Enhanced Systems for measuring and monitoring REDD+: opportunities to improve the accuracy of emission factor and activity data in Indonesia

by

Solichin

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Doctor of Philosophy
of the Australian National University
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Candidate’s Declaration

This thesis contains no material that has been accepted for the award of any other degree or diploma in any university. This thesis is my own work except where otherwise acknowledged. I clarify that my name on the ANU student records is ‘Solichin Solichin’, but for publication purposes I use the name of ‘Solichin Manuri’.

In paper 1 (Chapter 3), ‘Tree biomass equations for tropical peat swamp forest ecosystem in Indonesia’, Solichin Manuri formulated the idea, developed the methodology, collected data, performed statistical analyses and wrote the manuscript. Cris Brack supported the statistical analysis and revised the manuscript. Nunung Puji Nugroho, Nisa Novita, Chandra Agung Septiadi Putra and Eka Widyasari collected data and revised the manuscript. Kristell Hergoualc’h, Helmut Dotzauer and Louis Verchot revised the manuscript.

In paper 2 (Chapter 4), ‘Improved allometric equations for tree aboveground biomass estimation in tropical dipterocarp forests of Kalimantan, Indonesia’, Solichin Manuri and Cris Brack formulated the idea and developed the methodology. Solichin Manuri collected data, performed statistical analyses and wrote the manuscript. Cris Brack revised the manuscript. Fatmi Noor’an and Teddy Rusolono formulated the idea, developed methodology, collected data and revised the manuscript. Shema Mukti Anggraini, Helmut Dotzauer and Indra Kumara collected data and revised the manuscript.

In paper 3 (Chapter 5), ‘Effect of species grouping and site variables on aboveground biomass models for lowland tropical forests of the Indo-Malay Region’, Solichin Manuri, Cris Brack, Teddy Rusolono and Fatmi Noor’an formulated the idea and developed the methodology. Solichin Manuri collected data, performed statistical analyses and wrote the manuscript. Cris Brack, Teddy Rusolono, Fatmi Noor’an, Sandhi Imam Maulana, Wahyu Catur Adinugroho, Hery Kurniawan, Dian Wulansih Sukisno, Gita Ardia Kusuma, Arif Budiman, Rahmad Supri Anggono, Chairil Anwar Siregar, Onrizal, Dhanny Yuniati and Emma Soraya collected data and revised the manuscript.

In paper 4 (Chapter 8), ‘Advanced land cover mapping of tropical peat swamp ecosystem using airborne discrete return lidar’, Solichin Manuri formulated the idea and developed the methodology, collected data, performed the analyses and wrote the manuscript. Hans-Erik Andersen, Cris Brack and Bruce Doran revised the manuscript.
In paper 5 (Chapter 9), ‘Assessing influence of return density on estimation of lidar-based AGB in tropical peat swamp forests of Kalimantan, Indonesia’, Solichin Manuri formulated the idea and developed the methodology, collected data, performed the analyses and wrote the manuscript. Hans-Erik Andersen formulated the idea, developed the methodology, performed the analyses and wrote the manuscript sections on model-based inference. Robert Mcgaughey also developed the methodology and revised the manuscript. Cris Brack revised the manuscript.

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Abstract

The importance of accurate measurement of forest biomass in Indonesia has been growing ever since climate change mitigation schemes, particularly the reduction of emissions from deforestation and forest degradation scheme (known as REDD+), were constitutionally accepted by the government of Indonesia. The need for an accurate system of historical and actual forest monitoring has also become more pronounced, as such a system would afford a better understanding of the role of forests in climate change and allow for the quantification of the impact of activities implemented to reduce greenhouse gas emissions. The aim of this study was to enhance the accuracy of estimations of carbon stocks and to monitor emissions in tropical forests. The research encompassed various scales (from trees and stands to landscape-sized scales) and a wide range of aspects, from evaluation and development of allometric equations to exploration of the potential of existing forest inventory databases and evaluation of cutting-edge technology for non-destructive sampling and accurate forest biomass mapping over large areas.

In this study, I explored whether accuracy—especially regarding the identification and reduction of bias—of forest aboveground biomass (AGB) estimates in Indonesia could be improved through (1) development and refinement of allometric equations for major forest types, (2) integration of existing large forest inventory datasets, (3) assessing non-destructive sampling techniques for tree AGB measurement, and (4) landscape-scale mapping of AGB and forest cover using lidar.

This thesis provides essential foundations to improve the estimation of forest AGB at tree scale through development of new AGB equations for several major forest types in Indonesia. I successfully developed new allometric equations using large datasets from various forest types that enable us to estimate tree aboveground biomass for both forest-type specific and generic equations. My models outperformed the existing local equations, with lower bias and higher precision of the AGB estimates. This study also highlights the potential advantages and challenges of using terrestrial lidar and the acoustic velocity tool for non-destructive sampling of tree biomass to enable more sample collection without the felling of trees.

Further, I explored whether existing forest inventories and permanent sample plot datasets can be integrated into Indonesia’s existing carbon accounting system. My investigation
of these existing datasets found that through quality assurance tests these datasets are essential to be integrated into national and provincial forest monitoring and carbon accounting systems. Integration of this information would eventually improve the accuracy of the estimates of forest carbon stocks, biomass growth, mortality and emission factors from deforestation and forest degradation.

At landscape scale, this study demonstrates the capability of airborne lidar for forest monitoring and forest cover classification in tropical peat swamp ecosystems. The mapping application using airborne lidar showed a more accurate and precise classification of land and forest cover when compared with mapping using optical and active sensors. To reduce the cost of lidar acquisition, this study assessed the optimum lidar return density for forest monitoring. I found that the density of lidar return could be reduced to at least 1 return per 4 m².

Overall, this study provides essential scientific background to improve the accuracy of forest AGB estimates. Therefore, the described results and techniques should be integrated into the existing monitoring systems to assess emission reduction targets and the impact of REDD+ implementation.
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<tr>
<td>3D</td>
<td>Three-dimensional</td>
</tr>
<tr>
<td>ACIAR</td>
<td>Australian Centre for International Agricultural Research</td>
</tr>
<tr>
<td>AGB</td>
<td>Aboveground biomass</td>
</tr>
<tr>
<td>AICc</td>
<td>corrected Akaike Information Criterion</td>
</tr>
<tr>
<td>ALS</td>
<td>Airborne lidar system</td>
</tr>
<tr>
<td>ANCOVA</td>
<td>Analysis of Covariance</td>
</tr>
<tr>
<td>AV</td>
<td>Acoustic Velocity</td>
</tr>
<tr>
<td>BA</td>
<td>Basal area</td>
</tr>
<tr>
<td>BIOCLIME</td>
<td>Biodiversity and climate change program</td>
</tr>
<tr>
<td>BPS</td>
<td>Badan Pusat Statistik - Statistical Centre Agency</td>
</tr>
<tr>
<td>BSN</td>
<td>Badan Standarisasi Nasional - National Standardisation Agency</td>
</tr>
<tr>
<td>CBH</td>
<td>Circumference at breast height</td>
</tr>
<tr>
<td>CF</td>
<td>Correction Factor</td>
</tr>
<tr>
<td>CIFOR</td>
<td>Center for International Forestry Research</td>
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<tr>
<td>CO₂</td>
<td>Carbon dioxide</td>
</tr>
<tr>
<td>COP</td>
<td>Conference of parties</td>
</tr>
<tr>
<td>CRP</td>
<td>Cummulative return proportion</td>
</tr>
<tr>
<td>CStr</td>
<td>Cummulative return proportion of strata</td>
</tr>
<tr>
<td>D</td>
<td>Diameter of log section or tree diameter at breast height in Chapters 4, 5 and 10</td>
</tr>
<tr>
<td>DBH</td>
<td>Diameter at breast height</td>
</tr>
<tr>
<td>DM</td>
<td>Dry mass</td>
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<td>DTM</td>
<td>Digital terrain model</td>
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<td>E</td>
<td>Environmental stress</td>
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<td>EMRP</td>
<td>Ex mega rice project</td>
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<td>FAO</td>
<td>Food and Agriculture Organization</td>
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<tr>
<td>FG</td>
<td>Family grouping</td>
</tr>
<tr>
<td>FM</td>
<td>Fresh mass</td>
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<tr>
<td>FORCLIME</td>
<td>Forest and climate change program</td>
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<tr>
<td>FREL</td>
<td>Forest reference emission levels</td>
</tr>
<tr>
<td>G</td>
<td>Wood density or wood density variable</td>
</tr>
<tr>
<td>G&lt;sub&gt;AGB&lt;/sub&gt;</td>
<td>AGB change due to growth</td>
</tr>
<tr>
<td>GC</td>
<td>Wood density class</td>
</tr>
<tr>
<td>GHG</td>
<td>Greenhouse gas</td>
</tr>
<tr>
<td>GIZ</td>
<td>German International Cooperation</td>
</tr>
<tr>
<td>MRPP</td>
<td>Merang REDD Pilot Project</td>
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<tr>
<td>GPS</td>
<td>Global Positioning System</td>
</tr>
<tr>
<td>gVol</td>
<td>Green volume</td>
</tr>
<tr>
<td>H</td>
<td>Tree height</td>
</tr>
<tr>
<td>Ĥ</td>
<td>Tree bole height</td>
</tr>
<tr>
<td>I&lt;sub&gt;AGB&lt;/sub&gt;</td>
<td>AGB increment</td>
</tr>
<tr>
<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
</tr>
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<td>JAXA</td>
<td>Japan Aerospace Exploration Agency</td>
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<tr>
<td>Abbreviation</td>
<td>Full Form</td>
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<tr>
<td>KFCP</td>
<td>Kalimantan Forest Carbon Partnership</td>
</tr>
<tr>
<td>KfW</td>
<td>Kreditanstalt für Wiederaufbau - German government-owned development bank</td>
</tr>
<tr>
<td>LCCS</td>
<td>Land Cover Classification System</td>
</tr>
<tr>
<td>LDF</td>
<td>Lowland dipterocarp forests</td>
</tr>
<tr>
<td>LIPI</td>
<td>Lembaga Ilmu Pengetahuan Indonesia - Indonesian Institute of Sciences</td>
</tr>
<tr>
<td>Ln</td>
<td>Log natural</td>
</tr>
<tr>
<td>LULUCF</td>
<td>Land use, land use change and forestry</td>
</tr>
<tr>
<td>M\textsubscript{AGB}</td>
<td>AGB change due to mortality</td>
</tr>
<tr>
<td>MAH</td>
<td>Mean aboveground height</td>
</tr>
<tr>
<td>MARE</td>
<td>Mean absolute relative error</td>
</tr>
<tr>
<td>mean Dev</td>
<td>Mean deviation</td>
</tr>
<tr>
<td>mean RE</td>
<td>Mean relative error</td>
</tr>
<tr>
<td>MoE</td>
<td>Modulus of elasticity</td>
</tr>
<tr>
<td>MoEF</td>
<td>Ministry of Environment and Forestry</td>
</tr>
<tr>
<td>MoF</td>
<td>Ministry of Forestry</td>
</tr>
<tr>
<td>MoR</td>
<td>Modulus of rupture</td>
</tr>
<tr>
<td>MRE</td>
<td>Mean relative error</td>
</tr>
<tr>
<td>MRV</td>
<td>Monitoring, reporting and verification</td>
</tr>
<tr>
<td>NFI</td>
<td>National Forest Inventory</td>
</tr>
<tr>
<td>NFMS</td>
<td>National Forest Monitoring System</td>
</tr>
<tr>
<td>NIR</td>
<td>Near Infra Red</td>
</tr>
<tr>
<td>°C</td>
<td>Degree celcius</td>
</tr>
<tr>
<td>OLS</td>
<td>Ordinary least square regression</td>
</tr>
<tr>
<td>OPTI</td>
<td>Overall periodic timber inventory</td>
</tr>
<tr>
<td>P</td>
<td>Precipitation</td>
</tr>
<tr>
<td>PD</td>
<td>Patch Diameter (diameter of surface patch used in 3D reconstruction)</td>
</tr>
<tr>
<td>pH</td>
<td>Potential of hydrogen</td>
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<tr>
<td>PSF</td>
<td>Peat swamp forests</td>
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<td>PSP</td>
<td>Permanent sample plots</td>
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<tr>
<td>PT DRT</td>
<td>PT Diamond Raya Timber</td>
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<tr>
<td>QCRP</td>
<td>Quadratic CRP</td>
</tr>
<tr>
<td>QMAH</td>
<td>Quadratic MAH</td>
</tr>
<tr>
<td>QSM</td>
<td>Quantitative structure model</td>
</tr>
<tr>
<td>R</td>
<td>Region</td>
</tr>
<tr>
<td>R(^2), r(^2)</td>
<td>Coefficient of determination</td>
</tr>
<tr>
<td>R\textsubscript{AGB}</td>
<td>AGB change due to recruitment</td>
</tr>
<tr>
<td>R\textsubscript{dm/fm}</td>
<td>Ratio of dry mass and fresh mass</td>
</tr>
<tr>
<td>REDD</td>
<td>Reducing Emissions from Deforestation and Degradation</td>
</tr>
<tr>
<td>REDD+</td>
<td>REDD + sustainable forest management, carbon stock enhancement and conservation of carbon stock</td>
</tr>
<tr>
<td>REst</td>
<td>Ratio Estimator</td>
</tr>
<tr>
<td>RGB</td>
<td>Red Green Blue</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean square error</td>
</tr>
<tr>
<td>RSE</td>
<td>Residual standard error</td>
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<tr>
<td>Abbreviation</td>
<td>Description</td>
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<td>--------------</td>
<td>-------------</td>
</tr>
<tr>
<td>S&lt;sub&gt;AGB&lt;/sub&gt;</td>
<td>AGB change due to shrinkage</td>
</tr>
<tr>
<td>SE</td>
<td>Standard error</td>
</tr>
<tr>
<td>TDF</td>
<td>Tropical dipterocarp forest</td>
</tr>
<tr>
<td>TIN</td>
<td>Triangular Irregular Network</td>
</tr>
<tr>
<td>TLS</td>
<td>Terrestrial laser scanning</td>
</tr>
<tr>
<td>ToF</td>
<td>Time of flight</td>
</tr>
<tr>
<td>Tukey's</td>
<td>Tukey's Least Square Mean difference test</td>
</tr>
<tr>
<td>LSM</td>
<td>Least Square Mean</td>
</tr>
<tr>
<td>UNFCCC</td>
<td>The United Nations Framework Convention on Climate Change</td>
</tr>
<tr>
<td>UTM</td>
<td>Universal Transverse Mercator</td>
</tr>
<tr>
<td>VIF</td>
<td>Variance inflations factor</td>
</tr>
<tr>
<td>WD</td>
<td>Wood density</td>
</tr>
<tr>
<td>xyz</td>
<td>Three-dimensional point format</td>
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Chapter 1

Introduction

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1.1 **The Significance of Indonesia’s Tropical Forests**

Tropical deforestation is a global concern as emissions from deforestation contribute to global greenhouse gas accumulation. Greenhouse gas emissions from land use, land use change and forestry activities between 2000 and 2010 comprised 12.5% of total global emissions (Baccini *et al.*, 2012; Houghton *et al.*, 2012). More than 80% of agricultural development in tropical countries involves the conversion of existing forests (Gibbs *et al.*, 2010). Therefore, it is crucial to involve tropical countries in climate change mitigation programmes. Protecting existing tropical forests is an effective way of mitigating climate change (Stern *et al.*, 2006).

Tropical forests can either sequester carbon dioxide (CO₂) or emit it into the atmosphere, depending on how they are utilised and managed. Unsustainable forest utilisation, rampant illegal logging and extensive planned forest conversion for other land uses are the main causes of tropical deforestation and forest degradation in Indonesia, which have in turn led to huge CO₂ emissions. These historical choices have led to a great loss of forests capital and services.

Forest loss in Indonesia is substantial because of the unsustainable natural resource management associated with economic development and anthropogenic fires. More than 40% of pan tropical deforestation between 1990 and 1997 occurred in South East Asia, mostly because of conversion to agriculture, selective logging and fires (Achard *et al.*, 2002). A specific study in South East Asia suggested between 1990 and 2000, and 2000 and 2010, Indonesia contributed more than 97% and 56% to the deforestation in South East Asia, respectively (Stibig *et al.*, 2014). Between 1990 and 2000, deforestation rates in Indonesia were the second highest recorded, after Brazil. Between 1.1 – 1.9 million hectares of Indonesian forests were deforested annually during this period, (Hansen *et al.*, 2009; FAO., 2010; Stibig *et al.*, 2014). This rate was slightly higher than between 1987 and 1990 (Dauvergne, 1993). In 2009, the remnant natural forests comprised only 46% of total land area, almost half of the total in 1950 (85%) (Sumargo *et al.*, 2001). The island with the highest deforestation rate was Sumatra, which in 2010 was covered with only 30% remnant natural forests (Margono *et al.*, 2012).

As well as the overall rate of deforestation, it is important to consider how certain forest types are being affected. Between 2000 and 2010, deforestation rates for lowland dipterocarp forests (LDFs) were the highest estimated at 0.3 million hectares annually (Miettinen *et al.*, 2011). However, when looking at forest loss as a percentage of total
cover, peat swamp forests (PSFs) and mangroves suffered the most, with annual deforestation rates of 2.2% and 1.3%, respectively. Repeated burning of these carbon-rich forest ecosystems and conversion into production systems result in huge CO2 emissions (Murdiyarso et al., 2010; van der Werf et al., 2010). For instance, in 1997-1998 peat fires in Sumatra and Kalimantan contributed to almost 40% of global emissions (Page et al., 2002). Several factors have been identified as drivers of deforestation, including demographic, economic, institutional and technological factors (Geist and Lambin, 2001; Carr et al., 2005; Barbier and Burgess, 2001). These factors affect the decisions to exploit existing forests and their resources.

In 2005, a mechanism for reducing emissions from deforestation and forest degradation (Reducing Emissions from Deforestation and Forest Degradation [REDD]) was finally adopted at the Conference of parties (COP) 11 in Montreal, Canada. REDD provides financial incentives for tropical countries to reduce the rate of deforestation and forest degradation. In 2007, COP 13 in Bali, Indonesia, emphasised the need to include carbon stock enhancement, conservation and sustainable management of forests into the mechanism, which later became known as REDD+. Since then, the REDD+ methodology has been intensively discussed and debated at international fora. REDD+ demonstration activities are being implemented by developing countries as pilot testing and lesson learnt at local level.

Tropical developing countries that practice the most deforestation and forest degradation, such as Brazil and Indonesia, receive most international support to enable their participation in this global mechanism for climate change mitigation (Brown and Peskett, 2011). However, with the complexity of the problem, it is important for the countries to improve their capacity in forestry governance and forest monitoring. Since the incentive mechanism is designed to be paid on a performance basis, accurate measurement of carbon sinks and emissions is critically important. This requires a measureable, reportable and verifiable (MRV) system for carbon accounting to comply with international standards and subject them to independent verifications.

1.1.1 MRV system for REDD+

The main goal of REDD+ is quantified emissions reductions, on which the performance evaluation will be based. Accurate estimation of emissions from deforestation and degradation is crucial if REDD+ incentive is to be implemented credibly. The MRV system for REDD+ adopts five basic principles of reporting: consistency, transparency,
Chapter 1

comparability, completeness and accuracy (Eggleston et al., 2006). There are three levels of accuracy when measuring and reporting on the emissions from deforestation and degradation. Tier 1 has the lowest accuracy, and can be used to estimate unimportant sources of emissions or whenever the more accurate data is unavailable. The medium accuracy of Tier 2 allows countries to use a region or country-specific database for estimating emission factors. Tier 3 is the most accurate approach, and uses ground measurement for activity data and high resolution data for land-cover mapping.

The United Nations Framework Convention on Climate Change (UNFCCC) clearly states that to be able to participate in the REDD+ mechanism, developing countries must establish forest reference emission levels (FREL) based on historical data and national circumstances (UNFCCC, 2010). Emissions 10-20 years prior to the reference year must be estimated. Forest area changes (activity data) and changes in carbon stock (emission factors) must be calculated to estimate historical emissions. To support this, UNFCCC requested parties to develop a robust and transparent national forest monitoring system (NFMS) using remote sensing and ground measurements. Remote sensing technology is the most reliable method for measuring activity data, because it can cover a large area and provide consistency in the measurement. Although the capacity of most tropical countries, including Indonesia, for forest monitoring were increased, there is still much room for improvement, especially with carbon pool reporting (Romijn et al., 2015).

1.1.2 Uncertainties in forest carbon measurement

Indonesia reported a decline in annual deforestation rates from 1.9 million hectares in 1996–2000 to only 0.5 million hectares in 2000–2010 (FAO., 2010). However, this reported rate is considerably different from the rate shown on the current wall-to-wall land cover change map which uses 30-metre resolution at the global scale. According to this map, there is a trend towards an annual increase of deforestation in Indonesia (Hansen et al., 2013). Also, there have been many critics of the global forest resource assessment data compiled by FAO, because of the inconsistency of the methodology, changing of forest definitions and some data gaps (Matthews, 2001). This has led to a great deal of uncertainty about the reliability of estimations of emissions from deforestation and forest degradation (Figure 1.1).
In is inevitable that greater reliance will placed on remote sensing data for wall-to-wall mapping of land cover and carbon stock. Various studies show that differences in the data and processing procedures lead to uncertainties. Standardised forest classification terminology for interpreting and classifying images is becoming a crucial part of accurate, consistent and credible forest monitoring in tropical forests (Romijn et al., 2013).

Ground measurements, integrated with tree biomass models and remote sensing, are the most common methods of carbon accounting in the forestry and land use change sector (IPCC, 2006). Ground-based measurements are necessary for validating and modelling the biomass estimations, in combination with land cover or satellite imagery classification (Penman et al., 2016). It is important to have enough ground measurement plots proportionally distributed to represent each land-cover class. The higher the number of plots, the higher the confidence level of the estimates.

The current FREL of Indonesia, which was submitted to the UNFCCC during the COP 21 in Paris, only used national forest inventory (NFI) data for the emissions calculation. However, it acknowledges the need for more data to fill the gap of the NFI grid network throughout Indonesia. It is envisaged that existing data on forest inventory and forest permanent sample plots from various sources will be included in the forest carbon stock and emission calculation system (MoEF, 2015). Brown (1997) and Penman et al. (2016) provide clear guidance on how to make use the inventory data. However, many of the forest inventory data are not available or are just presented as a summarised result in report documents. In the latter case, conversion factors are needed to utilise the summarized data and to provide information for carbon accounting purposes. Also, data validation must be done before existing forest inventory data and information can be used (Harja et al., 2011).
Converting ground-based plot measurement data into biomass or carbon stock requires allometric models. The models with multi-variables—including tree diameter, total height and wood density—are found to be more accurate than the models relying only on tree diameter. Pelletier et al. (2012) found that emissions calculated using different equations or emission factors could lead to more than 100% deviation from estimates. The authors suggested that accurate estimations using Tier 3 will provide higher incentives due to a higher confidence level in the emission estimates, compared to estimations using Tier 1. The sources of uncertainty of emission calculations must be identified and reduced to achieve credible forest carbon accounting. Relevant and accurate allometric relationships must be used to estimate carbon stock of particular forest types. The best way to model tree biomass equations is based on tree species, and must be site-specific because of the high variations of biomass accumulation in different tree species and forest types (Keith et al., 2010). Species-specific equations will improve the accuracy of allometric models, when compared to models that use mixed species. However, due to the high diversity of tree species in tropical forests, such equations would be too costly to develop and too difficult to implement (Chave et al., 2005). Therefore, development of allometric equations based on mixed species is more common in tropical regions (Chave et al., 2005; Ketterings et al., 2001; Kenzo et al., 2009).

