Extended abstract No. 189

AIRBORNE LIDAR MEASUREMENTS TO ESTIMATE FOREST CARBON STOCK IN PEAT SWAMP FORESTS

UWE BALLHORN: Biology Department II, GeoBio Center, Ludwig-Maximilians-University, Grosshaderner Str. 2, D-82152 Planegg-Martinsried, Germany. -and- RSS Remote Sensing Solutions GmbH, Isarstr. 3, D-82065 Baierbrunn, Germany, Phone: +49 (0)89 48 95 47 66, Email: ballhorn@rssgmbh.de.

JUILSON JUBANSKI: RSS Remote Sensing Solutions GmbH, Isarstr. 3, D-82065 Baierbrunn, Germany.

KARIN KRONSEDER: Biology Department II, GeoBio Center, Ludwig-Maximilians-University, Grosshaderner Str. 2, D-82152 Planegg-Martinsried, Germany. -and- RSS Remote Sensing Solutions GmbH, Isarstr. 3, D-82065 Baierbrunn, Germany.

FLORIAN SIEGERT: Biology Department II, GeoBio Center, Ludwig-Maximilians-University, Grosshaderner Str. 2, D-82152 Planegg-Martinsried, Germany. -and- RSS Remote Sensing Solutions GmbH, Isarstr. 3, D-82065 Baierbrunn, Germany.

SUMMARY

Airborne Light Detection and Ranging (LiDAR) represents a potential technique for biomass quantification and monitoring. We estimated forest Above Ground Biomass (AGB) through correlating airborne LiDAR data to forest inventory data within a peat dominated study area in Central Kalimantan (Indonesia). The Centroid Height (CH) of the LiDAR height histograms, using LiDAR point densities as weighting factor, led to the highest correlation (R^2 = 0.88, n = 52). The results also showed that surveying with a LiDAR point density between 2 and 4 points per square metre (pt/m^2) had the best cost-benefit relation. An AGB Landsat based classification resulted in an overestimation of about 61% compared to the LiDAR derived AGB estimates.

KEYWORDS: Above ground biomass, Indonesia, LiDAR, REDD+, tropical peat

INTRODUCTION

It is estimated that in 2008, worldwide deforestation and forest degradation emissions contributed about 6% to 17% of the total anthropogenic carbon dioxide (CO_2) emissions (Van der Werf *et al.*, 2009). Between 1990 and 2005 about 13 million hectares (ha) of tropical forest were deforested annually and with 0.98% South and Southeast Asia had one of the highest annual deforestation rates for the time period of 2000 to 2005 (FAO, 2006). In Indonesia increased greenhouse gas (GHG) emissions are particularly evident in the coastal lowlands of Sumatra and Kalimantan, where peat fires and peat decomposition, due to peatland drainage, result in the release of huge amounts of CO_2 (Page *et al.*, 2002; Ballhorn *et al.*, 2009; Hooijer *et al.*, 2010). One important measure of the United Nations Framework Convention on Climate Change (UNFCCC) to curb GHG emissions from this sector is the programme on Reduced Emissions from Deforestation and forest Degradation in developing countries (REDD+) which involves the private sector of industrialized countries in the protection of the remaining tropical forests to compensate the exceeding of their GHG emission quota. To estimate GHG emissions from deforestation and forest degradation information on both the area of forest loss and/or degradation and the corresponding carbon stock of the land that is cleared and/or degraded is needed which remains a big challenge in tropical forests (Gibbs *et al.*, 2007). Especially GHG emission from forest degradation is difficult to monitor, particularly considering that degraded and regrowing forests are predicted to include increasingly large portions of the tropics (Gibbs *et al.*, 2007).

Airborne LiDAR provides three-dimensional information of forest structure and represents a potential technique for biomass quantification and monitoring. The main goal of this study was the estimation of AGB values for different tropical forests in the Indonesian province of Central Kalimantan through airborne small-footprint full-waveform LiDAR data analysis. Much of Central Kalimantan comprises a peat dominated landscape where large-scale peatland drainage systems and resulting repeating severe wildfires destroyed large tracts of these peatland ecosystems (Rieley and Page, 2005).

MATERIALS AND METHODS

The airborne LiDAR point clouds were analysed using two techniques: the Quadratic Mean Canopy profile Height (QMCH) (Asner *et al.*, 2010); and the CH, which was developed for this study. These parameters were correlated with the field-measured AGB on plot level (0.13ha) in order to establish robust non-linear biomass estimation models. As additional parameter to improve the robustness of the models, the LiDAR point density (pt/m^2) at each plot was treated as weight during the regression. In order to verify the influence of point density in the AGB accuracy, a rigorous covariance analysis was performed. The biomass estimation models were applied to 33,178ha of LiDAR tracks covering diverse forest types in Central Kalimantan. Further, the LiDAR AGB estimates were quantitatively compared to results obtained by an object-oriented land cover classification based on Landsat imagery for a 2,987,726ha study area. The AGB values of the different land cover types were based on results of a literature survey and assigned to the different land cover types classified in the satellite imagery.

