 and H45). Why did the authors not have followed the same methodology here? A more complete analysis of the effect of LiDAR metric on model performances would have been of interest.

Authors' response
Building on our results presented in the Kronseder et al., 2012 study we further explored different processing techniques and found that the metrics presented here very useful.

Referee#2
p. 11822, L. 1-2: What is the bin range used here? As you developed the DTM, you know which points are "ground" and others that are not. So why not more simply remove those points from further analyses?

Authors' response
The bin range was 1m. We preferred to use the whole dataset and cut the first bin in order to eliminate possible filtering outliers and echoes from aerial roots and undergrowth herbage. This approach was presented in (Lefsky, 1999), and used in many other studies e.g. (Asner, 2010).

Referee#2
p. 11825, L. 16: Why did you used only peatland values in your comparison? Is the entire region covered by peatland forests? Why did do this? Not clear to me. In Table 1 & 2 is seems that 'peat swamps forest pristine' (would rather used 'undisturbed' or 'unmanaged') only cover 36-39% of the area…

Authors' response
The focus of this study were undisturbed and disturbed peat swamp forests which grown on peat soil. We analyzed only LiDAR tracks which cover peatland (94% of the total area of 28 284 ha shown in Table 2).

Peat swamp forests are an important ecosystem in SE Asia, they play a major role in GHG emissions from LULUC and climate change (Page et a., 2001, Ballhorn et al., 2009, van der Werf et al., 2009).

Referee#2
Table 1 & 2: How do you explain that biomass estimates from LiDAR and those from field plots varies of 20 - 40% and you are concluding (p. 11829, l.19-20) that 'airborne LiDAR data is the most reliable solution'. Compared to what? SMA, field inventories, IPCC? As you biomass stock estimates derived from LiDAR metrics were calibrated on plot inventories, it seems to me that they should be taken as reference and the underestimation of biomass stocks with LiDAR discussed.

Authors' response
In-situ field plots of AGB are point measurements while LiDAR provides spatially contiguous AGB estimates. When we say 'airborne LiDAR data is the most reliable solution' than we compare these to other remote sensing approaches such as SAR. But also compared to in-situ field plots LiDAR provides better data because it is capable in taking thousands of AGB samples which cannot be obtained in the field in this extreme ecosystem. In the final Manuscript we will elaborate on this advantage in more detail.

Minor Revision:

Referee#2
General proofreading is required.

Authors' response
For the final manuscript we will proofread the paper with the help of a native English speaker.

Referee#2
p. 11816, L. 17: "overestimation of 46 % ",.. -> table 2 shows 43%

Authors' response
You are right it must be 43% and not 46%.

Referee#2
p. 11818, L. 2 : "is always inevitably" replace by "is inevitable"

Authors' response
We will change "inevitable" to "necessary", which would make our statement more clearly.

Referee#2
p. 11818, L. 3 : "RS data has" replace by "RS data have"

Authors' response
We will replace "has" by "have"

Referee#2
p. 11818, L. 21-22 : "due to natural growth condition" sounds odd to me. Do you mean variability in tree growth or environmental heterogeneity?

Authors' response
We propose the following change: "natural tree growth conditions (availability of nutrients, water logging etc.)".

Referee#2

p. 11822 – L. 2 : “from the further processing” replace by “from further processing”

Authors’ response
We will replace “from the further processing” by “from further processing”.

Referee#2
p. 11822 – L. 3 : “from LiDAR surveying”, do you mean surveys?

Authors’ response
We will replace “surveying” by “surveys”.

Referee#2
Table 1 : Why don’t you report your figures in Mg ha-1. It would help compare with other publications.

Authors’ response
In the final manuscript we will report in Mg ha^{-1}

Reference cited referee#2:

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