Another approach, which minimises the cost associated with the number of tree samples required, is to use genera or family-based relationships (Basuki et al, 2009). Species grouping for tropical tree species improves accuracy and keeps the measurement costs low. Tree diversity in tropical forests can reach to more than 200 species per hectare (Kartawinata, 1990). Therefore, the use of species-specific biomass equations is not a feasible option for tropical forests in Indonesia. Paul et al. (2013) found that species-specific equations performed only slightly better than mixed species. Alternatively, forest types classification based on geographical and ecological gradients improved the AGB estimates (Alvarez et al., 2012).

So far, only a limited number of published studies on allometric equations have appeared for estimating tree aboveground biomass in the tropical forests of Indonesia. Some of these equations were developed using a limited number of tree samples, or by using trees with a low diameter range. Development of biomass equations for various forest types are needed as they will contribute to the accuracy of carbon stock estimation for a greater number of tropical landscapes in Indonesia. Despite the lack of published studies, a
A review study suggests that there have been many unpublished studies on tree biomass involving destructive sampling of more than 5000 trees in Indonesia (Anitha et al., 2015). A database compilation of previous studies will provide more samples for better representation of various forest types and ecological gradients. Also, the authors suggest the need to expand the sampling to the eastern region because this area was under represented in previous studies.

Technological advances may help to improve the accuracy of emission calculations or reduce the measurement errors due to unstandardised ground measurement methods. For instance, airborne lidar and terrestrial laser scanning (TLS) have been widely explored for high-precision mapping and measurements in forestry. This approach will be useful in improving accuracy and reducing working time.

### 1.1.3 Advanced technology for forest monitoring and biomass estimation

Most forest areas in Indonesia are remote, making them difficult to access. Such difficulties make the logistics even more difficult for field campaigns. A combination of bad weather and steep terrain may affect the inventory crew’s conditions and therefore the quality of the data collected. As technology improves, the use of remote sensing with fine resolution for forest monitoring is increasing. The ability to integrate multiple datasets also allows researchers to create the new and more accurate information required. Data fusion of lidar points from airborne and terrestrial instruments can potentially be used to validate the accuracy of forest monitoring and carbon stock assessment. Laser technology is widely used for accurate, consistent and credible measurement of trees and forests (Lefsky et al., 2002; Williams et al., 1999; Hopkinson et al., 2004). However, the use of these cutting-edge technologies in tropical forest must be assessed and validated by ground measurement.

#### 1.1.3.1 TLS for tree AGB measurement

The development of allometric equations using the destructive method for biomass estimation at tree level is laborious and requires substantial logistic arrangements. Tree cutting in conservation and restoration areas is mostly restricted by law. Therefore, destructive sampling in these areas is not an option. TLS is a tool that could potentially be utilised for forestry research and application of forest measurement of tree diameters and heights (Thies and Spiecker, 2004). TLS provides an objective and consistent monitoring tool, and is able to give very accurate information (Dassot et al., 2011). Additionally, TLS can provide a three-dimensional (3D) reconstruction of trees and is an
alternative approach for non-destructive timber sampling for volume and biomass estimation (Vonderach et al., 2012).

The use of TLS in the forestry sector has been intensively investigated. Until now this type of laser scanning has primarily been used to measure forest parameters for forest inventories (Pfeifer et al., 2004; Watt and Donoghue, 2005; Hopkinson et al., 2004). For example, Aschoff and Spiecker (2004) developed a model for tree detection and to estimate diameter at breast height (DBH) based on TLS point cloud data derived from eight scanning points. The stem is the most observable part of a tree, so stem-based forestry measurement will achieve the highest accuracy in TLS application.

The use of TLS for biomass studies varies from simply deriving tree parameters (such as DBH, tree height, crown size and crown volume) for biomass calculation using available allometric equations (Holopainen et al., 2011; Kankare et al., 2013) to biomass estimation through conversion of volume estimates using specified wood data, using the point numbers as a parameter to estimate tree biomass (Seidel et al., 2011) and using the voxel-based approach for coniferous large trees (Marius et al., 2013). A cylinder fitting method has been developed for automatic reconstruction of tree trunks and branches based on TLS point clouds (Pfeifer et al., 2004; Aschoff and Spiecker, 2004). An improved cylinder fitting method, called the quantitative structure model (QSM) was developed. This method is a fully automatic approach and has a faster processing time (Akerblom et al.; Raumonen et al., 2013; Hackenberg et al., 2015). Further studies have found that the biomass estimates using TLS are more accurate than allometric models (Calders et al., 2015) and thus there is potential for developing or validating allometric equations (Olagoke et al., 2016).

1.1.3.2 Non-destructive approach for wood density measurement

Wood density is an important parameter for assessing wood characteristics, timber quality, and tree biomass when used in conjunction with tree volume. Conventionally, wood density measurement involved destructive sampling and traditional measurement of volume and dry weight. Several attempts have been made to estimate direct wood density on standing trees using force-related equipment, such as a torsiometer, a pilodyn, a nail withdrawal or a resistograph (Isik and Li, 2003). A review by (Gao et al., 2012) suggests that those tools have similar accuracy with coefficients of determination between 0.7 to 0.9. The main difference is the practicability and consistency across the measurement by different operators. In this regard, the resistograph has an advantage over
the others. However, moisture content in live trees affects the accuracy of density estimation.

In addition to these methods, spectral, ultrasound and acoustic-based technologies were also tested for their ability to provide a non-destructive evaluation of wood. They include NIR Spectroscopy (Schimleck et al., 2003), the Silvatest ultrasound instrument (de Oliveira and Sales, 2006; Hasegawa et al., 2011) and the Fakopp and The Hitman acoustic velocity tools (Chauhan and Walker, 2006). Wood density assessment using NIR and ultrasound techniques were promising with high correlations of around 0.8-0.9. However, NIR Spectroscopy and ultrasound tools require species and site-specific calibration and expensive laboratory work, respectively.

1.1.3.3 Airborne lidar

To integrate all forest-related emissions calculation from various activities, an area-based forest monitoring system is required (UNFCCC, 2010). For area-based forest monitoring, remote sensing application using medium-resolution satellite imageries has been widely used in tropical forests with low accessibility (Asner et al., 2002; Hansen and Loveland, 2012). To improve the accuracy, more advanced technology resulting in high resolution imageries (Chambers et al., 2007; Hirata et al., 2014) were explored. Additionally, airborne lidar scanning (ALS) technologies continue to be intensively explored due to their high accuracy in estimating forest metrics (Gobakken et al., 2012; Lefsky et al., 2002).

Laser technology, on which ALS is based, has been used for precise distance measurement. ALS using discrete return is commonly utilised for forest monitoring due to its ability to cover large areas (Wulder et al., 2012). Compared to satellite-based remote sensing technologies, the costs associated with ALS acquisitions are relatively high (Hummel et al., 2011). Given that the largest component of the costs of lidar acquisition is aeroplane flight time, it is more economical to acquire lidar by having an aircraft fly higher and faster (Goodwin et al., 2006). However, this results in a lower density of point cloud (and thus poorer spatial resolution). Previous studies on accuracy using various lidar densities have been conducted mostly in temperate regions (Gobakken and Næsset, 2008; Watt et al., 2014; Jakubowski et al., 2013). No lidar density studies were located in areas with very flat topography such as in PSFs. Also a number of recent studies explored the use of height-related (Kronseder et al., 2012) and return proportion-related metrics (Ioki et al., 2014; Sheridan et al., 2014) for estimating forest attributes, including
AGB. Further research is needed to find the best lidar metrics that have a strong correlation with forest attributes in flat tropical PSFs.

1.2 Research Aim and Objectives

The aim of this study was to contribute to the development of Indonesia’s MRV system by enhancing our ability to accurately estimate carbon stocks and to monitor emissions in tropical forests. To achieve this, the study included several research components for exploring and analysing the potential improvement of accuracy in AGB estimation at various levels (trees, stands and landscape levels). The research encompassed a wide range of aspects, from evaluation and development of allometric equations, to identification and compilation of existing forest inventory databases, and exploration of the potential of existing forest inventory data bases to estimate carbon stock and forest dynamic information and evaluation of the value cutting-edge technology for non-destructive sampling and accurate forest biomass mapping over large areas. Four subsidiary research objectives were designed to achieve this:

1. To validate existing AGB models and develop new equations using large samples of harvested trees from four major forest types in Indonesia: dipterocarp forest, peat swamp forest, other lowland forests and mangrove forest. Comparisons with existing local and global allometric equations were conducted to assess their uncertainty in AGB estimation.

2. To explore the potential use of TLS for 3D modelling of individual trees to validate existing equations or to develop new equations. Also, a device that measures acoustic velocity to test wood density was trialled as this would enable non-destructive sampling of tree AGB.

3. To identify, compile and evaluate the potential use of existing field-measurement data, such as permanent sample plots and timber inventories, for estimating AGB stock and increment in logged-over or degraded forests. In addition to that, a compilation of carbon stock estimations in primary forests from published literature was conducted for estimating emission factors from forest degradation and deforestation.

4. To explore the potential use of airborne lidar metrics for AGB and land cover mapping. The influence of lidar return density on the accuracy of AGB mapping was assessed to find whether it was feasible in terms of the cost, and whether it was accurate when monitoring large areas.
1.3 Thesis outline

This is a thesis by compilation following the guidelines of the College of Medicine, Biology and Environment and Fenner School of Environment and Society, the Australian National University. It consists of four published, one accepted and two unpublished papers/chapters, placed in the research component. All papers/chapters were written as stand-alone papers. Therefore, there is some duplication of methods and data used in some chapters. Inconsistencies in formatting, abbreviations, measurement units, referencing style, captions and so on also unavoidable because of different journals’ and editors’ requirements. The unpublished chapters were also written following a research article format, to allow submission to peer-review journals at a later stage.

The thesis is organised into three parts: introduction, main research and synthesis. The introduction consists of two chapters, Introduction and General Methods (Chapters 1 and 2). The research component is structured following the four research objectives (Chapters 3 to 9). Each research component (allometric development, TLS application, uncertainties assessment of AGB stock and increment estimates, and landscape assessment using airborne lidar) used different datasets, methods and scope, and it is outlined in a separate chapter. The synthesis consists of a concluding chapter (Chapter 10).

The thesis is structured as follows:

- Chapter 1. Introduction. Presents the research backgrounds, aim and objectives.
- Chapter 2. Study Approach and General Method. Presents an overview of the approach used in the study, outlines the thesis structure and describes the study area and general methods. The methods used in data collection and analysis are briefly described.
• Chapter 5. The Effect of Species Grouping and Site Variables on Aboveground Biomass Models for Lowland Tropical Forests in Indo-Malay Region – evaluates various variables for the development of generic allometric equations covering a wide geographical space. This chapter has been published online in *Annals of Forest Science* (2017) 74:23. DOI: 10.1007/s13595-017-0618-1.

• Chapter 6. Testing a Non-Destructive Method for Measuring Tree AGB Using a Terrestrial Laser Scanner. Presents the results of 3D model validation for volume and AGB estimation using non-destructive sampling in mangroves.

• Chapter 7. Synthesising Existing Forest Inventory Datasets for Estimating Historical AGB Stocks and Growth in Logged-Over Tropical Dipterocarp Forests. Presents the result of forest inventory data exploration from timber concessions, and assesses the uncertainties of AGB stock and increment estimation at stand levels.

• Chapter 8. Advanced Land Cover Mapping of Tropical Peat Swamp Forest using Discrete Return Lidar. Presents the results of utilizing airborne lidar data for forest and land cover mapping. This chapter has been published in *Geoplanning Journal* (2017) 4:1, 1-8. DOI: 10.14710/geoplanning.4.1.1-8.


• Chapter 10. Synthesis – This chapter synthesises the findings, identifies limitations and presents recommendations for implementation and further research.
References


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Chapter 1


Chapter 2

Study Approach and General Methods

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2.1 Study Approach and Research Components
The main aim of this study was to contribute to the development of Indonesia’s MRV system by enhancing the ability to accurately estimate carbon stocks and monitor emissions in tropical forests. The study involved four research components covering a range of aspects, including allometric development (Component 1) and method improvement (Component 2) at tree level, stand-level aboveground biomass (AGB) estimation (Component 3) and landscape scale analysis using airborne lidar (Component 4) (Figure 2.1).

![Figure 2.1. Research components and their relationship to each other.](image)

2.1.1 Component 1: Development of allometric equations for estimating tree AGB in various forest types
The main objective of Component 1 was to develop allometric equations for estimating tree AGB in major forest types in Indonesia. To achieve this goal, it was important to have large samples of harvested trees with a wide range of tree size, covering a variety of forest types. A total of 1348 samples of harvested trees were compiled from direct measurements and from published studies conducted in peat swamp forests, dipterocarp forests and lowland forests across the Indo-Malay region (Table 2.1 and Figure 2.2). This became a study on allometric equation development using the largest dataset in the region. The datasets from the literature were mostly identified as grey publications by Anitha et al. (2015) and Krisnawati et al. (2012). However, the distribution of the dataset was
skewed, with more information coming from the western part of the region (Kalimantan and Sumatra) and less from the eastern regions. Component 1 is addressed in Chapter 3 to Chapter 5.

2.1.2 Component 2: Non-destructive method for estimating tree AGB using TLS
Because destructive sampling is laborious and time consuming, a non-destructive approach was tested to allow more collection of samples, especially large trees. Component 2 was designed to achieve this aim. Mangrove forests were selected as the object of the study, because they are not represented by the compiled datasets in Component 1. Because of limitations in cutting permits as well as time and budget constraints, only two individual trees (with diameter of 32 cm and 58 cm) were scanned and felled for biomass measurements. The specific objective of Component 2 was to explore the potential and challenges of 3D reconstruction from TLS point clouds for estimating tree volume and acoustic tool for estimating wood density from fresh logs. Component 2 is addressed in Chapter 6.

2.1.3 Component 3: Uncertainties of stand-level AGB estimations using various AGB models and assessing AGB stock and increment of logged-over dipterocarp forests
Component 3 was constructed based on the premise that many forest measurement plots and timber inventory datasets are measured and compiled by timber companies, but few are used to fill in the gaps in forest inventory networks on a larger scale. The objective of this component was to identify, compile and examine these datasets for quality assurance, and to determine whether they are suitable for further use in forest AGB assessment. The selected datasets were used to assess the validity of various AGB models at stand level. The AGB models used in this analysis were derived from the results in Chapter 4 and Chapter 5. Component 3 is addressed in Chapter 7.

2.1.4 Component 4: Potential use of airborne lidar for AGB and land cover mapping at landscape level
Component 4 was constructed based on the need for accurate land cover and AGB mapping at landscape level. The potential of lidar technology to meet this need was tested. I used a wall-to-wall coverage lidar dataset covering 120 thousand hectares of peat swamp ecosystem with various degradation levels. Since the cost of airborne lidar was remarkably high, even when compared to existing high resolution satellite, this component also examined the potential and accuracy of low-density lidar point. Reducing the density of lidar returns reduces the cost of flight campaigns through, for example,
using higher or faster flights. Ground-truthing was conducted by the Kalimantan Forest Carbon Partnership (KFCP) project, part of the Indonesia-Australia Forest Carbon Partnership which aims to address the emission reductions from peat swamp forests. Eighty-eight vegetation plots were established, representing various land and forest cover classes. The vegetation plot dataset was converted into AGB using allometric equations developed in Chapter 3. Component 4 is addressed in Chapters 8 and 9.

Table 2.1: Summary of research components and their objectives

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<tr>
<th>Component</th>
<th>Research Objectives</th>
<th>Datasets</th>
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<tr>
<td>Component 1: Allometric equations for estimating tree AGB in various forest types (Chapters 3–5).</td>
<td>To develop new equations using large samples of harvested trees from four major forest types in Indonesia: dipterocarp forest, peat swamp forest, other lowland forests and mangrove forests. A comparison with existing local and global allometric equations was conducted to assess their uncertainty in AGB estimation. To improve the accuracy of the models, several potential predictor variables were tested and assessed, including species grouping, site characteristics and climatic variables.</td>
<td>• 148 harvested trees from peat swamp forests in Kalimantan and Sumatra. • 109 harvested trees from dipterocarp forests in Kalimantan • 1200 sample trees from lowland forests (including dipterocarp forests) in the Indo Malay region. Data was derived from direct measurement and the literature review.</td>
</tr>
<tr>
<td>Component 2: Non-destructive method for estimating tree AGB using TLS (Chapter 6).</td>
<td>To explore the potential use of TLS for 3D modelling of individual trees, to validate the existing equations or develop new equations. Additionally, an ultrasound technique was tested to estimate wood density to enable non-destructive sampling of tree AGB.</td>
<td>• Point cloud data of trees derived from multiple scanning. Three out of eight felled trees were scanned.</td>
</tr>
<tr>
<td>Component 3: Uncertainties of stand-level AGB estimations using various AGB models and assessing AGB stock and increment of logged-over dipterocarp forests (Chapter 7).</td>
<td>To identify and compile existing field-measurement data, such as permanent sample plots and timber inventories. To evaluate the usefulness of these existing resources for estimating AGB stock and increment in logged-over or degraded forests. Additionally, a compilation of carbon stock estimations in primary forests from published literature was conducted, for</td>
<td>• 24 1-ha permanent sample plots collected from timber concessions • 20,133 plots of timber inventory datasets from 33 timber companies in Kalimantan.</td>
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### Component Research Objectives Datasets

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<th>Component</th>
<th>Research Objectives</th>
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| Component 4: Potential use of airborne lidar for AGB and land cover mapping (Chapters 8-9). | To explore the potential use of airborne lidar for AGB and land cover mapping. Also, the influence of lidar return density on the accuracy of AGB mapping was assessed to find whether it was feasible in terms of cost and accuracy for large area monitoring. | • Point cloud dataset of 120 thousand hectares of PSF in Central Kalimantan.  
• 81 plots of ground measurements of vegetation.  
• Both datasets were provided by the KFCP. |

#### 2.2 Site Description

The datasets used in this study—in particular for Component 1—were compiled from a wide range of geographical locations and represent various tropical forests across Indonesia, including peat swamp forests, dipterocarp forests, lowland forests and mangrove forests (Figure 2.2). These four major forest types were included in this study.

The Chapters 3, 8 and 9 were based on studies conducted in peat swamp forests in Rokan Hilir in Riau, Sumatra, Musi Banyuasin in South Sumatra, Kapuas Hulu in West Kalimantan and an ex-KFCP project in Central Kalimantan, Indonesia. The Rokan Hilir study site was managed by a timber company (PT DRT) and was selectively logged, while the other sites were selectively logged by large concessionaires from the 1970s to the 1990s. Small-scale illegal logging continues to the present.

The Chapters 4 and 7 were based on studies conducted in tropical dipterocarp forests in Kalimantan, Indonesian Borneo. Dipterocarp forest is one of the most important forest types in Indonesia in terms of size and diversity of plant species (Kartawinata, 1990b). Tropical dipterocarp forests are naturally dominant in the Sunda region and cover in excess of 65 million hectares (35% of the total land area). This forest type is dominated by the large and highly commercial tree family, dipterocarpaceae. Because of the trees’ size, large amounts of carbon are stored within these forest type (Paoli et al., 2008). Since the 1970s, most of the tropical dipterocarp forests in Indonesia have been utilised for timber production.
The study of AGB estimation using TLS in Chapter 6 was conducted in a production forest near Sembilang National Park in Banyuasin, South Sumatra, Indonesia. The forest is located in an estuary of the Sembilang River and is dominated by mangrove trees. Four major dominant mangrove species could be found in this area, including *Rhizophora apiculata*, *Bruguiera gymnorhiza*, *Bruguiera sexangulata* and *Rhizophora mucronata*.

For the Chapter 5, we reviewed existing studies on tree biomass harvesting from lowland forests within the Indo-Malay Archipelago, including major island groups (Malay Peninsula, Sumatra, Borneo, Java, Nusa Tenggara, Maluku and Papua (Figure 5.1 in Chapter 5). The latitude and longitude of the study sites ranged from 10.31° south to 4.039° north and 98.79° east to 140.50° east. The mean annual precipitation of the study sites ranged from 1375 to 3992 mm with altitudes between 16 m to 1000 m above sea level.
2.3 General Methods

This section provides a brief description of the methods used in this study. Each compiled paper or chapter provides more detailed descriptions of the methods used.

2.3.1 Data Collection

This study involved various datasets compiled from direct field measurements and literature reviews, including tree AGB from various forest types, forest inventories, vegetation and permanent sample plot point clouds from TLS and ALS.

2.3.1.1 Tree AGB

I compiled the AGB of sample trees from PSF through destructive sampling in three timber concessions in Rokan Hilir, Musi Banyuasin and Kapuas Hulu. A total of 148 trees with diameter at breast height (DBH) of between 2 cm and 167 cm were felled and measured. For the tree allometry study in the TDF I conducted direct measurements through destructive sampling for AGB measurements in four timber concessions in Malinau, Bulungan, Kapuas Hulu and Seruyan districts as well as literature review from published and unpublished studies. The tree AGB dataset from mangrove was collected in a production forest near Sembilang National Park. A total of eight mangrove trees with a maximum DBH of 58 cm, were felled and weighed. The destructive sampling data from the mangroves was used to validate estimations using TLS.

The selection of forest compartments in which we felled the sample trees followed the current cutting plan. We identified potential trees from previous forest inventory lists or after rapid assessment of large trees. Before the felling, we measured the DBH (in cm) at 1.3 m from the ground or at 20 cm above tree buttresses. All trees were felled and fractioned into tree components: trunks, branches, twigs and leaves. All small stems and branches with diameter (D) ≤ 30 cm as well as the twigs and leaves were weighed in the field. We estimated the volume of large stems and branches (D > 30 cm) using the Smalian formula. All tree dimension measurements, including tree DBH, tree height and commercial bole height, were measured using cloth tapes after tree felling, giving a more accurate measurement than a standing tree measurement. Leaf voucher specimens were collected and shipped to the Research Centre for Biology, Indonesian Institute of Sciences (Lembaga Ilmu Pengetahuan Indonesia; LIPI) for species identification.
2.3.1.2 Individual Tree Scanning

Tree selection was based on the representativeness of tree species and DBH class. Two major species are available in the area (*Rhizophora apiculata* and *Bruguiera gymnorrhiza*). We used FARO Laser Scanner Focus 3D to measure the trees. We selected the second highest point density option and each scan took 20–30 minutes. Checker boards were placed around the targeted trees and between TLS positions. At first site, we placed five TLS positions to scan one large tree, while for second site we scanned two trees with four TLS scanning. The output format of the scanning was a point cloud data of xyz position and associated RGB value.