RESULTS

Fig. 1A shows the results for the regression using the CH as input. A high correlation coefficient (R^2 = 0.88, n = 52) was obtained when the LiDAR point densities were treated as weight during the regression. The derived coefficient of determination is similar to those reported in studies throughout various tropical biomes (e.g. Drake *et al.*, 2002; Asner *et al.*, 2009; 2010). Also, for the QMCH a high correlation was obtained (R^2 = 0.84, n = 52) when applying the LiDAR point density weighting (Fig. 1B). In both cases, the use of the LiDAR point densities as weight improved the regression models (9% and 8% for the CH and QMCH respectively).

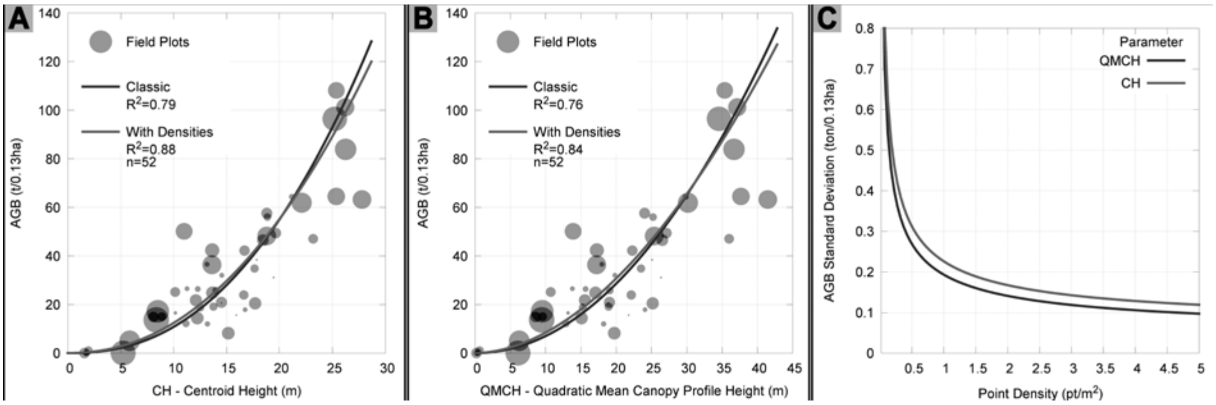

Figure 1 (A) In light gray the Centroid Height (CH) based Above Ground Biomass (AGB) regression model with LiDAR point density weighting (AGB = 0.0865 x $CH^{2.1564}$; $R^2 = 0.88$) and in dark gray without weighting (AGB = 0.0484 x $CH^{2.3494}$; $R^2 = 0.79$). (B) In light gray the Quadratic Mean Canopy profile Height (QMCH) based AGB regression model with LiDAR point density weighting (AGB = 0.1150 x $QMCH^{1.8656}$; $R^2 = 0.84$) and in dark gray without weighting (AGB = 0.0660 x $QMCH^{2.0277}$; $R^2 = 0.76$). The circle sizes represent the LiDAR point densities per square meter (pt/ m^2). The smallest circle has a LiDAR point density of about 0.2pt/m^2 and the biggest circle of about 3.5pt/m^2. (C) Standard deviation behaviour estimation curves for CH and QMCH based regression models (derived from the rigorous covariance propagation analysis).

The costs of LiDAR surveying are decreasing, but still relatively high, and are strongly related to the desired point density. To assess the influence of the LiDAR point density on the estimation of the AGB, a rigorous covariance propagation analysis was performed. The results of this analysis showed that the AGB standard deviation decreases significantly with increasing LiDAR point density until approximately 2pt/m^2 and for LiDAR point densities higher than 4pt/m^2 no significant standard deviation improvement could be observed (Fig. 1C). These results suggest that expensive LiDAR surveying with more than 4pt/m^2 are not necessary to achieve reasonable AGB regression models but, on the other hand, surveying with less than 1pt/m^2 can lead to significant inaccuracies, so that surveying with a point density between 2pt/m^2 and 4pt/m^2 shows the best cost-benefit relation.

Through applying the CH based regression model it was possible to quantify natural AGB variability (linked to soil properties and water availability) and the impact of previous logging operation and fire with high spatial resolution. Variability could also be detected in low AGB ranges. These disturbances cannot be identified unambiguously in Landsat imagery. By analysing spectral information, large areas of forest are assigned to be one class (e.g. pristine peat swamp forest). Thereby, the negative impact of named degradation activities on AGB or carbon content is neglected. The Landsat based classification approach resulted in an overestimation of 60.8% compared to the LiDAR derived AGB estimates for the 2,987,726ha study area.