2.3.1.3 Permanent Sample Plots and Forest Inventory Datasets

The data collection was carried out from February – May 2012 under the auspices of the FORCLIME-GIZ, the German-Indonesian cooperation in forestry and climate change. The datasets used in this study were compiled from timber concessions operating in project pilot provinces —West Kalimantan, East Kalimantan and North Kalimantan— which include permanent sample plots (PSPs) and overall periodic timber inventory (OPTI) plots from existing timber concessions operating in the study area. As some concessions are no longer operational, only active concessions were targeted for data compilation.

The KFCP project established PSPs for vegetation monitoring that were systematically placed in eight randomly selected zones representing land cover classes and disturbance levels (Graham et al., 2014). These datasets were used to validate airborne lidar data from the same site. Five zones were located near large canals and in highly degraded areas, while the other three zones were located in closed-canopy forests. Within each zone, three transects, spaced 150 m apart, were placed perpendicular to the canals or in an east to west direction from randomly located starting points. Four plots were established on each transect at a distance of 50, 100, 400 and 700 m from the canals or the starting points. The scientific tree names, the DBH and the height of all the trees within the plot were recorded.

2.3.1.4 Airborne Lidar

Lidar data sets were provided by the KFCP project. Lidar data of KFCP areas were captured with an average density of 2.8 returns per m² for the whole project area (120,000 ha). The lidar datasets were captured using Optech ALTM 3100 and Optech Orion M200 instruments mounted on a Pilatus Porter fixed wing aircraft from 15 August to 2 October.
2011. The vertical accuracy of the raw lidar data and the DTM products were 0.14 m and 0.18 m, respectively (Ballhorn et al., 2014).

2.3.2 Data Analysis

2.3.2.1 Allometric Development

Several considerations are crucial in selecting the best AGB models, including (1) statistical correctness (including the best goodness of fit of model parameters, applying an appropriate correction factor for log linear models, normal residuals distribution, excluding models with high collinearity among predictor variables); (2) high accuracy and predictive capability; and (3) practicality for field implementation (Overman et al., 1994).

Most statistical analyses were performed using JMP software and partly using R Statistical Analysis. Because the data exhibited heteroscedasticity, AGB data and all predictor variables were transformed into natural logarithms. For back-transforming the data, a correction factor was required to reduce the systematic bias associated with the log-transformations. Several correction factors were evaluated to select the best models, including Correction Factor (CF) from Sprugel (1983), Ratio Estimator (REst) from Snowdon (1991) and ‘MM’ correction factor (Shen and Zhu, 2008), as suggested by Clifford et al. (2013).

We performed a multicollinearity test to evaluate correlation between parameters. The multicollinearity was identified using a variance inflations factor (VIF). A high VIF (more than 10) indicates that the parameter is closely related to other parameter. The accuracy of existing models was evaluated by regressing the biomass values of the measured dataset and the values predicted by the models. We chose the best form of the mixed-species and species grouped models based on the highest coefficient of determination ($R^2$) and lowest residual standard error (RSE) and the corrected Akaike Information Criterion (AICc). Additionally, we calculated the mean relative error (MRE) and mean absolute relative error (MARE) of each model (Picard et al., 2015), and performed a regression analysis to fit the AGB$_m$ and the AGB$_p$ of all models to further evaluate the precision and bias of the models (Piñeiro et al., 2008).

2.3.2.2 3D Modelling for Tree Reconstruction

We used two forms of software to reconstruct tree 3D models: QSM (Raumonen et al., 2013) and CompuTree (Hackenberg et al., 2015). Both are based on a similar approach,
called cylinder fitting. Currently they are the most accurate and reliable method for reconstruction of whole trees used for biomass estimation. The model using the first software has good performance when estimating the tree volume with less than 10% error (Calders et al., 2015). However, the software requires trial and error to set the best parameters, which is improved by the later software for full automatic process.

2.3.2.3 Estimation of AGB Stocks and Dynamics
We computed the tree AGB of the compiled PSP datasets using various AGB equations for dipterocarp forests in Kalimantan (Manuri et al., 2016) and species group equations for lowland forests (Manuri et al, In Press). We used the selected PSP dataset, which has complete measurement of DBH, tree height and species identification and has long measurement period (more than five years). Net annual AGB increment ($I_{AGB}$) was calculated as the net annual AGB change due to growth ($G_{AGB}$), recruitment ($R_{AGB}$), mortality ($M_{AGB}$) and shrinkage ($S_{AGB}$) of trees annually averaged across the monitoring period.

We used OPTI dataset compiled from existing timber concessions in the study area. We used the AGB model which requires only tree DBH to estimate tree AGB. For comparison, we used the AGB-BA model which uses information of BA per plot for estimating the plot-level AGB.

2.3.2.4 Airborne Lidar Data Processing
Several lidar metrics were calculated in relation to vegetation heights and return proportions (Table 9.2). For generating a canopy height model, a 1-m resolution digital terrain model (DTM) was used for normalising the terrain effect on the vegetation height. A 5-m resolution canopy height model was generated in raster format. This study explored the canopy height model for defining the classification system for forest and vegetation cover. We interpreted the vegetation cover based on information derived from airborne lidar. Instead of ‘land use’, we used ‘land cover’ as a basic term for the classification of forest (Lund, 2002). Following the vegetation structures and classification defined by Dowling and Accad (2003), a modified classification of forest and land cover for peat land based on the canopy height model was generated (Table 8.1).

For duplicating the various levels of accuracy, the lidar return densities were reduced from the original density to simulate different acquisition specifications for the lidar data. We reduced the lidar returns from 2.8 returns per m² to one return per 100 m². The points
were selected randomly in cell sizes of 25 m$^2$. A similar approach has been applied in other studies (Leitold et al., 2015; Magnusson et al., 2007; Strunk et al., 2012; Ruiz et al., 2014). Two scenarios were applied to assess the effect of point density on the regression models. In the first scenario, each thinned dataset was normalised using the original DTM delivered by the lidar provider to remove terrain influence on vegetation height. In the second scenario, the thinned dataset was normalised using the corresponding DTM created from the thinned point data.

### 2.4 Processing Software

I use several software for data processing. I used mainly JMP for statistical analysis, and R Package whenever a robust code for a particular analysis is unavailable in JMP. For spatial analysis and map visualization, I used mostly ArcGIS 10 Desktop and ArcGIS 11 Desktop for data analysis in Chapter 8 and Chapter 9, respectively. For point cloud data processing from terrestrial lidar, I used CompuTree Beta Version 15 (Hackenberg et al., 2015) and QSM ver2.21 (Raumonen et al., 2013) running in Mathlab 2015b. Data registration and merging of TLS data were conducted using FARO Scene software. CloudCompare was used for manual extraction of tree point clouds and visualisation of tree 3D models. FUSION v3.42 was used to process all point cloud data derived from airborne lidar (McGaughey, 2014). To compute products over the entire acquisition area, the Lidar Toolkit (LTK) Processor tool in FUSION was used to create and manage the processing workflow.
References


Chapter 3

Tree Biomass Equations for Tropical Peat Swamp Forest Ecosystem in Indonesia

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Tree biomass equations for tropical peek swamp forest ecosystems in Indonesia

Solichin Manur

3.1 Introduction

Greenhouse gas emissions from land use, land-use change and forestry (LULUCF) account for about 12.5% of global emissions (Baccini et al., 2012; Houghton et al., 2012). In Indonesia, this sector represents 47% of national emissions and emissions from peat fires and an additional 13% (Ministry of Environment, 2010). Peat swamp forests (PSF) in particular suffered intense deforestation in Indonesia between 1990 and 2010 with around 4.6 million hectares being cleared out of the 1990 8.7 million hectares (Miettinen et al., 2011). In 2011, only 31% of Indonesian PSF were still in pristine condition (Ministry of Forestry, 2012). Peat swamp forest are carbon-rich ecosystems (Jaenicke et al., 2008) which store on average 220 Mg C ha⁻¹ in the phytomass (Hergoualc'h and Verchot, 2011) and 570 Mg C ha⁻¹ in the peat per meter depth of peat (Warren et al., 2012). Deforestation of PSF and drainage for cultivation of agricultural crops involve major shifts in the carbon and nitrogen cycles leading to substantial greenhouse gas emissions; especially when land-clearing fires are used (Hergoualc'h and Verchot, 2014). Peat swamp forests could hence play a potentially important role in climate change mitigation strategies involving forest conservation.

In 2005, a mechanism for reducing emissions from deforestation and forest degradation (REDD) was discussed at the 11th annual Conference of the Parties from the United Nations Framework

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Chapter 3

3.2 Materials and methods

3.2.1 Study sites

3.2.2 Destructive sampling

3.2.3 Laboratory work

The study was based on a relatively large dataset of 148 trees, destructively sampled during a series of research projects. The dataset included trees within a large range of diameters, heights and wood densities (Table 1). The samples consisted of 24 families collected from three sites of peat swamp forest in the Sumatra and Kalimantan islands in western Indonesia.

2.1 Study sites

The data was compiled from three different PSF sites: Rokan Hilir in Riau in Sumatra; Musi Banyuasin in South Sumatra; and Kapaus Hulu in West Kalimantan, Indonesia (Fig. 1). The mean annual rainfall in Rokan Hilir, Musi Banyuasin and Kapaus Hulu is 2637 mm, 2454 mm and 4100 mm, respectively. The peat depths were up to 5, 8.5 and 6.5 m in Rokan Hilir, Musi Banyuasin and Kapaus Hulu, respectively. The forests at all sites had been previously logged by timber companies or by illegal loggers. The Rokan Hilir study site was managed by a timber company (PT DRT) and was selectively logged, while the two other sites were illegally and moderately logged.

In Rokan Hilir the most frequent species were Eugenia sp., Palaquium obovatum, Ilex macrophylla, Horsfieldia glabra, and Shorea uliginosa. In Musi Banyuasin, the most dominant tree species were Melanorrhoea wallichii, Tetramerista glabra, Gongystus bancanus, Hydrocorpus woodii, Palaquium sp. and Dyera lowii, which represented 11%, 9%, 7%, 6%, 4% and 3% of the total trees measured during the previous forest inventory. In Kapaus Hulu, the dominant species were Melanorrhoea sp., Shorea sp., Callophyllum sp., Eugenia sp. and Dialium patens.

2.2 Destructive sampling

We carried out the destructive sampling from August 2008 to October 2012. A total of 148 trees with a DBH of between 2 cm and 167 cm were felled and measured. Tree selection was based on the dominance and abundance of tree species, derived from permanent sample plot data in Rokan Hilir or previous forest inventory plots in Musi Banyuasin and Kapaus Hulu. Further tree selection within the plots was applied based on diameter class representation. We prioritised the selection of large tree before selecting small trees, as trees smaller than 20 cm in DBH were abundant. We selected the trees which would most likely yield most biomass and potential carbon storage, and thus, reduce further damage to the remaining stand and avoided bias of selecting only certain quality trees.

Prior to felling, we measured the diameter at breast height (DBH) or, whenever there was a buttress, 20 cm above it. We used machetes or chainsaws (50 cm and 90 cm bar length) to cut down the trees. Tree heights were measured after each tree was felled using 50 m cloth tape. We collected specimens of unidentified trees for species identification at the national herbarium (Lembaga Ilmu Pengetahuan Indonesia-LIPI) or forestry research center (Pusat Penelitian dan Pengembangan Kehutanan-Puslitbang) in Bogor. Trees were divided into stems, branches, twigs and leaves as described by Ketterings et al. (2001). Stems of small trees or branches (mostly of diameter <30 cm) were cut into pieces to allow weighing using spring or digital scales with capacities of 50 kg, 100 kg or 200 kg. Commercial stems of large trees or very large branches (diameter ≥ 30 cm) were measured for their green volume at 2 m intervals and the volume was calculated as a frustum of a cone (except for Rokan Hilir and some of the Musi Banyuasin dataset, in which we weighed them all).

2.3 Laboratory work

Sub-samples of wood were extracted from at least two sections of each stem (at the base and the end of the sections) branches, twigs and leaves for dry mass and/or green volume determination.
The wood sub-samples collected were either disk-shaped or wedge-shaped with a 3–5 cm thickness. These sub-samples were weighed in the field to measure fresh mass, and were then packed, labelled and transported to a laboratory for dry mass and wood density (WD) analysis. We dried the wood and leaf samples with temperature of 105 °C for Rokan Hilir and Musi Banyuasin samples and 80 °C for Kapuas Hulu samples, respectively. All samples were dried until constant mass. The green volume of the samples were measured using water displacement method.

The wood dry mass and volume measurements were carried out at several laboratories, including the Sebelas Maret University for the Rokan Hilir dataset; the Forestry Research Center in Bogor and the CIFOR laboratory in Jambi for the Musi Banyuasin dataset; and the Tanjung Pura University for the Kapuas Hulu dataset. We calculated the ratio of dry mass and fresh mass of each subsample \((R_{\text{DM/FM}})\). We estimated wood densities by dividing the dry mass by the green volume of the wood samples. We calculated dry mass (DM) of each tree components, using the following formulae:

\[
DM = FM \times R_{\text{DM/FM}} \quad (1)
\]

\[
DM = gVol \times WD \quad (2)
\]
where FM is the fresh mass and gVol is the green volume measured in the field. DM of each tree component was calculated using the $R_{\text{leaf}}$ or WD value from the same section of each component. We then summed all component mass to calculate total AGB of the tree.

For determination of individual WD, we calculated the WD by averaging the WD values taken from the base and the end of the stems, and additionally from the middle part of the stem and the large branches of large trees. We did not measure the WD from the Rokan Hilir dataset, but we used instead the global WD dataset from Zanne et al. (2009).

### 2.4. Assessment of existing equations

We compared the performance of available pan-tropical and local equations, commonly used for estimating AGB in Indonesian forests (Table 2) through correlation of estimated data with measured biomass data. For this analysis, we excluded the biomass data from the two largest trees (160 cm and 167 cm of DBH) due to their unexpected/abnormal low tree height and biomass value. We further selected the best existing models in each model type to compare with our new equations.

### 2.5. Selection of model forms for new allometric equations

We selected several candidate model forms to fit our data, including common linear, polynomial and power forms (see Table 4). We categorized the models into four types, depending on the independent variables used, namely DBH, DBH–WD, DBH–H and DBH–WD–H types. As such, we provided a wide range of possibilities to estimate aboveground biomass in relation to the availability of measured parameters.

#### 2.6. Species, wood density and island groupings

We developed species-group models for estimating aboveground biomass. We evaluated the influence of the island in estimating AGB, as the datasets were collected from the two main islands in western Indonesia, namely Sumatra and Kalimantan. We generated dipterocarp and non-dipterocarp models. Our dataset included eight species from four genera (Shorea, Dryobalanops, Dipterocarpus and Carstenia) in the dipterocarp family.

Within the non-dipterocarp species, we further categorized the trees into two classes based on their mean WD, that is light/soft and hard wood. The WD values of non-dipterocarp trees ranged from 0.242 to 1.000 g cm$^{-3}$, with an average of 0.543 g cm$^{-3}$. We used the average WD as cut-off value between soft and hardwood. We assessed the influence of WD class in estimating aboveground biomass by generating soft and hard wood models for non-dipterocarp species.

### 2.7. Statistical analysis

All statistical analyses were performed using JMP software. The accuracy of existing models was evaluated by regressing the biomass values of measured dataset and the values predicted by the models. In a perfectly accurate relationship, the intercept would be 0 and the slope equal to 1. An unbiased but imprecise relationship would still go through 0 with a slope of 1 but observations

### Table 2

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Model Name</th>
<th>Specification</th>
<th>Sample data range</th>
<th>AGB Equations</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBH</td>
<td>Brown, et al. (2011)</td>
<td>Mixed species, pan-tropical forests, including lowland dipterocarp forests Asia and Latin America</td>
<td>DBH range: 5–148 cm</td>
<td>$n = 371$</td>
</tr>
<tr>
<td>Basuki, et al. (2009)</td>
<td>Mixed species, lowland dipterocarp forests, Kalimantan</td>
<td>$n = 122$: DBH range: 6–200 cm</td>
<td>$n = 83$: DBH range: 6–200 cm</td>
<td>$\exp (-1.145 + 2.195 \times \ln(\text{DBH}))$</td>
</tr>
<tr>
<td>Basuki, et al. (2009)</td>
<td>Mixed species, lowland dipterocarp forests, Kalimantan</td>
<td>$n = 30$: DBH range: 2–44 cm</td>
<td>$\exp (-0.1525 \times \text{DBH}^{2.34})$</td>
<td></td>
</tr>
<tr>
<td>Kenzo, et al. (2009a)</td>
<td>Mixed species, lowland secondary logged-over forests, Sarawak</td>
<td>$n = 4004$: DBH range: 5–156 cm</td>
<td>$\exp (-0.0673 \times (\text{DBH})^2 \times \text{WD} \times H^{0.576})$</td>
<td></td>
</tr>
<tr>
<td>DBH-WD</td>
<td>Chave, et al. (2014)</td>
<td>Mixed species, pan-tropical forests, Africa, America and Asia</td>
<td>$n = 4004$: DBH range: 5–156 cm</td>
<td>$\exp (\text{H} \times \exp (0.893 - 0.76 \times \ln(\text{DBH}) - 0.034 \times (\ln(\text{DBH}))^2 \times \text{E}<em>{\text{DBH}} = 0.1033 \times \text{E}</em>{\text{DBH}} = 0.01199 \times \text{E}_{\text{DBH}} = 0.0596)$</td>
</tr>
<tr>
<td>Basuki, et al. (2009)</td>
<td>Mixed species, lowland dipterocarp forests, Kalimantan</td>
<td>$n = 122$: DBH range: 6–200 cm</td>
<td>$n = 83$: DBH range: 6–200 cm</td>
<td>$\exp (-0.698 + 2.234 \times \ln(\text{DBH}) + 0.639 \times \ln(\text{WD})$</td>
</tr>
<tr>
<td>Basuki, et al. (2009)</td>
<td>Mixed species, lowland dipterocarp forests, Kalimantan</td>
<td>$n = 29$: DBH range: 5–50 cm</td>
<td>$H = \exp (-0.509 \times \ln(\text{DBH}))$</td>
<td></td>
</tr>
<tr>
<td>Keiterings, et al. (2001)</td>
<td>Mixed species, agroforestry land, Sumatra</td>
<td>DBH range: 5–50 cm</td>
<td>$H = \exp (-0.509 \times \ln(\text{DBH}))$</td>
<td></td>
</tr>
<tr>
<td>DBH-H</td>
<td>Yamakura, et al. (1986)</td>
<td>Mixed species, lowland dipterocarp forests, Kalimantan</td>
<td>DBH range: 4.5–130 cm, H up to 70.7 m</td>
<td>$n = 145$: DBH range: 4.5–130 cm, H up to 70.7 m</td>
</tr>
<tr>
<td>Chave, et al. (2014)</td>
<td>Mixed species, pan-tropical forests, Africa, America and Asia</td>
<td>DBH range: 5–156 cm</td>
<td>$n = 4004$: DBH range: 5–156 cm</td>
<td>$B = (0.01122 \times (B^2)<em>{\text{WD}} + 0.0146 \times (B^2)</em>{\text{H}} + 0.00673 \times (\text{DBH})^2 \times \text{WD} \times H^{0.576}$</td>
</tr>
</tbody>
</table>
Fig. 2. Mean relative difference in % between WD global dataset of Zanne et al. (2009) and measured WD (n = 93). Error bars represent the standard deviation.

Fig. 3. Correlation between measured biomass (AGBm) in trees (n = 146) of peat swamp forests of Sumatra and Kalimantan and predicted biomass (AGBP) by allometric equations from the literature. The circle marker is representing tree samples, while the cross marker represents tree outliers. The upper figures are the best existing equations from each model type.
Table 3
Test effects for linear AGB models performed using selected model types. Each model evaluates the relevancy of family (diptero-carpace and non-diptero-carpace), wood density (WD) classes (hard and soft wood) and island (Sumatra and Kalimantan) grouping. Significance is indicated by *** for P < 0.001, ** for P < 0.01 and * for P < 0.05.

<table>
<thead>
<tr>
<th>AGB model types</th>
<th>Effects</th>
<th>Prob &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBH</td>
<td>WD class</td>
<td>&lt;.001***</td>
</tr>
<tr>
<td></td>
<td>Family groups</td>
<td>0.005**</td>
</tr>
<tr>
<td></td>
<td>Island</td>
<td>0.651</td>
</tr>
<tr>
<td>DBH-WD</td>
<td>WD class</td>
<td>0.269</td>
</tr>
<tr>
<td></td>
<td>Family groups</td>
<td>0.002**</td>
</tr>
<tr>
<td></td>
<td>Island</td>
<td>0.662</td>
</tr>
<tr>
<td>DBH-H</td>
<td>WD Class</td>
<td>&lt;.001***</td>
</tr>
<tr>
<td></td>
<td>Family groups</td>
<td>0.013*</td>
</tr>
<tr>
<td></td>
<td>Island</td>
<td>0.207</td>
</tr>
<tr>
<td>DBH-WD-H</td>
<td>WD class</td>
<td>0.342</td>
</tr>
<tr>
<td></td>
<td>Family groups</td>
<td>0.009*</td>
</tr>
<tr>
<td></td>
<td>Island</td>
<td>0.302</td>
</tr>
</tbody>
</table>

Scatter plots of independent (tree DBH and H) and dependent (tree AGB) variables demonstrated heteroscedasticity of the data. We transformed the data using a natural logarithm to distribute the variance evenly across biomass values. In order to transform the data back to a biomass value, a correction factor to reduce the systematic bias associated with log-transformations of biomass was applied (Raskerville, 1972). Two alternative correction factors were used for the analysis: Correction Factor (CF) [Sprugel, 1983] and Ratio Estimator (RE) [Snowdon, 1991], where RE is residual standard error, \( y \) and \( \hat{y} \) are observed and predicted biomass of tree, and \( n \) is number of tree samples:

\[ CF = \exp \frac{RSE^2}{2} \]

\[ RE = \frac{\sum y_i/n}{\sum \hat{y}_i/n} \]

We performed multicollinearity test to evaluate correlation between parameters. The multicollinearity was identified using variance inflation factor (VIF). High VIF or more than 10 indicates that the parameter closely related with other parameter. VIF of a parameter was defined as in Eq. (5), where \( R^2 \) is a coefficient of variation from the model regressing the \( i \)th parameter on the other parameter.

Fig. 4. Plot residuals of mixed species models (upper figures) and species grouped models based on WD Class (lower figures). All species grouped models have normal distribution of plot residuals (slope of the fit line close to 0).

Table 4
Mixed species model description for the aboveground biomass estimation in peat swamp forests. df is degree of freedom. RSE is residual standard error. AICc is corrected Akaike Information Criterion. RE is ratio estimator. CF is correction factor. Dev RE is mean deviation of AGB transformed back using REst. Dev CF is mean deviation of AGB transformed back using CF.

<table>
<thead>
<tr>
<th>Model name</th>
<th>Model parameters</th>
<th>df</th>
<th>RSE</th>
<th>( R^2 )</th>
<th>AICc</th>
<th>REst</th>
<th>CF</th>
<th>Dev RE</th>
<th>Dev CF</th>
</tr>
</thead>
<tbody>
<tr>
<td>M0</td>
<td>( \ln(AGB) = a + b \times \ln(DBH) )</td>
<td>147</td>
<td>0.400</td>
<td>0.968</td>
<td>152</td>
<td>0.826</td>
<td>1.083</td>
<td>31.9</td>
<td>37.4</td>
</tr>
<tr>
<td>M1</td>
<td>( \ln(AGB) = a + b \times \ln(DBH) + c \times \ln(DBH)^2 )</td>
<td>147</td>
<td>0.395</td>
<td>0.969</td>
<td>150</td>
<td>0.949</td>
<td>1.081</td>
<td>32.3</td>
<td>37.0</td>
</tr>
<tr>
<td>M2</td>
<td>( \ln(AGB) = a + b \times \ln(DBH) + c \times \ln(WD) )</td>
<td>147</td>
<td>0.345</td>
<td>0.977</td>
<td>110</td>
<td>0.842</td>
<td>1.061</td>
<td>28.1</td>
<td>31.0</td>
</tr>
<tr>
<td>M3</td>
<td>( \ln(AGB) = a + b \times \ln(DBH) + c \times \ln(DBH)^2 + d \times \ln(DBH)^3 + e \times \ln(WD) )</td>
<td>147</td>
<td>0.331</td>
<td>0.979</td>
<td>100</td>
<td>1.038</td>
<td>1.056</td>
<td>28.1</td>
<td>29.7</td>
</tr>
<tr>
<td>M4</td>
<td>( \ln(AGB) = a + b \times \ln(DBH) + c \times \ln(H) )</td>
<td>147</td>
<td>0.358</td>
<td>0.975</td>
<td>121</td>
<td>0.952</td>
<td>1.066</td>
<td>28.5</td>
<td>32.3</td>
</tr>
<tr>
<td>M5</td>
<td>( \ln(AGB) = a + b \times \ln(DBH^2) )</td>
<td>147</td>
<td>0.359</td>
<td>0.974</td>
<td>121</td>
<td>0.982</td>
<td>1.067</td>
<td>28.2</td>
<td>32.4</td>
</tr>
<tr>
<td>M6</td>
<td>( \ln(AGB) = a + b \times \ln(DBH) + c \times \ln(WD) + d \times \ln(H) )</td>
<td>147</td>
<td>0.313</td>
<td>0.981</td>
<td>83</td>
<td>0.937</td>
<td>1.050</td>
<td>24.3</td>
<td>27.2</td>
</tr>
<tr>
<td>M7</td>
<td>( \ln(AGB) = a + b \times \ln(DBH^2) + c \times \ln(WD) )</td>
<td>0.152</td>
<td>0.904</td>
<td>94</td>
<td>0.531</td>
<td>1.144</td>
<td>26.1</td>
<td>28.3</td>
<td></td>
</tr>
</tbody>
</table>
\[ VIF_i = \frac{1}{1 - R_i^2} \]  

The effect of dipterocarp/non-dipterocarp family, wood density class and island grouping on the models was evaluated by linear regression analysis. We assessed the significance of each factor using the least squares fitting.

We chose the best form of the mixed-species and species grouped models based on the highest coefficient of determination ($R^2$) and lowest residual standard error (RSE), the corrected Akaike Information Criterion (AICc), mean relative error (mean RE) and mean deviation (mean Dev). Compared to the original Akaike Information Criterion (AIC), the AICc has less bias and is more suited to model selection (Hurvich and Tsai, 1991). AICc is defined as follows:

\[ AICc = -2 \log \text{likelihood} + 2k \left( \frac{n - 1}{n - k - 1} \right) \]  

where $k$ is the number of estimated parameters, including intercept and error terms in the model, and $n$ is the number of observations in the dataset.

To calculate mean RE (%) and mean Dev (%) of the AGB estimates, we used the Eqs. (7) and (8), where $\overline{AGB}_p$ and $\overline{AGB}_m$ are predicted and measured AGB, respectively.

\[ \text{mean RE} = \frac{100}{n} \sum \frac{\overline{AGB}_p - \overline{AGB}_m}{\overline{AGB}_m} \]  

\[ \text{mean Dev} = \frac{100}{n} \sum \frac{\overline{AGB}_p - \overline{AGB}_m}{\overline{AGB}_m} \]  

Finally, we plotted the relative error (%) of each AGB estimates against DBH distribution to assess and compare the performance of the best existing equations with our equations. We generated the kernel smoother lines using the spline method (with lambda 100,000).

3. Results

3.1. Wood density

Similarly to Fayolle et al. (2013), we found almost 70% of total tree species in the WD global database. A total of 52 out of 58 tree species had been identified at species level, and only 14 species were not available in the database. However, we found that the correlation between the measured dataset and the global database was very low ($R^2 = 0.169$; $n = 93$). The WD values of small trees (DBH < 50 cm) in the global database tended to be higher than the measured ones (Fig. 2).

3.2. Selection of the best existing equations

Most of the estimation using local equations with only DBH as predictor showed good correlation but tended to underestimate the measured AGB of peat swamp trees, with slope far less than 1 (Fig. 3b-d). Only Brown,dbh equation had a slope of more than 0.9 in this model type (Fig. 3a). Although WD was added as an additional parameter, the local equations Basuki1dbh-wd and Basuki2dbh-wd did not significantly improve the Basuki1dbh and Basuki2dbh models, respectively. The other local equation developed from a lowland dipterocarp forest (Yamakura, 2004), on the other hand, had good performance, in spite of its complexity (Fig. 3i). Both new pan-tropical equations (Chavedbh-WD-E and Chavedbh-WD-H) performed well with slopes around 1 (Fig 3e and j). However, we included the two largest trees (represented by cross marker in Fig 3) in the correlation analysis, all Chave’s and Brown’s equations tended to overestimate the predicted AGBs, while Basuki’s equations provided more accurate estimates (Fig. 3f and g).

3.3. Important factors in assessing tree aboveground biomass

Island grouping was not a significant factor ($p > 0.1$) for all model types, which we assume is due to the fact that each site shares similar characteristics, such as average peat depth and dipterocarp species domination. However, this study found that family group was a significant factor for biomass estimation in PSF. It influenced the aboveground biomass estimation in all model types. WD Class factor was significant only in the models without WD parameter (Table 3).

Pilot residuals of mixed species models with WD as parameter has normal distribution across WD values (Fig. 4.2), while mixed species models without WD (Fig. 4.1and 4.3) have trending residuals distribution with slope very significantly different from 0. In contrast, plot residuals of species-grouped models based on WD class have slightly normal residual distribution (Fig. 4.4 and 4.6), even though without WD as parameter. While the species grouped model with WD, has slope very close to 0 (Fig. 4.5) (see Table 4).

### Table 5

<table>
<thead>
<tr>
<th>Model name</th>
<th>Species groups</th>
<th>Model parameters</th>
<th>df</th>
<th>RSE</th>
<th>$R^2$</th>
<th>AICc</th>
<th>Rest</th>
<th>CF</th>
<th>Dev Rest</th>
<th>Dev CF</th>
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<tr>
<td>MDbh</td>
<td>Dipterocarpaceae</td>
<td>$-2.155, 2.562$</td>
<td>26</td>
<td>0.339</td>
<td>0.984</td>
<td>22</td>
<td>0.929</td>
<td>1.036</td>
<td>23.4</td>
<td>28.6</td>
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<td>0.963</td>
<td>132</td>
<td>0.972</td>
<td>1.058</td>
<td>26.8</td>
<td>29.6</td>
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<tr>
<td></td>
<td></td>
<td>- Hard wood</td>
<td>56</td>
<td>0.337</td>
<td>0.975</td>
<td>42</td>
<td>0.972</td>
<td>1.058</td>
<td>26.8</td>
<td>29.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Light wood</td>
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<td></td>
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<td>1.052</td>
<td>24.4</td>
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<tr>
<td></td>
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<td>Non-dipterocarpaceae</td>
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<td>0.990</td>
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<td>1.018</td>
<td>20.2</td>
<td>20.4</td>
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<td>Non-dipterocarpaceae</td>
<td>$-2.852, 2.092$</td>
<td>114</td>
<td>0.318</td>
<td>0.978</td>
<td>69</td>
<td>0.972</td>
<td>1.058</td>
<td>23.2</td>
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<tr>
<td></td>
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<td>- Hard wood</td>
<td>56</td>
<td>0.265</td>
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<td>0.998</td>
<td>1.036</td>
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<tr>
<td></td>
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<td>- Light wood</td>
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<td>0.327</td>
<td>0.977</td>
<td>45</td>
<td>0.862</td>
<td>1.055</td>
<td>25.8</td>
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</table>
Fig. 5. Relative error (%) in aboveground biomass estimates of the peat swamp models and existing models. From left to right row: mixed species, dipterocarp, non-dipterocarp hardwood and non-dipterocarp softwood model.
3.4. New allometric equations for peat swamp forest

The models for mixed species, which use DBH, H and WD as parameters, explained 98% of tree biomass variation (see Table 4), while those which use only DBH as predictor only explained 97% of the variation. We found that the Ratio Estimator (REst) is better than the correction factor (CF) for transforming back to biomass value, as it provides lower deviations for all equations.

The common log linear model forms, performed better than polynomial log linear and DBH-power log linear models. The multicollinearity test showed that Ln DBH3 has multicollinearity problem with (Ln DBH)^2 and (Ln DBH)^2, with VIF of 297, 1279 and 395, respectively. Therefore, for each model type we suggest the use of common log linear form models (M_DBH : M_DBH-WD: M_DBH-H and M_DBH:WD:H). Accordingly, we further used the model forms for developing specific species group models.

All species grouped models for the dipterocarp family performed better (higher R^2, lower AICc and RSE) than did mixed species models (Table 5). Similarly, the WD-based grouping for non-dipterocarp species reduced the RSE and increased the R^2 for most models.

3.5. Accuracy comparison between new equations and the best existing equations

The Brown_DBBH and Yamakura_DBBH-H equations were the best fit in estimating biomass of dipterocarp trees. This may be because most of the sample trees used to develop the equations were collected from lowland dipterocarp forests of Indonesia and Malaysia. However, the equations tended to underestimate the non-dipterocarp hard wood trees and overestimate the softwood trees (Fig. 5e-h and u-x).

Both the Chave_DBBH-WD-H and Chave_DBBH-WD-H equations showed similar mean Dev to our M_DBH-WD and M_DBH-WD-H mixed species models (Table 6). They both performed very well for large dipterocarp trees but underestimated dipterocarp trees with DBH < 50 cm (Fig. 5n and ad). They are also valid for estimating AGB of non-dipterocarp hardwood trees.

Tree height was the most important estimator after DBH when estimating non-dipterocarp soft wood trees of peat swamp forest. Our models without H as predictor (M_DBH and M_DBH-WD) tended to underestimate the non-dipterocarp softwood trees (see Fig. 5d and l) when compared to the more accurate M_DBH-H and M_DBH-WD-H models (Fig. 5t and ac). In an opposite trend, the existing models without H as variable (Brown_DBBH and Chave_DBBH-WD-H) tended to overestimate the biomass of non-dipterocarp softwood trees (Fig. 5h and p).

The use of species-group models increases the overall accuracy of the estimates. They perform better than the best existing models and our mixed species models (Table 6). The total error of species group M_DBH models is less than 1%, which is much better than the mixed species model which has a total error of 12.7%. The mean Dev of species group models is less than that of both the existing and our mixed species models. Without using an additional predictor, the M_DBH species group models could achieve a mean Dev similar to that of the new pan-tropical Chave_DBBH-WD-H.

None of the existing equations, including ours, can estimate non-dipterocarp softwood trees accurately, due to two large outlier trees. The outliers were the only samples representing large trees with DBH > 150 cm. By including them, the equations tend to underestimate the other trees in the mixed and softwood models. We therefore updated the equations by excluding the outliers for mixed and softwood models (Fig. 6, Table 7). The new models performed very well for mixed species and non-dipterocarp softwood trees. Despite of the outliers exclusion, most of the existing models were not valid for estimating non-dipterocarp softwood trees (Fig. 6d, h and l), except for the new pan-tropical equation from Chave_DBBH-WD-H which has relatively flat slope close to 0 (Fig. 6p). The Chave_DBBH-WD-H equation performed quite well for large trees, but slightly underestimated small trees. All our mixed species models performed very well in estimating AGB.

4. Discussion

4.1. Factors affecting accuracy in biomass estimation

Our results demonstrated that dipterocarp and non-dipterocarp grouping is an additional significant factor in AGB estimation in peat swamp forest. This finding is in agreement with the results of (Basuki et al., 2009), that taxon-based species grouping can improve the performance of AGB model. It explains AGB variation beyond the traditional parameters (DBH, WD and H) can explain.

We developed 3 species groupings according to their major family (dipterocarp and non-dipterocarp) and WD classes. By doing so, we kept the sample number high, rather than grouping them by genera or family. In fact, it is more practical to use fewer equations, rather than accommodating all genera or family, in estimating biomass in highly diverse tropical forest (Kartawinata, 1990; Slik et al., 2003; Phillips et al., 2002). The significance level of WD parameters became less when the model was developed based on WD class grouping. In the absence of WD as an independent variable, the use of WD class grouping models can reduce the variation in estimating the biomass of mixed species models.

Tree height was the most important parameter after DBH when estimating non-dipterocarp soft wood trees of peat swamp forests. Several studies outlined the lack of tree height data in most historical inventories in tropical forest. Up-to-date tree height inventories remain scarce due to visual limitations in dense tropical forests (Basuki et al., 2009). However, LiDAR has recently been utilized to determine not only forest canopy height (Asner et al., 2012), but also individual tree height and height growth (Andersen et al., 2011). In addition, H–DBH models have also provided an alternative solution (Feldpausch et al., 2010; Feldpausch et al., 2012; Rutishauser et al., 2013; Chave et al., 2014). Developing a tree height model using handheld laser technology has also been tested, with promising accuracy for biomass estimation in tropical forests (Rutishauser et al., 2013). Another possibility is the use of bore height instead of total tree height, which is more easily measured in the dense tropical forests, as suggested by Basuki et al. (2009), or in conjunction with the Terrestrial Laser Scanning application (Yang et al., 2013).

4.2. Biomass equations for peat swamp forests

The biomass in large trees with DBH > 100 cm was highly variable in the peat swamp forests studied. Such a variation in a few
Fig. 6. Relative error ($\bar{b}$) in aboveground biomass estimates of the models and existing models for mixed species and non-dipterocarp soft wood trees. The models excluded outliers.
### Table 7

Corrected equations of mixed species and species group developed without outliers and include correction factors. df is degree of freedom. RSE is residual standard error. AICc is corrected Akaike Information Criterion.

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Equations</th>
<th>df</th>
<th>RSE</th>
<th>$R^2$</th>
<th>AICc</th>
</tr>
</thead>
<tbody>
<tr>
<td>M_{AB}, mixed species</td>
<td>0.136 + DBH^{0.213}</td>
<td>76</td>
<td>0.361</td>
<td>0.56</td>
<td>3.8</td>
</tr>
<tr>
<td>M_{AB}, species group</td>
<td>Dipteroncusp: 0.106 + DBH^{0.662}</td>
<td>26</td>
<td>0.327</td>
<td>0.67</td>
<td>3.7</td>
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<tr>
<td></td>
<td>Non-dipteroncusp hardwood: 0.138 + DBH^{0.537}</td>
<td>56</td>
<td>0.337</td>
<td>0.75</td>
<td>3.6</td>
</tr>
<tr>
<td></td>
<td>Non-dipteroncusp softwood: 0.149 + DBH^{0.935}</td>
<td>61</td>
<td>0.342</td>
<td>0.87</td>
<td>3.2</td>
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<tr>
<td>M_{AB}, woody species</td>
<td>0.242 + DBH^{0.172} + WD^{0.276}</td>
<td>76</td>
<td>0.331</td>
<td>0.46</td>
<td>3.2</td>
</tr>
<tr>
<td>M_{AB - WD}, woody species</td>
<td>Dipt: 0.141 + DBH^{0.575} + WD^{0.231}</td>
<td>26</td>
<td>0.335</td>
<td>0.64</td>
<td>3.5</td>
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<tr>
<td></td>
<td>Non-dipteroncusp hardwood: 0.185 + DBH^{0.653} + WD^{0.401}</td>
<td>56</td>
<td>0.317</td>
<td>0.87</td>
<td>3.0</td>
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<tr>
<td>M_{AB - WD}, woody species</td>
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<td>0.355</td>
<td>0.97</td>
<td>3.6</td>
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<tr>
<td>M_{AB - WD}, species group</td>
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<td>0.278</td>
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<td>0.97</td>
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<td>M_{AB - WD - woody species}</td>
<td>0.15 + DBH^{1.480} + WD^{0.564} + tP^{0.956}</td>
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<td>0.307</td>
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<td>0.279</td>
<td>0.98</td>
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<td>0.232</td>
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</table>

trees is difficult to model accurately using a single predictor in mixed-species models. The inclusion of the two largest old non-dipteroncusp trees but with relatively low AGB, *Tetramerista glabra* with a DBH of 160 cm and *Mangifera quadrifida* with a DBH of 167 cm, resulted in compromised equations that avoided the large positive deviation caused by large trees but allowed for the negative deviation on smaller trees. The low biomass of these large DBH trees may be the result of their relatively short height, which is similar to that of emergent Shorea trees that have a DBH of only about 90 cm. A study in lowland dipterocarp forest in East Kalimantan found similar characteristics, where some large trees with unexpected very low height occurred in logged-over forests, but not in primary forests (Rutishauser et al., 2013). However, this is in contradiction with those in the lowland forest of Peru, where large but short trees found to have relatively large biomass stored in the canopy, i.e. 44% of total AGB (Goodman et al., 2014).

We found that the equation of Kenzo et al. (2008a) underestimated the measured AGB. This may be due to the fact that the study was conducted in a secondary forest dominated by small diameter trees. The equation failed to accurately estimate AGB of large trees with a DBH beyond its DBH range. The new pan-tropical equations (Chave et al., 2014) and the new Brown’s equations (Brown et al., 2011) performed better than the existing local equations developed by Basuki et al. (2009) and Ketterings et al. (2001), which underestimated measured AGB. This underestimation is in agreement with previous studies in Indonesian tropical forests by Brown et al. (2011) and Rutishauser et al. (2013). It is certainly that Kettering’s equation unable to predict AGB beyond its DBH range and species composition. However, Basuki’s equations, which developed using large DBH range, sample size and similar species composition (dipterocarps dominated) did not perform well to our dataset. The reason might be there were some differences in soil properties (i.e. mineral soil vs. organic soil) and forest type (lowland dipterocarp forest vs. peat swamp forest), or maybe due to unexpectedly short and low in biomass of the large sample trees used for allometric development, since the local equations from Basuki performed better than all pan-tropical equations when estimating AGB of the large but short trees in our peat swamp forest datasets.

Our results showed that the new pan-tropical equations, Chave~dbh~ WD-1 and Chave~dbh~ WD-1-H performed almost similar to our model for mixed-species trees in tropical peat swamp forests. The representativeness of Indonesian tropical forests as well as large in DBH range and sample size, used in Chave et al. (2014) study, could be the reason of this similar performance. The new pan-tropical equations performed quite well in estimating AGB of large dipterocarp trees, but was less accurate in the case of small trees. This inaccuracy may fade away at plot and landscape level, if the tree WD variations are similar to those in mixed tropical forests. In the absence of local allometric equations, the existing pan-tropical equations are still reliable for estimating AGB in tropical forests, even for peat swamp forests. However the pan-tropical equations need to be used carefully for estimating AGB of large but short trees in logged peat swamp forests, from which most commercial large emergent dipterocarp trees have been extracted.

We found that AGB models developed based on species grouping performed better than mixed model. This is because the species grouped models taken into account variation within dipterocarp and non-dipteroncarp families and wood density class.

4.3. The use of wood density in models

The inclusion of WD as a predictor in allometric models could generate inaccurate results, especially when the identification of tree species is ambiguous or based on commercial inventories instead of scientific research, which is common in most forest inventories in developing countries. In the absence of field data it is a common practice to use WD global databases in estimating tree biomass, which has large uncertainties in our study. Some studies even use an averaged WD value in estimating AGB in a forest ecosystem. This may induce errors due to variations in WD, not only between species but also among individual trees within species (Henry et al., 2010) and among tree sections (Iida et al., 2012). Although it is noted that WD variation within species is less than between species.

Henry et al. (2010) demonstrated that the variation in WD is not only influenced by species and light-demanding factors, but also by the tree size and distance of wood sample to the bark. The low correlation we found between measured WD and WD values in the global database of Zanne et al. (2009) illustrates well the existing high variation in WD. It is likely that the data used to compile this global database originated from commercial-sized trees, thus that the database under-represents smaller trees. Finally, methodological differences (i.e. percentage of water content or average WDs vs. WD at a DBH point) may also explain discrepancies between WD values from field measurements and those from the global database (Reyes et al., 1992). Defining WD classes and integrating these into biomass estimation models would be more practical and cost-efficient and would help to narrow WD variation-derived errors.
5. Conclusions

This study provides more accurate AGB estimates in PSF through species-grouping models which were developed from a dataset with wide range of species, DBH, WD and H. Species-group equations based on dipterocarp and non-dipterocarp family and WD class improve the performance of mixed-species equations in AGB estimation. In the absence of WD values, WD classes-based equations will improve the accuracy of the estimation. Tree height is an additional key parameter in estimating aboveground biomass in peat swamp forests, especially for large non-dipterocarp trees. Although all of the existing equations performed similarly to our mixed-species and dipterocarp models, they systematically underestimated or overestimated the AGB of certain species-groups, especially for non-dipterocarp trees. However, if an accurate and validated local equation is not available, the new pan-tropical equations developed by Chave et al. (2014) are more reliable than local equations which developed using limited samples and DBH range.

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Chapter 4

Improved Allometric Equations for Tree Aboveground Biomass Estimation in Tropical Dipterocarp Forests of Kalimantan, Indonesia

Published in *Forest Ecosystems* (2016) 3:28

Authors: Solichin Manuri, Cris Brack, Fatmi Noor’an, Teddy Rusolono, Shema Mukti Anggraini, Helmut Dotzauer, Indra Kumara

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Improved allometric equations for tree aboveground biomass estimation in tropical dipterocarp forests of Kalimantan, Indonesia

Solichin Manuri1, Cris Brack1, Fatmi Noor‘an2, Teddy Rusolono3, Shema Mukti Anggraini3, Helmut Dotzauer4,5 and Indra Kumara6

Abstract

Background: Currently, the common and feasible way to estimate the most accurate forest biomass requires ground measurements and allometric models. Previous studies have been conducted on allometric equations development for estimating tree aboveground biomass (AGB) of tropical dipterocarp forests (TDFs) in Kalimantan (Indonesian Borneo). However, before the use of existing equations, a validation for the selection of the best allometric equation is required to assess the model bias and precision. This study aims at evaluating the validity of local and pantropical equations; developing new allometric equations for estimating tree AGB in TDFs of Kalimantan; and validating the new equations using independent datasets.