CONCLUSION

The quantification of tropical forest carbon stocks over large geographic areas is a key challenge in creating a basic methodology for REDD+ projects. As the main carbon pool of tropical forests is typically the AGB (Brown, 1997; Chave *et al.*, 2005; Gibbs *et al.*, 2007) we estimated AGB of different tropical forests in the Indonesian province of Central Kalimantan through correlating airborne LiDAR data to forest inventory data. Two metrics, the QMCH and the CH from the LiDAR height histogram, which was developed for this study, were analysed. The regression models could be improved through the use of the LiDAR point densities as weight. The highest coefficient of determination was achieved for CH ($R^2 = 0.88$, n = 52). Rigorous covariance propagation analysis showed that surveying with a LiDAR point density between 2 pt/m^2 and 4 pt/m^2 results in the best cost-benefit relation. A Landsat based classification approach resulted in an overestimation of 60.8% compared to the LiDAR derived AGB estimates for a 2,987,726ha study area. This AGB overestimation can lead to significantly wrong emission estimates and compensation payments.

The best solution to monitor tropical forest carbon stocks would be the continuous mapping with airborne LiDAR data, which is not feasible for large-scale use due to the relatively high cost of operation. The combination of satellite data, LiDAR, and field plots, however, would be a cost effective alternative and reduces uncertainty in estimating carbon densities for REDD+ projects. Further, the new approach presented here, through using CH and the LiDAR point densities as weight, has a high potential to improve current estimates of carbon stocks in these highly inaccessible tropical rainforests.

ACKNOWLEDGEMENTS

We would like to thank Suwido Limin and his team from CIMTROP for the logistical support during the field inventory and Sampang Gaman (CIMTROP) and Simon Husson (Orang Utan Tropical Peatland Project, OUTROP) for providing tree species lists. Further, we would like to thank FORRSA (Forest Restoration and Rehabilitation in Southeast Asia) project of the EU-funded Asia Link programme for financially supporting the field trips to Indonesia. The LiDAR data set was acquired by Kalteng Consultants.

REFERENCES

Asner, G.P., Hughes, R.F., Varga, T.A., Knapp, D.E. and Kennedy-Bowdoin, T. (2009). Environmental and biotic controls over aboveground biomass throughout a tropical rain forest. *Ecosystems* **12**, 261-278.

Asner, G.P., Powell, G.V.N., Mascaro, J., Knapp, D.E., Clark, J.K., Jacobson, J., Kennedy-Bowdoin, T., Balaji, A., Paez-Acosta, G., Victoria E., Secada, L., Valqui, M. and Hughes R.F. (2010). High-resolution forest carbon stocks and emissions in the Amazon. *Proceedings of the National Academy of Sciences of the United States of America* **107**, 16738-16742.

Ballhorn, U., Siegert, F., Mason, M. and Limin, S. (2009). Derivation of burn scar depths and estimation of carbon emissions with LIDAR in Indonesian peatlands. *Proceedings of the National Academy of Sciences of the United States of America* **106**, 21213-21218.

Brown, S. (1997). *Estimating biomass and biomass change of tropical forests: A primer*. FAO Forestry Paper 134, 1-84.

Chave, J., Andalo, C., Brown, S., Cairns, M.A., Chambers, J.Q., Eamus, D., Fölster, H., Fromard, F., Higuchi, N., Kira, T., Lescure J.-P., Nelson, B.W., Ogawa, H., Puig, H., Riera, B. and Yamakura, T. (2005). Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologica* **145**, 87-99.

Drake, J.B., Dubayah, R.O., Clark, D.B., Knox, R.G., Blair, J.B., Hofton, M.A., Chazdon, R.L., Weishampel, J.F. and Prince S.D. (2002). Estimation of tropical forest structural characteristics using large-footprint lidar. *Remote Sensing of Environment* **79**, 305-319.

FAO (2006). *Global Forest Resources Assessment Reprot 2005.* Food and Agriculture Organization, Rome, Italy.

Gibbs, H.K., Brown, S., Niles, J.O. and Foley, J.A. (2007). Monitoring and estimating tropical forest carbon stocks: making REDD a reality. *Environmental Research Letters* **2**, 045023.

Hooijer, A., Page, S., Canadell, J.G., Silvius, M., Kwadijk, J., Wösten, H. and Jauhiainen, J. (2010). Current and future CO2 emissions from drained peatlands in Southeast Asia. *Biogeosciences* **7**, 1505-1514.

Page, S.E., Siegert, F., Rieley, J.O., Böhm, H.D.V., Jaya, A. and Limin, S. (2002). The amount of carbon released from peat and forest fires in Indonesia during 1997. *Nature* **420**, 61-65.

Rieley, J.O. and Page, S.E. (2005). In J.O. Rieley and S.E. Page (eds.), *Wise Use of Tropical Peatlands: Focus on Southeast Asia*. ALTERRA, Wageningen, Netherlands.

Van der Werf, G.R., Morton, D.C., DeFries, R.S., Olivier, J.G.J., Kasibhatla, P.S., Jackson, R.B., Collatz, G.J. and Randerson, J.T. (2009). CO_2 emissions from forest loss. *Nature Geoscience* **2**, 737-738.