Methods: We used 108 tree samples from destructive sampling to develop the allometric equations, with maximum tree diameter of 175 cm and another 109 samples from previous studies for validating our equations. We performed ordinary least squares linear regression to explore the relationship between the AGB and the predictor variables in the natural logarithmic form.

Results: This study found that most of the existing local equations tended to be biased and imprecise, with mean relative error and mean absolute relative error more than 0.1 and 0.3, respectively. We developed new allometric equations for tree AGB estimation in the TDFs of Kalimantan. Through a validation using an independent dataset, we found that our equations were reliable in estimating tree AGB in TDF. The pantropical equation, which includes tree diameter, wood density and total height as predictor variables performed only slightly worse than our new models.

Conclusions: Our equations improve the precision and reduce the bias of AGB estimates of TDFs. Local models developed from small samples tend to systematically bias. A validation of existing AGB models is essential before the use of the models.

Keywords: Allometric equation, Local and pantropical models, AGB, Model validation, Destructive sampling, Tropical dipterocarp forest

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Background

Tropical dipterocarp forest (TDF) is one of the most important tropical ecosystems in the Indonesian archipelago. The forest harbours a high diversity of plant and animal species as well as a high density of carbon stock (MacKinnon 1996; Kartawinata 2005; Paoli et al. 2008). Over the last three decades, unsustainable management practices coupled with pressures from illegal logging, fires and plantation expansion have led to substantial rates of deforestation and degradation of natural forests (Hansen et al. 2009; Miettinen et al. 2011). This has greatly contributed to national greenhouse gas emissions (MoEF 2015).

To halt further forest losses, a performance-based incentive mechanism to reduce emissions from tropical deforestation and forest degradation (known as REDD+) has been discussed at a global forum (UNFCCC 2015). This mechanism, however, relies on accurate estimations of biomass stocks in forests (Asner 2011). Credible estimations on aboveground biomass (AGB) stocks and emission factors are essential data required for REDD+ reference emission levels, which is the benchmark for evaluating the performance of activities under the REDD+ framework (IPCC 2006).

Most studies on forest biomass in tropical regions have been carried out using remote sensing technology, which provides wall-to-wall and consistent estimates across spatial, temporal and ecological variations (Avitabile et al. 2016; Halpern et al. 2016). However, this approach requires validation through ground measurement and appropriate allometric equations to convert tree metrics derived from field measurements into tree biomass. Many plot-level-based studies on AGB stock have been carried out for TDFs in Borneo (Berry et al. 2010; Griscom et al. 2014), mostly without destructive sampling efforts to validate existing or develop new equations. Some studies used existing local equations which developed from relatively small samples (Hiratsuka et al. 2006; Krisnawati et al. 2014). Unbiased allometric equation is essential for accurate estimates of forest AGB stocks and carbon emissions associated with deforestation and forest degradation activities at landscape level (van Breugel et al. 2011; Johnson et al. 2014).

Traditionally, AGB equations rely on the relationship between AGB and tree diameter, wood density and tree height (Chave et al. 2014), as well as the crown size (Henry et al. 2010; Goodman et al. 2014) as predictor variables. A large-scale tropical forest inventory campaign requires a simple and robust method to be implemented in a cost-effective and consistent way. Because of optical obstruction of the multi-layered canopies of dipterocarp forest, total tree height or crown measurements are relatively difficult, time consuming and subject to measurement errors. Several authors have suggested more practical solutions, including the use of the tree height-diameter model (Feldpausch et al. 2012) or bole height measurement, instead of total height measurement (Basuki et al. 2009).

The number of local or site-specific allometric studies in Indonesia is high compared with studies in other countries in South-East Asia (Yuen et al. 2016), including studies in the TDFs of Indonesian Borneo (Kalimantan) by Yamakura et al. (1986a), Basuki et al. (2009) and Hashimoto et al. (2004). The first two studies are the most well known and were conducted on TDFs with relatively large samples and a wide range of trunk diameter. Basuki et al. (2009) compared the locally developed equations with the pantropical equations and found that the mean percentage errors of the pantropical equations were more than 40% when applied to the local dataset. Yamakura’s equations were constructed for each tree component rather than for the total tree, and thus can introduce bias if simply added together for estimating total tree AGB. Hashimoto et al. (2004) developed species-specific and mixed-species biomass equations for pioneer trees in a secondary forest in East Kalimantan. Although Hashimoto et al. (2004) study involved large sample size was (N = 106), the diameter range of the trunk was limited to a maximum of only 20.3 cm. In addition, some pantropical equations were developed and widely used for estimating AGB in tropical regions, e.g. Brown (1997) and Chave et al. (2014). Both studies used large samples and a wide range of tree diameter compiled from tropical region, including Indonesia. Before the use of existing equations, a validation for the selection of the best allometric equation is required to assess the model bias and precision (Pearson et al. 2005).

Our interest lies in the validation and improvement of existing equations for more credible AGB estimations in TDFs. The study has three objectives: (1) to evaluate the validity of existing equations; (2) to develop new allometric equations in estimating tree AGB for TDFs in Kalimantan; and (3) to validate the new equations using independent datasets.

Methods

Study sites

This study was carried out in the tropical dipterocarp forests of Kalimantan. The tropical dipterocarp forest is one of the most important forest types in South East Asia and it provides high biodiversity and endemism, as well as economic values such as timber and important ecosystem services. As the name implies, the forests are dominated by some genera from the dipterocarp family, including Shorea spp., Dipterocarpus spp., Hopea spp., Parashorea spp., Anisoptera spp. and Dryobalanops spp. The trees are well known for their tall and emergent canopies and straight-bole commercial trunks. The field
data were collected in primary forests of four timber concessions, that is, PT Erna Djuliatin in Seruyan, PT Inthinutu Nunukan, PT Intracwood Manufacturing in Malinau and PT Karya Rekanan Bina Bersama in Kapuas Hulu districts (01°30’00’’S to 04°02’22’’N and 112°03’00’’E to 116°58’42’’E) at an elevation of 202–540 m above sea level and a mean annual rainfall of 2936–3235 mm.

**Data collection**

We carried out destructive samplings for AGB measurements in four timber concessions, in Malinau, Bulungan, Kapuas Hulu and Seruyan districts (Fig. 1). Forest compartments, in which we felled the sample trees were purposively selected following the current cutting plan. We identified the potential trees from previous forest inventory list. All large commercial non-deformed trees, with tree diameter (D) greater than 80 cm, from various species were first selected and the potential felling directions were estimated. To minimize the logging damage, we selected and felled small trees within the area that potentially will be impacted by the felling of large trees. We also selected trees from the potential logging and skidding roads. However, we excluded deformed trees and included a wide range of tree genera or family as much as possible.

Before the felling, we measured the D (in cm) at 1.3 m from the ground or at 20 cm above tree buttress. All trees were felled and fractioned into tree components: trunks, branches, twigs and leaves. All small stems and branches with D ≤ 30 cm and the twigs and leaves were weighed in the field using the OCS-L Crane digital scales with a capacity of 100 and 50 kg. We estimated the volume of large stems and branches (D > 30 cm) using the Smalian formula. We measured diameters over bark at the beginning and end of each 2-m section. The end of the first section becomes the beginning of the second section and so on. All tree dimension measurements, including tree height (H) and commercial bole height (h), were measured using cloth tapes after tree felling, giving a relatively more accurate measurement than a standing tree measurement. Leaf voucher specimens were collected and shipped to the Research Center for Biology, Indonesian Institute of Sciences (Lembaga Ilmu Perengetahun Indonesia; LIPI) for species identification.

**Laboratory analysis**

Wood and leaf samples of each component (disc or wedge-shaped samples for stems and branches) were collected and weighed, before being packed and transported to the nearest wood laboratories (i.e., Mulawarman University in East Kalimantan, Tanjungpura University in West Kalimantan and Bogor Agricultural University in West Java) for dry weight and wood density analysis. Samples were dried in ovens at a temperature of 80°C or 105°C until achieving constant dry weights. The laboratory of Tanjungpura University measured the green wood volume of the sample using the water displacement method, and the labs of Mulawarman University and Bogor Agricultural University measured the volume of cube-shaped samples. G was measured in g cm⁻³. All field-measured volume data were converted into biomass by multiplying with the associated G derived from laboratory analysis. We multiplied the fresh weight by the ratio of dry weight to fresh weight of the associated samples to derive dry weight or biomass values.

**Data analysis**

We carried out data analysis in three steps. First, we selected existing models developed from local and pantropical datasets which have been widely applied for AGB studies in Indonesia (Table 1). We evaluated the existing models using our destructive sampling dataset. We computed the mean relative error (MRE) and the mean absolute relative error (MARE) of each model using the following equations:

\[ \text{MRE} = \frac{\sum (\text{AGB}_p - \text{AGB}_m)}{\text{AGB}_m} \]

\[ \text{MARE} = \frac{\sum |\text{AGB}_p - \text{AGB}_m|}{\text{AGB}_m} \]

where AGBₘ and AGBₚ are measured and predicted AGB, respectively. We also evaluated the performance of the models by regressing their AGBₘ against AGBₚ. In a perfectly accurate relationship, this would be a linear relationship with an intercept of zero, a slope of one and a coefficient of determination of one.

Second, we transformed our AGB dataset into a natural logarithm to solve the heteroscedasticity problem of the data. We developed equations from a wide range of model forms to accommodate the availability of field data parameters. Several equation forms suggested by Chave et al. (2014) and Sileshi (2014) were selected. We performed ordinary least squares linear regression to explore the relationship between the AGB and the predictor variables, that is, D, H, h and G in the natural logarithmic form. Correction factors calculated using Ratio Estimator (REst) (Snowdon 1991) were used to reduce systematic bias from back transformation. REst was calculated as \((\sum y_i/n)/(\sum x_i/n)\), where \(y_i\) and \(x_i\) are observed and predicted AGB of tree, and \(n\) is sample size. The selection of the best equations was based on the highest coefficient of determination (\(r^2\)), the lowest root mean square error (RMSE) and the lowest corrected Akaike information criterion (AICc). AICc is particularly useful for model selection with small sample size, and
the corrected-version AICc provide better performance than AIC (Hurvich and Tsai 1989).

Third, we validated our developed equations using independent datasets. Two independent datasets, derived from previous studies by Yamakura et al. (n = 69) and Samalca (2007) (n = 40), were used for this analysis. The datasets had previously been used for the development of site-specific allometric models by Yamakura et al. (1986a) and Basuki et al. (2009), respectively, which were compared in the first step. Similar to the first step, we computed the MRE and MARE of our selected models and the existing local models. In addition, we performed a regression analysis to fit the $\text{AGB}_{\text{B}}$ and the $\text{AGB}_{p}$ of all models to evaluate further the precision and bias of the models (Pineiro et al. 2008).

### Results

The dataset used for developing and validating AGB models covered a wide range of diameter, height, wood density and tree species (Additional file 1). A total of 108 sample data were collected from destructive harvesting in East, Central and West Kalimantan. The largest tree had a diameter of 172 cm and a total height of 75 m. Fifty per cent of the samples were trees with $D > 50$ cm, while trees with $D > 100$ accounted for 10% of the total samples (n = 11). The dataset consisted of 80 species from 27 families. Thirty per cent of total felled trees were from the dipterocarp family.

### Accuracy of the existing equations

We evaluated the precision and bias of previously published local AGB equations using our dataset. Most of the previously published equations had an MRE and MARE of more than 0.21 and 0.31, respectively. Only $\text{DH}_{\text{Yan}}$ had an MRE of less than 0.1 and a slope close to 1 (Table 1). The pantropical equations performed better than the existing local equations. The MRE of all pantropical equations were less than 0.1. $\text{DH}_{\text{Cha}}$ had the smallest MARE among the existing equations. However, only $\text{DH}_{\text{Bro}}$ had the deviation of less than 5% (slope of 0.964).

The regression analysis between the log-transformed measured AGB and the log-transformed predicted AGB of existing local equations showed an underestimated trend, especially the $\text{DG}_{\text{Bas}}$ and $\text{DH}_{\text{Bas}}$ models (Fig. 2). The $\text{DH}_{\text{Bas}}$ model, which was developed from a low range of tree diameter from secondary succession, failed to accurately estimate the tree AGB from primary TDFs. $\text{DH}_{\text{Bas}}$ showed a systematic bias at all diameters. The regression lines of $\text{LD}_{\text{Bas}}$ and $\text{LD}_{\text{Bas}}$ depicted underestimation of small trees and overestimation of large trees, with the points of intersection at 5.15 and 5.24, respectively.

### New aboveground biomass equations for tropical dipterocarp forests

Table 2 depicts the indicators of model fit obtained by using model forms with different predictor variables, after back transformation from a logarithmic form using REst correction factor. All residual plot of the linear models showed normal distributions (Additional file 1). The DGH and DG models explained more than 90% of tree AGB variation, while the $D$ and $DH$ models explained less than 90% of the variation. Based on the AIC, RMSE and adjusted $r^2$ values (Table 2) and considering the plots of predicted against the observed Ln AGB (Fig. 2), we selected the best models with combinations of variables, these are: $\text{D1}, \text{DHF3}, \text{DHF5}, \text{DGH8}, \text{DGH9}$ and $\text{DGH10}$. However, the inclusion of $H$ as predictor variable did not improve the performance of the equations significantly. $\text{DHF5}$ had lower AICc but higher RMSE compared to the $\text{D1}$, while the $\text{DGH10}$ performed worse than $\text{DG8}$.

### Table 1: Local AGB equations from previous studies and their errors, when compared with our dataset

<table>
<thead>
<tr>
<th>Model Name</th>
<th>AGB Equations</th>
<th>MRE</th>
<th>MARE</th>
<th>Intercept (SE)</th>
<th>Slope (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{DG}_{\text{Bas}}$ (Basuki et al. 2009)</td>
<td>$\text{AGB} = 0.318 \cdot D^{1.35}$</td>
<td>-0.210</td>
<td>0.370</td>
<td>-305 (407)</td>
<td>1.865 (0.084)</td>
</tr>
<tr>
<td>$\text{DG}_{\text{Bas}}$ Brown (1997)</td>
<td>$\text{AGB} = 4.269 - 12.8 \cdot D + 1.242 \cdot D^2$</td>
<td>0.085</td>
<td>0.352</td>
<td>-649 (411)</td>
<td>1.345 (0.066)</td>
</tr>
<tr>
<td>$\text{D}_{\text{Bas}}$ Brown (1997)</td>
<td>$\text{AGB} = \exp(-2.134 + 5.23 \ln(D))$</td>
<td>0.043</td>
<td>0.321</td>
<td>576 (393)</td>
<td>0.961 (0.045)</td>
</tr>
<tr>
<td>$\text{DG}_{\text{Bas}}$ (Basuki et al. 2009)</td>
<td>$\text{AGB} = 0.4975 \cdot D^{0.199} \cdot G^{0.057}$</td>
<td>-0.232</td>
<td>0.312</td>
<td>-602 (284)</td>
<td>1.885 (0.057)</td>
</tr>
<tr>
<td>$\text{DH}_{\text{Bas}}$ (Basuki et al. 2009)</td>
<td>$\text{AGB} = 0.106 \cdot D^{0.20} \cdot G^{0.442}$</td>
<td>-0.345</td>
<td>0.392</td>
<td>-358 (410)</td>
<td>2.143 (0.098)</td>
</tr>
<tr>
<td>$\text{DH}_{\text{Bas}}$ Hashimoto et al. (2004)</td>
<td>$\text{AGB} = 0.08127 \cdot D^{0.66}$</td>
<td>-0.495</td>
<td>0.508</td>
<td>353 (395)</td>
<td>2.196 (0.101)</td>
</tr>
<tr>
<td>$\text{DH}_{\text{Yan}}$ (Yamakura et al. 1986a)</td>
<td>$\beta_{1} = 0.02908 \cdot (D^{2}H^{0.8813})$ [ \beta_{1} = 0.1192 \cdot (D^{2}H^{1.389}) ] $\beta_{1} = 0.00946 \cdot \beta_{1}^{2} + \beta_{1}^{0.7266}$ [ \text{AGB} = {0.02909 \cdot (D^{2}H^{0.8813}) + 0.1192 \cdot (0.02909 \cdot (D^{2}H^{1.389}) + 0.00946 \cdot \beta_{1}^{2} + \beta_{1}^{0.7266}) } ]</td>
<td>-0.087</td>
<td>0.320</td>
<td>1185 (385)</td>
<td>0.933 (0.045)</td>
</tr>
</tbody>
</table>

$a$ and $b$ denote significant difference to 0 and 1, respectively. $\text{AGB}$ is in kg, $D$ is tree diameter (cm), $H$ is total tree height (m), $H$ is commercial bole height (m) and $G$ is wood density (in gr cm$^{-3}$). Values in parentheses are standard errors.

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Model validation
We validated our equations using datasets from independent datasets. We found significantly different results between our models and most of the existing local models. Our models outperformed local models considerably. Both $D_{bas}$ and $DG_{bas}$ equations showed underestimation trends, even when applied to their own dataset, in particular for the large trees (Fig. 3). Although both models have relatively normal precisions, the biases of the models are very large (Table 3). For example, $DG_{bas}$ has MRE and MARE of −0.042 and 0.304, respectively, with the slope of the regression between observed and predicted AGB close to two. Slopes of two indicate large bias, whereas the estimates are twice smaller than the predicted, if the intercepts are zero. $D_{bas}$, $D_{bro}$ and $DH_{Yam}$ had negative intercepts that significantly different to zero, suggesting the overestimation of small trees. In contrast, $DG8$ and $DGH9$ had intercepts that were not significantly different to zero and slope more than 0.95, indicating bias of less than 5%.

Only the $DH_{Yam}$ model that had lower MRE and MARE than our model that has the same predictor variables (Table 3, Fig. 3). The reason could be that the dataset used for developing $DH_{Yam}$ was the validation dataset in this study. However, the deviation of the estimated AGB using $DH_{Yam}$ was larger than the deviation from our $DH3$ model, indicated by the intercept that was different from zero and the greater slope. This large deviation was mainly due to the underestimation of large trees and overestimation of small trees (Fig. 3). $DH_{Yam}$ used a complex model form because it was originally developed for estimating biomass of tree components (Table 1). Similarly, $DGH_{Cha}$ and our $DGH9$ model had comparable MRE and MARE values, with deviation from the actual estimates 11.1 and 4.6% respectively.

Discussions
Our new AGB equations outperformed all existing local equations. Most of the local models tended to have a systematic errors, potentially due to field measurement errors or biased samples. The existing pantropical equations performed only slightly worse than our new equations. The $DGH_{Cha}$ in particular, performed consistently well when applied to our dataset and the validation data. $DGH_{Cha}$ was developed using large number of samples from Borneo, including the validation dataset used in this study (Chave et al. 2014). Therefore previous studies on forest aboveground biomass stocks in TDF of Kalimantan or Borneo using $DGH_{Cha}$ should be valid.

Our $DGH9$ model performs better than other models, with lower bias and better precision. Individual tree height measurements in closed-canopy
TDFs are difficult and thus have high uncertainty. In that case, the DG8 should be used. However, due to a very high diversity of tree species in the TDF, identification of tree taxonomy could be problematic. Tree taxonomy identification during forest inventory for large area creates logistical and financial burden for the collection, shipment and identification of the herbarium specimens. For timber extraction planning purpose, tree identification was commonly carried out only using local names without involving botanist, and thus difficult to obtain accurate wood density values from the existing wood databases. Therefore, for estimating AGB from existing timber inventory dataset, we suggested to use the D1 or DH5 (if the bole height is available).

AGB models developed from a small number of samples and limited tree diameter range have the potential risk to be biased, especially when applied beyond their sample characteristic as well as geographical, biophysical and forest boundaries (van Breugel et al. 2011; Manuri et al. 2014). However, although the samples used by Basuki et al. (2009) were sufficient in number and diameter range, their models were not able to predict AGB accurately, even using the dataset they partly used for the models development. We suspect these inaccuracies are due to differences in sampling strategy (e.g., sample selection), assumptions in model development (e.g., correction factor) or approach in AGB field measurements (e.g., assumptions of regular shapes of stems and branches with diameter more than 15 cm).
Table 2 The parameter estimates and indicators of model fit from new AGB equations

<table>
<thead>
<tr>
<th>Model ID</th>
<th>Equations</th>
<th>Parameter estimates</th>
<th>n</th>
<th>Adj$^2$</th>
<th>RMSE</th>
<th>ACC</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>$0.125 \times 2^{2.533}$</td>
<td>0.125 (0.033)</td>
<td>2.533 (0.062)</td>
<td>108</td>
<td>0.821</td>
<td>3215</td>
</tr>
<tr>
<td>D2</td>
<td>$\exp(-2.845 + 2.726 (\ln N) - 0.094 (\ln D) - 0.271 (\ln D)^2) \times 1.071$</td>
<td>$-2.845 (0.479)$</td>
<td>$2.726 (0.122)$</td>
<td>$-0.094 (0.104)$</td>
<td>$-0.271 (0.141)$</td>
<td>108</td>
</tr>
<tr>
<td>D3</td>
<td>0.068 $\times D^{0.245}$</td>
<td>0.068 (0.027)</td>
<td>2.268 (0.215)</td>
<td>0.483 (0.203)</td>
<td>108</td>
<td>0.813</td>
</tr>
<tr>
<td>D4</td>
<td>0.041 $\times D^{0.986}$</td>
<td>0.041 (0.013)</td>
<td>0.995 (0.024)</td>
<td>108</td>
<td>0.804</td>
<td>3358</td>
</tr>
<tr>
<td>D5</td>
<td>0.062 $\times D^{0.386}$</td>
<td>0.062 (0.027)</td>
<td>2.388 (0.084)</td>
<td>0.326 (0.132)</td>
<td>108</td>
<td>0.823</td>
</tr>
<tr>
<td>D6</td>
<td>0.05 $\times D^{0.591}$</td>
<td>0.050 (0.016)</td>
<td>1.011 (0.027)</td>
<td>108</td>
<td>0.798</td>
<td>3409</td>
</tr>
<tr>
<td>D7</td>
<td>0.236 $\times D^{0.999}$</td>
<td>0.236 (0.042)</td>
<td>2.500 (0.040)</td>
<td>1.079 (1.079)</td>
<td>108</td>
<td>0.918</td>
</tr>
<tr>
<td>D8</td>
<td>0.277 $\times D^{0.668}$</td>
<td>0.277 (0.042)</td>
<td>1.238 (0.019)</td>
<td>108</td>
<td>0.924</td>
<td>2095</td>
</tr>
<tr>
<td>D9</td>
<td>0.071 $\times D^{0.993}$</td>
<td>0.071 (0.014)</td>
<td>0.973 (0.016)</td>
<td>108</td>
<td>0.909</td>
<td>2287</td>
</tr>
<tr>
<td>D10</td>
<td>0.093 $\times D^{0.795}$</td>
<td>0.093 (0.021)</td>
<td>0.994 (0.020)</td>
<td>108</td>
<td>0.895</td>
<td>2452</td>
</tr>
</tbody>
</table>

Correction factors had been incorporated into the equations. The models presented in bold are the best equations from each model type. Values in parentheses are the standard errors.

In contrast with the dataset used by Basuki et al. (2009), which used only 40 species, our total number of species was doubled. The percentage of dipterocarp trees in the Basuki et al. (2009) dataset was more than 50%, while we had only 30%. Our dataset composition seems to be more similar to the floristic composition in the primary dipterocarp forests, with a percentage of total trees of about 25% (Sist and Saridan 1999). In Danum Valley, the dipterocarp population accounted for only 16% of total trees sampled in the primary dipterocarp forests. Nevertheless, they dominated the forest, representing about 50% of the basal area owing to their large and emergent trees (Newbery et al. 1992).

Basuki et al. (2009) calculated the biomass of stems and branches, which diameter greater than 15 cm, using volume-based measurement, while we weighed all stems and branches that had a diameter of less than 30 cm or had irregular shapes, other than a cylindrical shape. Therefore, we also weighed most of the irregular stumps. The kernel smoother line representing the error distribution of $D_{bas}$ model across Ln AGB, intersected at the value of 4.7 with the zero line (Fig. 3) which equals 110 kg of AGB or 14.3 cm of tree diameter. This suggested that the $D_{bas}$ equation tend to underestimate the AGB of trees with diameter of more than 14.3 cm. This supports our supposition regarding the possible error of biomass measurement of trunks or branches with diameters greater than 15 cm. Such different approaches or assumptions in field measurement might introduce bias. Differences in the destructive sampling method used in independent research are unavoidable (Manuri et al. 2014, under review), which may lead to incomparable tree biomass datasets. Thus, standardised methods for principal measurement components are required to ensure the measured datasets are valid. Such related initiatives have been carried out globally (Picard et al. 2012) and nationally (BSN 2011).

Some of our wood samples have exceptionally large values of wood density (>1 gr-cm$^{-3}$) compared to the existing wood density databases. For example the 45 cm-diameter Dipterocarpus stellatus has wood density of 1.3 gr-cm$^{-3}$, which is greater than any records from Dipterocarpus genus. We checked the field and laboratory records, and did not find any inconsistencies in the measurements. This species is endemic to Borneo. We did not find any record of the wood density from this species from the existing wood density databases. Soerianegara and Lemmens (1993) and Zanne et al. (2009) recorded the highest wood density from Dipterocarpus genus were 1.07 and 0.89, respectively. There are two possible main reasons that explain this. First, wood density variation occurs among individual within species (Henry et al. 2010), which influenced by tree diameter size and guild status (Henry et al. 2010; Iida et al. 2012), climatic variables (Onoda et al. 2010) and soil fertility (Muller-Landau 2004). Second, there are some differences in the method for wood density measurement between tree biomass and wood characteristic studies. Our wood density measurement involves wedge or pie-shaped samples, which include barks, from various trunk sections and tree compartments. This is to ensure that the measured wood densities are closed to the actual values of tree wood densities (Williamson and Wiemann 2010).

A validation of existing AGB models is essential before the use of the models. We found that the use of MRE and MARE are not sufficient for evaluating the AGB model performance, since they only represent the mean
Fig. 3 Relative error distribution of the existing and new models. The orange circles and the green diamonds represent the datasets from Yamakura et al. and Samalca (2007) datasets, respectively. The solid purple curves were generated using loess method.
errors, not the trend of the residuals. To address this gap, a simple linear regression analysis between the observed and predicted values of the models is required to quantify the general tendency of the residuals (Pinheiro et al. 2008). The $r^2$ and RMSE indicate the precision of the estimates, while the slope and the intercept of the fitted line describe the bias of the estimates.

**Conclusion**

Most of the existing local AGB equations tend to be biased and imprecise. Local models developed from small samples tend to systematically biased. We recommend not using the local models for estimating AGB or to validate prior their use especially if the models were developed from other region outside the study site, even within the same forest type. We developed new allometric equations for tree AGB estimation in the TDFs of Kalimanatan using a relatively large dataset with a maximum tree diameter of 175 cm. Through a validation using independent datasets, we found that our equations improve the precision and reduce the bias of AGB estimates.

**Additional file**

Table 3 Model validation using datasets from previous studies

<table>
<thead>
<tr>
<th>Model ID</th>
<th>Adj $r^2$</th>
<th>RMSE (kg)</th>
<th>MRE</th>
<th>MARE</th>
<th>Intercept (SE)</th>
<th>Slope (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>0.935</td>
<td>1220</td>
<td>0.025</td>
<td>0.263</td>
<td>-123 (123)</td>
<td>1.201 (0.030)</td>
</tr>
<tr>
<td>DH3</td>
<td>0.971</td>
<td>819</td>
<td>0.069</td>
<td>0.240</td>
<td>-142 (83)</td>
<td>1.133 (0.019)</td>
</tr>
<tr>
<td>DG8</td>
<td>0.941</td>
<td>1157</td>
<td>-0.084</td>
<td>0.202</td>
<td>113 (115)</td>
<td>0.955 (0.023)</td>
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<tr>
<td>DG10</td>
<td>0.953</td>
<td>395</td>
<td>0.049</td>
<td>0.142</td>
<td>66 (39)</td>
<td>0.954 (0.036)</td>
</tr>
<tr>
<td>DO40</td>
<td>0.915</td>
<td>1392</td>
<td>0.056</td>
<td>0.383</td>
<td>-438 (144)</td>
<td>2.349 (0.069)</td>
</tr>
<tr>
<td>D100</td>
<td>0.932</td>
<td>1253</td>
<td>-0.486</td>
<td>0.507</td>
<td>-202 (127)</td>
<td>2.891 (0.073)</td>
</tr>
<tr>
<td>D150</td>
<td>0.908</td>
<td>1453</td>
<td>0.053</td>
<td>0.289</td>
<td>-437 (150)</td>
<td>1.669 (0.051)</td>
</tr>
<tr>
<td>D200</td>
<td>0.935</td>
<td>1221</td>
<td>0.043</td>
<td>0.272</td>
<td>-125 (123)</td>
<td>1.295 (0.033)</td>
</tr>
<tr>
<td>D250</td>
<td>0.937</td>
<td>1197</td>
<td>-0.042</td>
<td>0.304</td>
<td>-206 (121)</td>
<td>1.946 (0.048)</td>
</tr>
<tr>
<td>D350</td>
<td>0.988</td>
<td>514</td>
<td>-0.025</td>
<td>0.217</td>
<td>-137 (52)</td>
<td>1.243 (0.013)</td>
</tr>
<tr>
<td>DGH</td>
<td>0.953</td>
<td>395</td>
<td>0.005</td>
<td>0.146</td>
<td>71 (39)</td>
<td>0.889 (0.007)</td>
</tr>
</tbody>
</table>

$^a$ and $^b$ denote significant difference to 0 and 1, respectively.

The authors are grateful to the G27-Fordline project, a bilateral project between Indonesia and German governments, for funding the field measurements. We would like to thank Pak Glono, Pak Tolekera and Erik Solichin Manuri gratefully acknowledges the support of Australia Award Scholarship from 2013 to 2017. All authors reviewed and revised the manuscript. All authors read and approved the final manuscript.

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**References**


Chapter 5

Effect of species grouping and site variables on aboveground biomass models for lowland tropical forests of the Indo-Malay region

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Effect of species grouping and site variables on aboveground biomass models for lowland tropical forests of the Indo-Malay region

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Abstract

- **Key message** This study assessed the effect of ecological variables on tree allometry and provides more accurate above-ground biomass (AGB) models through the involvement of large samples representing major islands, biogeographical

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\textit{Contribution of the co-authors:}

SM, CB, TR and FN formulated the idea and developed methodology. SM, TR, FN, SIM, WCA, HK, DWS, GAK, AB, RSA, CAS, O, ES and DY collected data. SM performed statistical analyses and wrote the manuscript. TR, FN, LV, SIM, WCA, HK, DWS, GAK, AB, RSA, CAS, O, DY and ES revised the manuscript.

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zones and various succession and degradation levels of natural lowland forests in the Indo-Malay region. The only additional variable that significantly and largely contributed to explaining AGB variation is grouping based on wood-density classes.

- **Context** There is a need for an AGB equation at tree level for the lowland tropical forests of the Indo-Malay region. In this respect, the influence of geographical, climatic and ecological gradients needs to be assessed.

- **Aims** The overall aim of this research is to provide a regional-scale analysis of allometric models for tree AGB of lowland tropical forests in the Indo-Malay region.

- **Methods** A dataset of 1300 harvested trees (5 cm ≤ trunk diameter ≤ 172 cm) was collected from a wide range of successsion and degradation levels of natural lowland forests through direct measurement and an intensive literature search.

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of principally grey publications. We performed ANCOVA to assess possible irregular datasets from the 43 study sites. After ANCOVA, a 1201-tree dataset was selected for the development of allometric equations. We tested whether the variables related to climate, geographical region and species grouping affected tree allometry in the lowland forest of the Indo-Malay region.

**Results** Climatic and major taxon-based variables were not significant in explaining AGB variations. Biogeographical zone was a significant variable explaining AGB variation, but it made only a minor contribution on the accuracy of AGB models. The biogeographical effect on AGB variation is more indirect than its effect on species and stand characteristics. In contrast, the integration of wood-density classes improved the models significantly.

**Conclusion** Our AGB models outperformed existing local models and will be useful for improving the accuracy on the estimation of greenhouse gas emissions from deforestation and forest degradation in tropical forests. However, more samples of large trees are required to improve our understanding of biomass distribution across various forest types and along geographical and elevation gradients.

**Keywords** Tree AGB · Allometric equation · Regional model · Destructive sampling · Biogeographical zones

## 1 Introduction

Tropical lowland forests are one of the most important forest types in the Indo-Malay Archipelago, owing to its extent, species diversity and biomass accumulation (Whitten 1987; Jepson et al., 2001; Marshall and Beehler 2007). The forests in this region play a crucial role in economic development and in biodiversity conservation, environmental protection and climate-change mitigation (FAO 2015; MoEF 2015). Accurate estimation of forest biomass is important for understanding carbon balance and the dynamics of tropical ecosystems (Cramer et al., 2004; Clark and Kellner 2012). Landscape studies on biomass balance assessment commonly use ground measurement and remote sensing techniques, which require allometric equations to convert tree metrics derived from ground measurements to tree aboveground biomass (AGB) (Slik et al., 2008; Henry et al., 2015).

Unbiased and precise allometric equations would provide more accurate estimates of forest AGB stock and CO₂ emissions associated with deforestation and forest-degradation activities (Chave et al., 2014). The term of bias used is to define systematic departure of predicted values from observed values (Avery and Burkhart 1983). Unbiased models have regression slopes between predicted and observed values not significantly different from zero and intercepts not significantly different from zero. The scatter of the points around the line of observed and predicted values is a measurement of precision. Precision is commonly measured using standard deviation or root mean square error (RMSE).

The most accurate AGB equations commonly include traditional variables as predictor variables in the form of AGB = Exp (Ln α + Ln β₀D²GH + ε), where AGB is a function of diameter at breast height (D, in cm), tree height (H, in m), specific wood density (G, in grammes cm⁻³), α and β are model parameters and ε is the error term (Chave et al., 2005; Vieilledent et al., 2012). However, the choice of AGB models often depends not only on the accuracy of the model but also on the availability of the variables recorded during field inventories. In the absence of G or H, several authors use other model forms, for example, AGB = Exp (Ln α + Ln β₀D²H + ε); AGB = Exp (Ln α + Ln β₀D²G + ε) or AGB = Exp (Ln α + Ln β₀D + ε) (Basuki et al., 2009; Sileshi 2014). The more comprehensive the field measurements, the greater the logistical requirements. Thus, several models have been developed using fewer predictor variable, which leads to a trade-off between cost and accuracy (Brown et al., 1989). To overcome the logistical problem or reduce the cost for measuring every tree height, development of a local H-D model is often suggested for AGB estimation in tropical forests (Feldpausch et al., 2012). Ledo et al. (2016) found that local H-D model developed using the three-parameter Weibull model form was the most unbiased models compared to various H-D model forms.

Attempts to improve the AGB models have included adding more and a wider range of samples or explored additional predictor variables. Goodman et al. (2014) concluded that crown size is an additional important predictor variable, and that it is more influential than the tree-height variable in estimating tree AGB in Peru. However, performance assessment of model with additional variables needs to be carried out comprehensively, because the coefficient of determination will always increase when more predictor variable is added to the model (Neter et al., 1996).

G is another important factor, but it is not easy to define the appropriate values using global wood-density databases due to the high variation of G between and within species. Further, identifying tree species accurately from highly diverse tropical forests during forest inventory is difficult. In the absence of a scientific tree name, a simple species grouping based on similar wood classes improves AGB estimates in tropical peat swamp forests (Murari et al., 2014). Further, taxon-based grouping improves the performance of the AGB model (Basuki et al., 2009; Paul et al., 2016).

Several studies have suggested developing regional allometric equations for nation-wide scales (Vieilledent et al., 2012; Ishihara et al., 2015). However, the influence of geographical, climatic and ecological gradients to the model need to be assessed to ensure precision of the AGB estimates and avoid biases of the estimates when the generic model is
applied locally. A regional AGB equation for the Indo-Malay
region has not been developed. Developing such a model
requires a large dataset of destructive sampling collected from
a wide range of geographical and environmental conditions.
Anitha et al. (2015) found as many as 168 studies (mostly
unpublished) on the development of local AGB equations in
21 forest ecosystems in Indonesia. Unfortunately, these local
AGB equations were developed from either a low number of
sample trees or a limited range of tree diameters. In addition,
more than 68% of the equations were developed for species-
specific equations, and thus were impractical for use in highly
diverse tropical forest ecosystem. Compilation of existing
datasets from published and unpublished studies is thus re-
quired for the development of the regional model to ensure
the validity of the model across a vast area of the lowland
tropical forests of the region.

Tree diversity can reach more than 200 species per hectare
in lowland tropical forests of the Indo-Malay region, making it
one of the most diverse forest types in the world (Kurtawan-
ita 1999). The development of species-specific biomass equa-
tions is not a feasible option for such highly diverse tropical
forests. However, specific equations based on geographical,
climatic and ecological gradients can be used to improve the
AGB models (Alvarez et al., 2012). Differences in vegetation
characteristics and species diversity among the geographical
regions of Indo-Malay are evident (Van Welzen et al., 2011).
The Indo-Malay regions have been divided by the imaginary
Wallace and Lydekker lines. Although these lines were drawn
based on the faunal distinction and the historical geological
formation (Mayr 1944), this division can be used for differenti-
ating phytogeographical zones because the lines discontinu-
ted or lessened the dispersal of many plant species
(Van Welzen et al., 2011).

The overall aim of this research is to provide a regional-
scale analysis on tree biomass allometric models for lowland
forests across the Indo-Malay Archipelago. The study comp-
piled harvested tree AGB databases of lowland tropical forests
and developed regional allometric equations for lowland for-
est on mineral soils. The study also assessed the influence of
species grouping and site-related variables (including climatic
and geographical variables) on tree AGB variations.

2 Material and methods

2.1 Study sites

We compiled sampled sites with lowland forests within the
Indo-Malay Archipelago, including major island groups (i.e.
Malay Peninsula, Sumatra, Borneo, Java, Nusa Tenggara,
Maluku and Papua; see Fig. 1). The latitude and longitude of
the study sites ranged from 10.31° south to 4.039° north and
98.79° east to 140.50° east. The mean annual precipitation of
the study sites ranged from 1375 to 3992 mm with altitudes
between 16 and 1000 m above sea level. We limited our study
to only natural lowland forests on mineral soils. Therefore, we
excluded mountain forests, peat swamp forests, mangroves
and plantation forests from this study. Our interest lies not
only in primary forests but also in logged-over and secondary
forests. We divided our study sites into three regions: west,
middle and east following the biogeographical theory based
on floristic similarities (Fig. 1). The dominance of Dipterocarpaceae in the western region diminished towards the
middle and eastern parts of the region, replaced by Eriaceae,
Monimiaceae and Sapindaceae (Van Welzen et al., 2011). In the southeastern part of the middle region,
with the influence of dry climate, savannah and deciduous
vegetation dominate the landscape (Monk et al., 1997).

2.2 Tree AGB data

We collected data through direct measurement and supple-
mented these data with a literature review of principally grey
publications (see Appendix S1 for detail of the method
applied and Appendix S4 for a list of compiled studies). A
total of 1463 of destructive-sampling data from direct mea-
surement and literature were compiled from 22 independent
studies in 43 different sites (Table 1, Appendix S5). Eighty-six
per cent of our datasets were originally derived from lowland
dipterocarp forest in the western region, and only 4% and 9% of
the total samples were derived from lowland forests in the
middle and eastern regions of the Indo-Malay region, respec-
tively. Approximately 30% of the datasets were derived from
Chave et al. (2014) with n = 425 (Appendix S5). We excluded
trees with D less than 5 cm due to their small contribution to
the landscape-level carbon budget and high variation of resid-
uals, which resulted in a total of 1300 samples compiled from
direct measurements and literature review (Table 1).

Compiled datasets from the literature were principally col-
piled from independent studies. They were collected using
different methods for field and lab measurements. Some of the
studies did not provide details of how the data were collected
and could not be verified further for data validation.
Therefore, we performed ANCOVA for the 43 sites to evalu-
ate possible outlier trends of each dataset. Dataset that is rep-
resented by a separate regression line may be collected using
different method and thus should be excluded in the analysis.
We found that two datasets (Esakal10 and Centkal2) were
represented by separated regressions lines (Fig. 2). These
datasets were collected from lowland dipterocarp forests in
Borneo, which is one of the major forest types in Borneo
and well represented in our samples. We suspected this is
because of systematic errors in definition and assumptions
used during the field-data collection and laboratory analysis
(Mamuri et al., 2016).
5.2.3 Assessment of influencing factors on AGB estimation

Given that not all studies measured G, we used the global wood-density database from Chave et al. (2009) based on the closest taxonomy to fill in the missing data. We validated the species names following the nomenclature from the available tree flora checklists (Slik 2009 onwards; The Plant List 2013). For evaluating the influence of site variables, we extracted mean annual precipitation (P) from global climate data (Hijmans et al., 2005) and global environmental stress data (E) provided by Chave et al. (2014) for each field plot.

2.3 Assessment of influencing factors on AGB estimation

D, G and H are the most frequently used predictor variables in estimating tree AGB due to their capability in explaining AGB variation in tropical forests (Brown 1997; Chave et al., 2014). In addition to those traditional variables, we performed a regression analysis to assess other additional factors related to climatic conditions, biogeographical regions (R) and species grouping based on wood density and taxonomy. We used mean annual precipitation (P) and environmental stress (E) as variables related to climatic conditions. We tested the potential of species grouping, using tree family (F) and wood-density class (GC) (i.e. low, medium and high-density classes). GC was derived from the G values by applying threshold values of 0.5 and 0.6 cm$^3$ g$^{-1}$. Due to the high diversity of tree species, family grouping (FG) was also defined based on major family groups, dipterocarp and non-dipterocarp. To assess the variable effect to the model, we compared LogWorth values of the variables, which were calculated as $-\log_{10}(p$ value) for better scaling purpose (Sall 2002). We evaluated the multicollinearity of each variable using the variance inflation factor (VIF). Variables with VIF more than five were expected to have multicollinearity (Sileshi 2014). The model forms, in which the variables have large VIF, were excluded in the model development.

2.4 Development of AGB equations

Several considerations are crucial in selecting the best AGB model, i.e. (1) statistical correctness (including the best goodness of fit of model parameters, applying appropriate correction factor for log linear models, normal residuals distribution, excluding models with high collinearity among predictor variables), (2) high accuracy and predictive capability and (3) practical for field implementation (Overman et al., 1994).

Through the Breusch–Pagan test and abridged White’s test (Gujarati 2014), we found that our data exhibited heteroscedasticity ($p < 0.0001$; see Appendix S2). Therefore, we transformed AGB into a natural logarithm to overcome the heteroscedasticity problem. To reduce systematic bias from
back-transformation, we tested two correction factors, i.e. the 'MM' correction factor (Shen and Zhu 2008), as suggested by Clifford et al. (2013), and ratio estimator (REst) (Snowdon 1991). Manuri et al. (2014) suggested that back-transforming using REst provide more accurate models than using correction factor suggested by Baskerville (1972).

To accommodate the availability of field-data parameters, we developed equations from a wide range of model forms as suggested by Chave et al. (2014) and Silesi (2014). We categorised the AGB models, based on the use of traditional predictor variables, into four model types (i.e. those using D, DH, DG and DGH). The selection of the best equations was based on the highest adjusted coefficient of determination (adj $R^2$), the lowest RMSE and the lowest corrected Akaike information criterion (AICc). To test the accuracy of the AGB model that incorporated the local H-D model, we developed a regional H-D
model using the three-parameter Weibull model form (Bailey 1988; Feldpausch et al., 2012; Lemo et al., 2016).

We evaluated the precision and bias of the models when applied to the individual dataset, species groups and forest type. Unbiased models have regression slopes between predicted and observed values not significantly different to 1 and intercepts not significantly different from 0. Precision is commonly measured using adj $R^2$ or RMSE. Additionally, we calculated the mean relative error (MRE) and the mean absolute relative error (MARE) of each model (Picard et al., 2015). Most of the statistical analyses in this study were performed using JMP 12 software (SAS II, 2015). For calculating the MM correction factors, we used the code provided by Clifford et al. (2013) for R statistical package (R-Development-Core 2013).

3 Results

3.1 Factors affecting AGB estimation

We assessed the influence of traditional (i.e. Ln D, Ln G, Ln H) and additional variables (i.e. R, GC, P, FG and E) when fitted to various linear Ln AGB models using regression analysis. We found that the traditional and most of the additional variables were significant at $p < 0.05$ for estimating AGB (Table 2). The traditional variables had larger LogWorth values than the additional variables. This means that they had greater influence in explaining the variation of AGB.
Chapter 5

5.3.2 AGB equations for lowland forests

We developed linear models with a combination of traditional factors (i.e. D, H and G) and additional factors (i.e. GC and R). The previous analysis provided justification for selection of the best eight model types. All the multivariate model forms involving the D and H variables separately revealed multicollinearity with VIF > 5 (Table 2). The selected linear AGB models were fitted to the compiled dataset from the lowland tropical forests of Indo-Malay region (Appendix S3) and were back-transformed using the MM and REst correction factors. We found that models back-transformed using REst performed better than the ones back-transformed using MM correction factor. The MREs and MAREs of the REst back-transformed models were lower than the MM back-transformed models, except for all DH models (Appendix S6). Therefore, we used the models that back-transformed using REst correction factors for further analysis.

The simplest model (D1) was the least precise and unbiased model, with the highest MRE and MARE (14.0 and 41.5%, respectively) (Table 3). Residuals of D1 and DH1 against wood-density values did not depict normal distribution, with regression slopes further from zero (Appendix S7). This means that trees of high wood density tended to have positive errors and vice versa. The inclusion of GC in the D2 and DH2 models reduced the slopes of residual distribution to close to zero. GC integration in the D2 and DH2 models increased the adjusted $R^2$ by 3.3 and 3.7%, respectively. The inclusion of G variable reduced bias (MRE) and precision (MARE), 35 and 26%, respectively (Table 3). The $H$ variable was less influential in the models performance, increasing $R^2$ by only 0.3-0.4%. In addition, the DG2 and DGH2 models did not perform better than the models without the additional variable of R (DG1 and DGH1).

To assess the accuracy of the AGB model that involved the $H-D$ model, we developed a regional model using three-parameters Weibull function ($n = 1057$). We found that tree

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Goodness of fit and errors of the developed models. Correction factors were incorporated in the equations</th>
</tr>
</thead>
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<td>Equations (REst)</td>
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<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>D1</td>
<td>0.071(D)2.667</td>
</tr>
<tr>
<td>D2</td>
<td>H: 0.118(D)2.585</td>
</tr>
<tr>
<td></td>
<td>Med: 0.099(D)2.585</td>
</tr>
<tr>
<td></td>
<td>L: 0.066(D)2.585</td>
</tr>
<tr>
<td>DH1</td>
<td>0.028(D)3.164</td>
</tr>
<tr>
<td>DH2</td>
<td>H: 0.103(D)0.970</td>
</tr>
<tr>
<td></td>
<td>Med: 0.045(D)0.970</td>
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<tr>
<td></td>
<td>L: 0.034(D)0.970</td>
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<tr>
<td>DHw</td>
<td>0.038(D)2.694</td>
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<tr>
<td>DG1</td>
<td>0.171(D)2.5861G0.500</td>
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<tr>
<td>DG2</td>
<td>W: 0.167(D)2.5861G0.889</td>
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<td></td>
<td>M: 0.151(D)2.5861G0.889</td>
</tr>
<tr>
<td></td>
<td>E: 0.206(D)2.5861G0.889</td>
</tr>
<tr>
<td>DGH1</td>
<td>0.088(D)2.5861H0.500</td>
</tr>
<tr>
<td>DGH2</td>
<td>W: 0.088(D)2.5861G0.955</td>
</tr>
<tr>
<td></td>
<td>M: 0.094(D)2.5861G0.955</td>
</tr>
<tr>
<td></td>
<td>E: 0.099(D)2.5861G0.955</td>
</tr>
<tr>
<td>DGHw</td>
<td>0.088(D)2.5861H0.500</td>
</tr>
</tbody>
</table>

Adj $R^2$ adjusted coefficient of determination. RMSE root mean square error. MRE mean relative error. MARE mean absolute relative error. H, Med and L, high-, medium- and low-density woods, respectively. W, M and E western, middle and eastern regions, respectively. D, G, H and Hw, are tree diameter, tree-wood density, tree height and tree height derived from the Weibul H-D model.
diameter explained 85.6% of tree-height variation (Fig. 3). We integrated the H-D model into the DHw and DGHw models. Both models performed only slightly worse than the original models that used measured H (Table 3; Fig. 4).

Finally, we evaluated the precision and bias of the models on various islands, forest types, and tree families. The models have high bias and low precision for the Java and Sulawesi datasets (Fig. 5). We found that most of the models did not perform well on the secondary forest, heat forest, and agroforestry datasets, particularly the D and DH models. At the tree-family level, Rutaceae, Asteraceae, Apocynaceae, Sabiaceae, Rhizophoraceae, Euphorbiaceae, Cannabaceae, Crypteroniaceae, Piperaceae, Anisophyllaceae, and Sapindaceae show high bias, where −0.5 > MRE > 0.5 (Fig. 5).

4 Discussion

4.1 Importance of traditional variables in explaining tree AGB variations

The model with the diameter as the only predictor variable performed worse than the models with the added variables of tree height and wood density. This finding was in agreement with other studies on highly diverse tropical forests (Chave et al., 2014; Manuri et al., 2014) but contrasted with several studies in low-diversity ecosystems such as secondary forests (Hashimoto et al., 2004), Australian dry sclerophyll forests (Paul et al., 2013) and swidden fallow forests (McNicol et al., 2015). The inclusion of wood-density classes improved the performance of our models for lowland tropical forests. Substantial differences of mean wood density among species, forest type and successions influenced the variation of tree allometry in tropical forests (Hashimoto et al., 2004; Slik 2006). We concluded that diameter and wood density are essential variables in estimating AGB in highly diverse tropical ecosystems. We also found that the inclusion of H variables only slightly improved the performance of the regional AGB models, and performed no better than when G was included. The potential reason could be that H and D in our datasets have strong correlation and thus introduce colinearity.

4.2 Effect of site-related and species-grouping variables in tree allometry

Most of the additional variables had less influence on the AGB models than the traditional variables. Although mean annual precipitation and environmental stress were significant variables in explaining AGB variations, their inclusion only slightly improved the precision of the models. The inclusions of climate-related variables were not considered worthwhile given the effort of collecting the variable data. Further, their influence diminished with the introduction of the G and H variables to the models. This was likely because climate influences stand characteristics more than AGB variation directly (Durán et al., 2015). For example, a low-precipitation environment tended to have trees with high wood density (Onoda et al., 2010) and stimulated taller trees (Banin et al., 2012). Thus, the inclusion of G and H into the AGB model could explain the AGB variation created by the climate-related variables.

Despite the evident differences in the vegetation characteristics and species composition between the western and eastern regions of Indo-Malay (Van Welzen et al., 2011), our biogeographical-wise equations only slightly improved the accuracy of AGB estimation. The influence of the biogeographical region remained prominent in the AGB model without the variables of wood density and tree height. Further, the effect of the region on the H-D model was more influential than it was on the AGB models (results not shown). In addition, edaphic and climatic factors associated with biogeographical variables had correlations with tree-wood density (Slik et al., 2010). This suggests that the biogeographical effect on AGB variation is more indirect than its effect on species and stand characteristics such as wood density and tree height.
We found that the wood-density class was the only additional variable that contributed to a substantial improvement in the accuracy of AGB estimation. This finding was in agreement with an earlier study conducted in tropical peat swamp forests (Manuri et al., 2014). Kenzo et al. (2009) also emphasized the need for differentiating tree allometry of primary forests and secondary forests, which are substantially different in the mean value of their wood density. Thus, species groupings based on similar wood density could be factored into biomass equations for a wide range of characteristics related to wood density, including heavy and light timber species, climax and pioneer species or secondary and primary forests (Slik 2006). However, our species grouping, which was based on major family groups (i.e., dipterocarp and non-dipterocarp) had little influence in explaining the variation of tree AGB. This finding is in contrast to the study in tropical peat swamp forests, where species grouping based on dipterocarp and non-dipterocarp family group improves the accuracy of AGB estimation (Manuri et al., 2014). Although our analysis demonstrated that the species grouping based on family was a significant variable to AGB estimates (result not shown), we decided not to develop taxon-based models due to their inapplicability in highly diverse tropical forests and an insufficient sample number to represent each family.

4.3 Implication for forest-biomass assessment approach

Our regional models were developed based on samples collected from several tropical lowland forest types on mineral soils on several major islands in the Indo-Malay region. Thus, these models are more representative of major lowland forest types than the existing local models that have been created from the region. None of the existing local models perform better than our regional models because the sample sizes used for developing the local models were generally limited in number, diameter range, species diversity and environmental condition (Ishihara et al., 2015). Our samples better represent the various succession and degradation levels of the natural lowland forests than the samples used in the local models. Given these limitations, the local models fail to estimate AGB accurately beyond their range of validity. Thus, validation is crucial before the use of local models, particularly when estimating forest AGB outside the area where the models were developed.

It is common that during the process of forest inventory, the field crew measure only trunk diameter due to difficulties in species identification, occlusion of tree tops or simply because of logistical constraints (Higgins and Ruokolainen 2004). The use of an H-D model and the recording of local commercial names instead of scientific species names were endorsed through a government regulation for forest inventories conducted by timber concessionaires or local communities in Indonesia (MoF 2007). Therefore, the results of this study should be able to overcome the limitations in measuring H.

As there is a high uncertainty in H measurement of trees in dense tropical forests, a simple approach using the H-D model was suggested to substitute H values in AGB models (Feldpausch et al., 2012). Our testing on the integration of H prediction into AGB models suggested that the models had almost similar precision to the model using H from field measurement. However, the models demonstrated a larger bias than the model with field-measured H. Therefore, we suggest further evaluation of the use of H prediction in the AGB models using the whole-plot datasets.

In cases where tree height (both from field measurement and local H-D model) cannot be determined, the D2 and DG1 models, which perform at a comparably level of accuracy to our more complex DGH1 model, should be used. During forest inventory, G was commonly estimated using the proxy data (i.e., tree taxonomy). This could be a source of error due to G variation inter and within species (Henry et al., 2010), which was influenced by species life strategy, individual competition and site characteristics (Muller-Landau 2004). He and Deane (2016) concluded that tree size also plays a role in explaining the variation of wood density of tree trunks and branches.

A globally compiled wood-density database was often used for this purpose, which potentially introduced error, particularly for trees of small diameter and uncommercial trees (Manuri et al., 2014). Furthermore, the number of species listed in the global database is far less the total global species number, whereas tropical tree species contributed to a major unmeasured species (Williamson and Wiemann 2010). However, the error of G estimation at species level from the taxon-based approach should not be of great concern when estimating AGB at plot and landscape level because the G variation at tree level is strongly related to the G at genus level (Chave et al., 2006; Slik 2006).

The D2 model included species grouping based on wood-density class, which improved the accuracy of the original D1 model. Such an approach will be very useful for field biomass measurements made by timber concessions or small-scale community forests. Determining high-density or low-density wood without a scientific name should not be problematic. Often forest managers employ villagers who can accurately identify tree species based on local names. Databases linking local names and wood-density values are commonly initiated at local levels (Martawijaya et al., 2005; Putra et al., 2011). Alternatively, the collection of data on wood density using non-destructive techniques (e.g., small cores or pilodyn) should be able to provide accurate wood-density values or
Fig. 5 Relationship between MARE and MRE of the AGB models for each (a) island, (b) forest type and (c) family
classes and thus AGB accuracy (Williamson and Wiemann 2010; Kotowska et al., 2015).

Finally, for more accurate AGB estimations, we propose using the DGH1 or DG1 models because the influence of region is trivial for the accuracy of the AGB estimates. When G is unavailable, we suggest using D2 or DH2, which have additional variables for wood-density classes. Our models should be valid for AGB assessment in a wide range of succession and degradation levels of natural lowland forests in the region.

4.4 Limitations and future research directions

Although the coverage of forest types used in this study accounted for more than 65% of total forests from their original distribution (Whitten 1987; MacKinnon 1996; Marshall and Beehler 2007), our samples were drawn principally from dipterocarp forest and a limited number of samples from other vegetation types such as non-dipterocarp lowland forests, limestone forests, heath forests and deciduous forests. Further research is thus required to fine-tune these equations, and should focus on lowland non-dipterocarp forests, particularly freshwater swamp forests, forests on ultrabasic soils, and deciduous forests. Further, the datasets used for this study were skewed in geographical distribution. Thirty-one of 43 sites were located in the western Indo-Malay region. Due to the high variation in ecological and geographical conditions among islands, more datasets derived from islands in the central (Sulawesi and Maluku) and eastern regions (Papua) are required to improve our understanding of biomass distribution across various forest types and along geographical and elevation gradients. We also suggest further sampling of non-dipterocarp species and from the middle and eastern regions, which are underrepresented in our study. However, although the dipterocarp trees are better represented in this study, the model precision of this species group is still relatively low due to the high diversity of the dipterocarp family.

Datasets from independent research are often subjected to incomparable datasets due to unstandardised methods in destructive sampling. Although a national standard for tree allometric development has been developed for Indonesia (BSN 2011), most of the studies in Indonesia did not comply with this standard. Specific attention must focus on standardising the G measurement method for converting stem and large branch volumes into biomass during destructive sampling. Williamson and Wiemann (2010) identified several common mistakes in G measurement, including unrepresentativeness of wood samples, low temperature drying and incorrect measurement of wood-sample volume.

More than 5000 trees were felled for studies on local biomass equations using destructive sampling in Indonesia (Amitha et al., 2015). However, the datasets were difficult to access due to the scarcity of published reports or literature. Database repositories that compile data from existing studies must be created because destructive sampling is time-consuming and logistically demanding, particularly in relation to managing felling permits and local logistical arrangements.

Further, the focus of such data repositories and data collection should be for large trees with trunk diameters of more than 60 cm. New methods of terrestrial laser scanning (TLS) used for generating three-dimensional (3D) features using point clouds could be a potential approach for non-destructive sampling of very large trees (Olagoke et al., 2016). The number of TLS studies on forest structures and individual trees has increased in the past decade, including studies that perform tree-volume estimation using the 3D cylinder-fitting method. Pfeifer et al. (2004) and Raumonen et al. (2013) found that tree AGB estimates using TLS were more than 90% accurate, and thus far, better than estimates using allometric equations. Such methods will be very useful for assessing the AGB of large trees, particularly in areas where tree harvesting is restricted by legal or logistical limitation.

5 Conclusion

This study provides more accurate regional AGB models through the involvement of large samples representing major islands, biogeographical zones and various succession and degradation levels of natural lowland forests in the Indo-Malay region. Our models outperformed existing local models. The traditional variables explained more AGB variation than additional variables related to species grouping and site characteristics. Wood-density class is the most influential additional variable to tree AGB allometry. Despite its significance in explaining AGB variations, the inclusion of biogeographical region as an independent variable only slightly improved the accuracy of AGB models.

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Compliance with ethical standards

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Chapter 6

Non-Destructive Technique Using Terrestrial Laser Scanner and Acoustic Velocity Measurement for Estimating Aboveground Biomass of Mangrove Trees in Sumatra, Indonesia

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6.1 Introduction

The pronounced contribution of tropical mangroves in global carbon dynamics and country revenue has been recognised (Murdiyarso et al., 2015), but accurate and comprehensive estimates of carbon dynamics and productivity of mangrove ecosystems are still limited (Alongi et al., 2015; Alongi, 2014). Accurate estimation of carbon stored in mangroves is essential, not only for understanding the magnitude of the role of tropical mangroves in global climate change, but also for understanding the ecosystem services that support biodiversity and local livelihoods (Mumby et al., 2004; Willemen et al., 2013).

Indonesian mangrove forests play a crucial role in climate change mitigation. Yet despite their importance, uncertainty of biomass and emissions estimations remains high for this ecosystem (MoEF, 2015). The mangrove ecosystem is one of the most studied tropical ecosystems, especially in relation to species-specific allometric equations. Allometric equations for aboveground biomass (AGB) estimation have been developed for all major tree species in mangrove ecosystems in tropical Asia (Komiyama et al., 2008). However, they were developed from a limited number of samples and diameter ranges. Such models are subject to bias when applied to other regions, even within the same forest type (Manuri et al., 2016). The only mangrove allometric equations developed using large samples were modified from a study on tree volume equations and were not parsimonious (Kauffman and Cole, 2010).

Traditionally, development of allometric models deployed destructive sampling techniques to measure the fresh weight of all tree components. Such approaches are laborious, requiring tremendous consistency of measurement and substantial logistics and permit arrangements. They are also very often limited by legal constraints (i.e., in national parks or forest restoration areas). The field measurements of mass of large stem and branches were often conducted through measurement of volume and wood density (WD). This seemed to be favoured due to less efforts and maintaining of the commercial log shapes, rather than chopping the logs into weighable sizes (Alvarez et al., 2012; Manuri et al., 2014), although other studies suggested using additional heavy equipment (Picard et al., 2012). Moreover, destructive sampling of large mangrove trees is more difficult than any other dryland ecosystem due to muddy ground and tidal dynamics.
Terrestrial laser scanner (TLS) application has been studied and utilised for forestry research and application (Thies and Spiecker, 2004), as it provides an objective and consistent monitoring tool in forest measurements, with accountable information (Dassot et al., 2011). The use of TLS for biomass studies has varied, from simply deriving tree parameters (such as diameter, height, crown size and crown volume) for estimation using available allometric equations (Holopainen et al., 2011) to developing relationships between tree metrics and number of point clouds (Seidel et al., 2011) or voxel-based metrics (Marius et al., 2013).

Further, TLS has been studied and evaluated for reconstruction of trees in 3D models, and has been suggested as an alternative approach utilising non-destructive sampling for timber volume and AGB estimation (Vonderach et al., 2012; Raumonen et al., 2013). Studies have found that biomass estimates using TLS are more accurate than allometric models (Calder et al., 2015), suggesting potential for developing or validating allometric equations (Olagoke et al., 2016).

A cylinder fitting method has been developed for automatic reconstruction of tree trunks and branches based on TLS point clouds (Pfeifer et al., 2004; Aschoff and Spiecker, 2004). An improved cylinder fitting method called the quantitative structure model (QSM) was introduced for a fully automatic approach and faster processing time (Akerblom et al.; Raumonen et al., 2013). Currently, the most frequently used method for fast automatic reconstruction of whole trees using TLS point cloud is QSM (Raumonen et al., 2015; Hackenberg et al., 2015a). The model demonstrates good performance in estimating tree volume, with a less than 10% error margin (Calder et al., 2015).

However, TLS can only generate 3D point clouds, which are rendered to reconstruct a 3D shape of the tree’s elements to measure the volume of the tree. To convert tree volume to AGB requires accurate WD, which represents the mean value of the whole tree. Because of the high diversity of tree species in tropical regions, WD is an important variable that can explain the AGB variation at the species level (Manuri et al., 2014; Chave et al., 2005). However, WD varies not only at the species and individual levels, but also in tree size and within components.

Traditionally, WD measurement involved wood sample collection through destructive sampling or small cores, which were then analysed in the laboratory for volume and dry
weight measurement. Several non-destructive attempts have been initiated to directly estimate WD on standing trees using force-related equipment, such as the torsiometer, the pilodyn, nail withdrawal and resistograph (Isik and Li, 2003). In addition, spectral, ultra sound and acoustic technologies were tested for non-destructive evaluation on wood, for instance, using NIR Spectroscopy (Schimleck et al., 2003), ultra sound instrument (de Oliveira and Sales, 2006; Hasegawa et al., 2011) and acoustic velocity tool (Chauhan and Walker, 2006).

There are two types of acoustic velocity (AV) measurements: time of flight (ToF) and resonance-based mechanism. The first deploys two probes, the transmitter and receiver, which are set along the stem for measurement. This is suitable for measuring standing trees at around breast height. By using a hammer, the transmitter probe generates an acoustic wave, which is received by the other probe. The tool then measures the ToF of the acoustic wave between the two probes. The resonance-based tool is suitable for logs or lumber. The tool is placed at one end of the log, while a hammer taps the log to produce an acoustic wave. The tool calculates the AV from the second resonant frequency. There is a strong linear relationship between AV generated from ToF-based equipment and resonance-based equipment (Carter et al., 2005).

This study sought to explore the possibility of a non-destructive approach for quantification of the AGB of mangrove trees. The specific aims were to assess uncertainty related to WD estimates and to assess the accuracy of biomass and WD estimates using TLS and AV tools.

6.2 Methods

6.2.1 Study sites
The main study site was in a mangrove forest in a coastal area of South Sumatra province, situated between 104° 12’–104° 55’ and 1° 38’ N–2° 25’ S. The forest is allocated as national park and production forest, with the size of about 3,000 km². The annual precipitation is 2,648 mm, with dry months from May to September. Tides vary between 50 and 450 cm, with the highest in January and the lowest in June (Suwignyo et al., 2012). Four major dominant mangrove species can be found in this area, including two *Rhizophora* species (*R. apiculata* and *R. mucronata*) and two *Bruguiera* species (*B. gymnorrhiza* and *B. sexangulata*). This mangrove ecosystem is home to many endangered
species (Verheugt et al., 1991), including the Sumatran tiger (Panthera tigris), tapirs (Tapirus indicus) and Irrawady dolphins (Orcaella brevirostris).

6.2.2 Individual tree scanning
Tree selection was based on the representativeness of tree species and diameter class. Two major species in the area (Rhizophora apiculata and Bruguiera gymnorhiza), with DBH ranging from 12.6 to 58 cm, were selected for tree samples, totalling three trees from two sites. Checker boards were placed around the target trees and between TLS positions. At the first site, we scanned one of the largest trees (R. apiculata) from five TLS positions. At the second site, we scanned two (medium and small) trees (B. gymnorhiza) from four scanning locations.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Specifications</th>
</tr>
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<tbody>
<tr>
<td>Wavelength</td>
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<tr>
<td>Laser power</td>
<td>20 mW</td>
</tr>
<tr>
<td>Beam divergence</td>
<td>0.16 mrad</td>
</tr>
<tr>
<td>Field of view</td>
<td>360° horizontal and 305° vertical</td>
</tr>
<tr>
<td>Scan resolution</td>
<td>0.009°</td>
</tr>
<tr>
<td>Measurement speed</td>
<td>Up to 976,000 pts/s</td>
</tr>
</tbody>
</table>

Table 6.1. FARO Focus 3D TLS specifications

We used FARO Laser Scanner Focus 3D for trees, scanning with horizontal/vertical resolution of 0.009° at a wavelength of 905 nm (see Table 1). We used the second highest point density option (488,000 points per second), which took about 20–30 minutes for each scan. The output format of the scanning was a point cloud data with XYZ coordinates and associated RGB value. PT Datascrip conducted data registration using FARO Scene software. Individual tree segmentation was conducted manually using CloudCompare (Girardeau-Montaut, 2016). We manually extracted three trees that were felled for AGB measurements (Figure 1).
Figure 6.1. Point cloud data of trees used in this study. A large, medium and small trees, was each scanned and felled for volume and AGB measurement.

6.2.3 3D reconstruction

We used two approaches in reconstructing tree 3D models: QSM version 2.21, hereafter called QSM, (Raumonen et al., 2013; Raumonen et al., 2015) run in Matlab 215b and CompuTree version 15 beta (Hackenberg, 2015). Both approaches employ similar concepts of cylinder fitting for 3D reconstruction, but a substantial difference is the initial process for creating the cylinder. QSM uses small patches generated from a neighbouring group of points that cover the surface of the tree. These small patches are the basis for the cylinder fitting and branch segmentation. The user defines the minimum and maximum size of the patches (hereafter called Patch Diameter [PD]) to cover small branches and large branches, respectively (Raumonen et al., 2013). Conversely, CompuTree use spheres, their centre located in the skeleton of the tree. The spheres identify point clouds that form circular structures in the cross-sectional area with the spheres. These identified circular forms are used for cylinder fitting (Hackenberg et al., 2015a). For identifying and
improving outlier cylinders, QSM and CompuTree automatically performed correction steps involving taper function and allometric relationship, respectively. Compared with QSM, CompuTree provides a more automatic process (rather than trial and error) for parameter setting.

For QSM, we tested several parameter settings to best model each tree, based on the comparison with the reference volumes and the visual appearance of the 3D models. The quality of reconstruction depends on the optimal size of a surface diameter of patches (hereafter called $PatchDiam$) used to segment point clouds in QSM, which could be different among tree sizes or TLS resolutions (Calders et al., 2015). Several $PatchDiam$ minimum and maximum values were tested to fit each point cloud tree. We compared the total volume estimated with the references from destructive sampling. In addition, we inspected the 3D reconstruction visually, focusing on trunk and main branches, which stored the largest proportion of AGB.

In contrast, CompuTree involves a fully automatic approach. The software searches the optimal parameters based on the input data. The only initial setting the user must provide is the cutting height and the option for using allometric correction to improve the branch and twig proportions (Hackenberg et al., 2015a).

The output of both programmes are matrices detailing the cylinder location, size and branching identification and structures. We fractioned the reconstructed trees into stump, commercial stems, very large branches, large branches, medium branches and small branches (see section 6.2.4 for the classification). We converted the volume of each cylinder into AGB by multiplying it with the associated WD measured in the laboratory. We compared the AGB estimated using TLS with the reference AGB values derived from field measurements.

6.2.4 Destructive sampling
To evaluate the accuracy of the estimation, we performed destructive sampling for total above ground biomass estimation. Due to restriction regulation of tree felling at the national park, destructive sampling data collection was performed outside the park. After scanning, trees were felled and fractioned into five main components: stump, bole trunk, branches, twigs ($D<4$ cm) and leaves. All components above the bole trunk with a diameter equal to or larger than 4 cm, which construct the canopy, were considered to be branches. Branches were further fractioned into very large ($D>30$ cm), large
(20 ≤ D < 30), medium (10 ≤ D < 20) and small (4 ≤ D < 10) components. Except trunk and very large branches, we weighted all tree components in the field using a Crane digital scale with a capacity of 50 and 100 kg. Stems and very large branches were measured in 2-m sections for their volumes, using Smalian’s equations (Avery and Burkhart, 2015). In addition to the three scanned trees, we felled another five trees for WD and AGB measurements.

Wood samples were collected from each compartment of all trees and stem sections, either in disc or wedge form, to ensure a good proportion of woods from piths to barks. After weighting and labelling, we transported the samples to the Forestry Research Agency (Balai Penelitian Kehutanan) and the Forest Seedling Agency (Balai Perbenihan Tanaman Hutan) laboratories in Palembang for WD analysis. All samples were dried in an oven at 105°C temperature until constant weight, then weighted using high accuracy scales. Volume of the samples was measured using the water displacement method. All large stems and large branches were multiplied with their associated WD for biomass calculation. In addition, ratios of dry mass and fresh mass were calculated for all samples, including twigs and leaves. We converted the field measurement fresh weight into biomass using the associated ratios. We estimated the weighted mean WD of trees based on the WD from the wood samples and the biomass of each tree section they represented. The weighted WD was compared to the WD measured at the breast height and WD from global database (Chave et al., 2009).

6.2.5 Wood AV measurement

We measured the AV of logs from bole stems, from which wood samples were collected for further WD analysis in the laboratory. Logs from three species were measured: Rhizophora apiculata, Bruguiera gymnorhiza and Xylocarpus granatum. We used The Hitman HM200 from Fiber-Gen to measure AV of the logs (Carter et al., 2005). The tool is placed at one end of a log, while a hammer taps the log to produce an acoustic wave. The tool calculates the AV from the second resonant frequency. We recorded four velocity data (kilometre/second) for each log and used the maximum value for the comparison with the associated WD values.
6.3 Results

6.3.1 WD estimation

Most of tree average WD values were lower than the WD values measured at DBH, suggesting that stem woods at breast height were denser than the upper stem or branch woods, especially *R. apiculata* (see Figure 6.2). In contrast, *X. granatum* had a WD of the stem at DBH lower than the WD of the upper parts. However, both WD values of all trees were higher than the WD values derived from the species-specific global WD database.

![Graph showing wood density variation](image.png)

**Figure 6.2.** Variation of the estimated wood density of the felled trees based on the weighted average of WD measured at various tree components, measurement at DBH and values from WD global database.

The relationship between the AV and WD was very weak (adjusted $r^2 = 0.049$), showing that the AV was unable to estimate WD accurately. When we included species as a variable for predicting the WD, the relationship was not only stronger (adjusted $r^2 = 0.678$), but the AV variable was significant in explaining the variation of WD (see Figure 6.3).
6.3.2 Tree 3D reconstructions

Based on the visual inspection of trunk and large branch reconstruction, we found that the best parameter setting in QSM for each model was different to each other (see Figure 6.4). The larger the tree, the larger the PD that should be used. For instance, the best minimum and maximum PD for large trees was 15 and 20 cm, respectively, 5 and 10 cm for medium tree, and 2 and 8 cm for small tree. However, it was not possible to model the whole large tree (including its stump with prop roots) using a single set of parameters in QSM. Therefore, we separated the tree into two files: stump with prop roots and the upper part. For reconstruction in QSM, we vertically inverted the point cloud data of the stump with prop roots, which enabled the software to form a reconstruction as if it was a tree with a trunk and canopy. Because the QSM software selected the base of the trunk as the starting point and considered it the largest part of the tree, the reconstruction using the complete set of this point cloud data always resulted in unrealistic models, particularly at the prop root part (see Figure 6.4 A).
Figure 6.4. The visual appearance of the reconstructed models using various parameters on the large tree with prop roots (A), large trees where the prop roots were removed (B), medium tree with small buttress (C), and the small tree (D). The two rightmost trees were modelled using CompuTree. Bold texts show the best models.
In contrast, the CompuTree reconstructed better models of the complete large tree, with a more realistic shape of the prop roots (see Figure 6.4.A). However, it was not able to realistically reconstruct the canopy of the large tree without stump and prop roots (see Figure 6.4.B). In addition, most of the canopy reconstructions for medium and small trees appeared to be unrealistic, due to overestimation of tree branches (see Figures 6.4.C and 6.4.D). However, the models with allometric corrections tended to be less overestimated. Therefore, we selected the models with allometric correction as the best models from CompuTree for further volume comparison.

**Figure 6.5.** Reconstruction of stump with prop roots from *R. apiculata* using various parameters. The two most bottom right stumps were generated using CompuTree. The bold text was the best model.

We were able to reconstruct the stump with prop roots more realistically than the stump with buttress. Based on visual inspection, we selected the root model with PD of 6 to 11 cm as the best root model using QSM and the allometric corrected model from CompuTree (see Figure 6.5). Prop roots are common in *Rhizophora spp.*, while buttress
roots are common in *Bruguiera spp.* QSM was unable to reconstruct the buttress, while CompuTree showed better results with this kind of stump (see Figures 6.4.C and 6.4.D).

### 6.3.3 Tree volume and biomass comparisons

The estimated tree volumes from the QSM models produced fewer errors than those from CompuTree. Except for the stump and bole trunks, CompuTree-derived models of all canopy elements were overestimated with a relative error of more than 80% (see Figure 6.6). The QSM models for medium branches and small branches were also highly overestimated, because of the small branches of large and medium trees and the medium branches of the large trees (see Table 6.2).

![Figure 6.6. Mean relative errors of estimated volumes using QSM and CompuTree.](image)
Table 6.2. Relative error of estimated volume from each tree element using QSM.

<table>
<thead>
<tr>
<th>Tree Element</th>
<th>Relative Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Small tree</td>
</tr>
<tr>
<td>Small branch</td>
<td>-3.1</td>
</tr>
<tr>
<td>Medium branch</td>
<td>-</td>
</tr>
<tr>
<td>Large branch</td>
<td>-</td>
</tr>
<tr>
<td>Very large branch</td>
<td>-</td>
</tr>
<tr>
<td>Bole trunk</td>
<td>1.7</td>
</tr>
<tr>
<td>Stump/prop roots</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 6.3 presents the error comparison among AGB estimates generated from TLS volume multiplied with various WD values, including the WD from each tree element, WD at DBH and WD values from global database. The mean relative error of the whole-tree models was in the magnitude of 20–40%. The AGB estimates using the species-specific global database had the lowest error rate for the whole-tree model. However, this small error rate was due to the balancing out of the underestimated bole trunk and large branches with the overestimated smaller branches. We further excluded the tree components that experienced large errors, as identified in Table 6.2; we found that AGB estimates of the whole tree using global database WD was greatly underestimated (13.9% from the measured AGB) compared with other estimates (less than 4%; see Table 6.3).

Table 6.3. Mean relative error (%) of AGB estimation generated from TLS volume and various WD values.

<table>
<thead>
<tr>
<th>Element</th>
<th>Include all</th>
<th>Exclude small branches of medium and large trees, and medium branches of large tree</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WD of elements</td>
<td>WD at DBH</td>
</tr>
<tr>
<td>Stump with roots</td>
<td>8.4</td>
<td>19.8</td>
</tr>
<tr>
<td>Bole trunk</td>
<td>-0.1</td>
<td>1.9</td>
</tr>
<tr>
<td>Very large branch</td>
<td>-8.9</td>
<td>2.3</td>
</tr>
<tr>
<td>Large branch</td>
<td>-6.6</td>
<td>-2.4</td>
</tr>
<tr>
<td>Medium branch</td>
<td>177.4</td>
<td>208.3</td>
</tr>
<tr>
<td>Element</td>
<td>Include all</td>
<td>Exclude small branches of medium and large trees, and medium branches of large tree</td>
</tr>
<tr>
<td>--------------</td>
<td>-------------</td>
<td>----------------------------------------------------------------------------------</td>
</tr>
<tr>
<td></td>
<td>WD of elements</td>
<td>WD at DBH</td>
</tr>
<tr>
<td>Small branch</td>
<td>416.7</td>
<td>496.8</td>
</tr>
<tr>
<td>Whole tree</td>
<td>33.1</td>
<td>40.3</td>
</tr>
</tbody>
</table>

**6.4 Discussion**

**6.4.1 Tree WD estimation**

Stem wood at breast height was denser than the upper stem or branch woods, in particular among *R. apiculata*. This is because older woods have a larger proportion of heart woods and secondary chemical compounds than younger woods. A similar pattern has been observed in a large number of neotropical trees (Sarmiento et al., 2011), trees from Central America (Swenson and Enquist, 2008) and tropical mangrove species in French Guyana (Olagoke et al., 2016). However, we found that *X. granatum* had an opposite pattern to *R. apiculata*. Branch woods denser than stem woods have also been observed in several tree species in the Amazon and central Asia (Sarmiento et al., 2011; He and Deane, 2016). Sarmiento et al. (2011) also found that family-based taxon can explain the variations among these patterns. Further, He and Deane (2016) have suggested that tree size and species maximum height influence this pattern, which may explain the denser branch wood in *X. granatum*. *X. granatum* can grow to a relatively small or medium tree, 20–30 m tall, compared with *B. gymnorhiza*, which can grow to 40 m tall (Sosef et al., 1998).

Another important aspect of this study related to WD was how to estimate WD without destructive sampling. This study found that acoustic measurement failed to accurately estimate WD of the sample logs from different mangrove species. It is obvious that there are other inherent factors, beside WD, influencing AV. Various studies have found that AV is influenced by tree diameter (Chauhan and Walker, 2006); moisture and temperature (Chan et al., 2011); and wood stiffness, rupture strength and growth rate (Auty and Achim, 2008).
This study found a significant influence of AV variable in explaining WD variation within species. Chauhan and Walker (2006) found that the relationship between AV and WD was much better than that found in the present study, with coefficient of determination of 0.5. However, it was derived from various tree sizes within the same species. A combination of other techniques may improve the correlation between AV and WD.

The use of single WD values from global database is common for estimating tree AGB (Chave et al., 2014; Feliciano et al., 2014). WD variations within species and individuals are high because of different environmental factors and growth histories of the individuals, which lead to uncertainty when applying a single value for a species or genus to estimate tree AGB at the local level (Olagoke et al., 2016; Basuki et al., 2009; Manuri et al., 2014). Further studies are recommended for estimating standing tropical trees using other forms of non-destructive portable equipment, such as pylodins, torsiometers, resistographs or nail withdrawals. A recent review has suggested that resistographs and nail withdrawals are the most accurate methods for estimating tree WD, with coefficient of determination more than 0.9 (Gao et al., 2012). Alternatively, small cores at appropriate locations could be used to estimate the WD without severely damaging or killing the trees (Williamson and Wiemann, 2010).

6.4.2 Tree 3D reconstruction

The large proportion of biomass of the stump with prop roots of large mangrove trees, such as in R. apiculata, deserved close attention. All attempts using various sets of parameters to reconstruct trees with prop roots produced large errors. The QSM model reconstructed an unrealistic prop root system, because it is designed to model trees with cylindrical stems. The QSM model assumes that the largest part of the stem is in the lower part. CompuTree provided a better result when reconstructing the prop roots system, without the need to separate the roots into different files. However, when the prop roots were separated from the upper part of the tree and reversed vertically to imitate tree canopy structure, we found that QSM modelling of the separated reversed prop roots resulted in more realistic 3D root reconstruction than the CompuTree model. Several studies have been conducted to generate 3D models of buttressed trees using point slice and basal area measurement (Olagoke et al., 2016; Noelke et al., 2015). The only previous study on estimating mangrove trees with prop roots was using the point slice and basal area measurement to estimate prop root volume based on torus and cylinder shapes (Feliciano et al., 2014). A more automatic and accurate approach has been suggested
using modified QSM for stump and root system, which separate the stump and roots for 3D reconstruction based on triangulation and cylinder fitting, respectively (Smith et al., 2014; Liski et al., 2014).

The reconstructions of the upper stem and crown using CompuTree were unrealistic. This was most likely due to poor-quality data. During some scanning, wind blew quite hard, causing the upper part of the trees to move, thereby inflicting the overestimation of branches. In addition, the upper parts of the trees had less point resolution due to occlusion and longer distance from the scanner. This may suggest that CompuTree is more sensitive to data quality than QSM.

Dassot et al. (2012) found that the accuracy of estimating trunk and branch volume were 10% and 30%, respectively. We found that the accuracy of estimating small branches was high among small trees and decreased for tall trees. Hackenberg et al. (2015b) concluded that the uncertainty of TLS estimates was low for tree elements up to 10 m height, and increased to more than 50% relative error for tree elements up to 20 m height. The height of the medium and large trees of our sample were 25.1 and 33.5 m, respectively, enforcing lower point density in the canopy. This study suggests the need for more than four and five scanning positions for small trees and large trees taller than 20 m, respectively, to overcome this problem. To reduce the error of estimating AGB of the canopy using TLS, some studies incorporate biomass expansion factors or allometric relationships for estimating small branches and leaves (Olagoke et al., 2016; Feliciano et al., 2014).

This study suggests that good quality data is required to reconstruct 3D models of mangrove trees from TLS point clouds to accurately estimate the total volume of the stumps, trunks and branches. This will encompass more scanning from various angle positions to minimise occlusion, scanning when the wind does not blow hard and reducing errors of data registration. The second element—wind—will be the most challenging, as wind will always be present due to the nature of the coastal ecosystem. However, the timing of field work based on weather prediction may reduce the risk. Even so, the accuracy of the volume estimates of the branches at the top of the tree will still be relatively low compared with the trunk section due to occlusion and lesser point density of lasers over longer distances.
6.5 Conclusions
The non-destructive approach to estimate tree AGB accurately has many challenges, but at the same time has showed promising progress. This study demonstrates the capability of TLS in estimating tree volume of trees in mangrove ecosystems and the potential of AV tools in explaining WD variation within species and among individuals. We can estimate most total tree AGBs without leaves ad small branches with high accuracy. Several limitations were identified regarding the scanning of small branches of large trees and issues in tree WD estimation. Our findings and suggestions will improve the understanding of requirements for better tree scanning, modelling and AGB estimation in mangrove ecosystems.

Acknowledgement
This study was made possible through financial support for field data collection from GIZ Biocline Palembang, Indonesia, and CIFOR. We would like to thank Gatot Priyo Laksono and his team from PT Datascrip Jakarta for providing access to a FARO laser scanner and the technical support in using the scanner and data registration. We also thank the Waiariki Institute (Rotorua, New Zealand) for providing access to The Hitman HM-200. We acknowledge the support of Teguh Imansyah and his team from Sembilang National Park during the hard field work. We also thank Pasi Raumonen for providing the QSM codes and Alvaro Lau Sarmiento for developing the codes for branch restructuring. Solichin Manuri is supported by the Australia Award Scholarship.
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Chapter 7

Synthesising Existing Forest Inventory Datasets for Estimating Historical Aboveground Biomass Stocks and Growth in Logged-over Tropical Dipterocarp Forests of Kalimantan, Indonesia

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Abstract

Extensive forest inventory data is available from commercial timber companies. For this study, over 20,000 plots were compiled for North, East and West Kalimantan provinces, with more than 17,000 of these exceeding our quality assurance tests. This study aimed to: (1) explore the potential use of existing permanent sample plots and forest inventory data established and measured by timber concessions; (2) assess uncertainties of aboveground biomass (AGB) estimates using various allometric models; (3) analyse the dynamics of AGB in logged-over dipterocarp forests; (4) analyse AGB stocks and emission factors in tropical dipterocarp ecosystems. Two types of forest monitoring datasets measured by timber companies in Indonesia were compiled and assessed in this study: permanent sample plots (PSPs) (24 1-ha plots), and the overall periodic timber inventory (OPTI) (17,301 plots). We found that the model using only tree diameter (D) as a predictor variable tended to be unbiased when aggregating the estimates at larger plots. We also found that the basal area (BA) per hectare could explain the variation of AGB at plot level (adjusted $r^2 = 0.911$; root mean square error [RMSE]: 27.8). We overlaid the OPTI plot with the land cover map and estimated the mean AGB of the associated land cover classes. The mean AGB of primary dryland forest, secondary dryland forest and bush classes were 281.1 ± 4.0 Mg/ha, 231.5 ± 1.7 Mg/ha and 179.0 ± 5.0 Mg/ha, respectively. Nine years after logging, the mean AGB is still lower than the mean AGB two years after logging. The growth rate (2.5%) was still lower than the mortality rate (3.1%), and recruitment (0.2%) did not occur until seven years after logging. The results of this study suggest that the existing forest monitoring data should be incorporated into the carbon accounting system at district, province and national level to improve the estimation of forest biomass and emission factors related to forest degradation and deforestation.

7.1 Background

Tropical lowland dipterocarp forests (LDF) play a crucial role in economic development, ecological service and carbon balance. Over the last several decades, the tropical LDFs have reduced in size and quality because of rapid deforestation and forest degradation (Stibig et al., 2014). The causes are mostly economic, such as excessive timber extraction and conversion to agricultural land and plantation (Gibbs et al., 2010; Geist and Lambin, 2001). To reduce deforestation and forest degradation in tropical regions, the United
Nations Framework Convention on Climate Change (UNFCCC) developed an incentive mechanism under the climate change mitigation framework to reduce emissions from land use and forestry (UNFCCC, 2010). Accurate estimates of carbon dioxide (CO₂) emissions from deforestation and forest degradation, as well as sequestration from forest conservation, sustainable forest management and forest carbon stock enhancement, are required to assess the impact of Reducing Emissions from Deforestation and Forest Degradation (REDD+) activities and contribution to global climate change mitigation efforts (Herold and Skutsch, 2009).

A major source of emissions in tropical forests is not only deforestation but forest degradation (Huang and Asner, 2010). Forest degradation is associated with a reduction in quality of forest structures or biophysics, such as timber stock, biomass or biodiversity (Lund, 2009). The main causes of forest degradation are selective cutting and small-scale illegal logging (Hosonuma et al., 2012). Compared to tropical deforestation, the impact of forest degradation in a unit area is smaller and more difficult to monitor (Lambin, 1999), but occur over substantial number of hectares (Gaveau et al., 2014) and contribute to a larger greenhouse gas emission than from deforestation (Pearson et al., 2017). A better understanding of forest dynamics in selectively-logged forests is crucial for policy development related to sustainable forest management and climate change mitigation.

Monitoring of REDD+ related activities is still problematic and uncertain because of limited research on the tropical region (Herold et al., 2011). Although the monitoring of deforestation and forest carbon stock are more advanced because of the availability of relevant satellite imageries, the scope of existing studies is mostly global, with medium to low-resolution satellite imageries used (Baccini et al., 2012; Saatchi et al., 2011). Therefore, to quantify the carbon impact of forest degradation and carbon stock enhancement activities on a regional scale using global scale studies is common (Penman et al., 2016).

IPCC suggested two methods for estimating emissions from forests: stock-difference and gain-loss methods. The first method requires aboveground biomass (AGB) stocks at two different measurements to generate emission factors. The later method requires AGB growth and loss measurement to estimate annual net increment. In the forest reference emissions level document, Indonesia acknowledges the need to utilise the existing data on forest inventory and forest permanent sample plots (PSPs) established and measured by timber companies (MoEF, 2015). Almost half of forest estates in Indonesia were
designated as production forests for timber extraction, managed by concessionaires. As part of the requirement for yield management, all timber concessions were required to establish PSPs for monitoring of forest growth. However, the regulation was revoked in 2009, and most concessions have not reported the PSP datasets to the forestry institutions since then (Tata et al., 2010). Instead, the government issued a regulation to conduct overall periodic timber inventory (OPTI) for the whole timber concession area every 10 years (MoF, 2007). The first batch of OPTI measurement was conducted from 2008 to 2011.

These datasets should be included for the calculation system of the forest carbon stock and emissions (MoEF, 2015). Brown et al. (1989) explore opportunities to make use of the inventory data. There are limited studies on biomass increment in tropical forests owing to requirements in a long-term measurement. Beside the national forest inventory (NFI), the only long-term plot measurement available for Indonesia was established in Berau East Kalimantan, representing a small geographic area, and thus necessitating the wider coverage of a long-term forest monitoring network (Sist et al., 2015).

Timber companies are obliged to establish forest inventory plots in their area and growth models from PSPs for defining the sustainable annual allowable cuts (MoF, 2014). In 2014, a total of 227 timber companies operated across Indonesia, a decline of 30% from 2001. They are mostly in Kalimantan, Sulawesi, Maluku and Papua, where intact forests remain (BPS, 2016). This could be a potential source of data for estimating historical forest carbon stocks, and thus national greenhouse gases from the forestry sector, to fill the gaps of the NFI. However, data validation needs to be done prior to the use of existing forest inventory data and information. Only limited studies on forest biomass estimation used this large dataset (Krisnawati et al., 2014), but evaluation of the quality of the data is limited, if not unavailable, see Harja et al. (2011) for NFI data.

AGB estimates that using models with tree diameter, wood density and tree height as predictor variables is more accurate than using the models with fewer predictor variables (Chave et al., 2005). However most forest inventory data collected by timber companies lacks scientific names and tree height information. It is important to understand whether the uncertainties of the AGB models without wood density or tree height variables will be accumulated or reduced at plot and landscape levels. Also, most forest inventory data are difficult to access or just presented as summarised results in report documents. Certain conversion factors are required to utilise data and information for carbon accounting.
purposes. Burrows *et al.* (2002) and Slik *et al.* (2010) found that the relationship between AGB and basal area (BA) is relatively high in eucalyptus forests in Australia and tropical dipterocarp forests in Borneo. Such approaches will be very practical for estimating AGB stock based on historical reports from forest inventory, because of the difficulty in accessing the raw datasets. However, such methods require the implementation of validation and calibration in specific ecological areas.

This study aimed to: (1) explore the use of existing PSPs and forest inventory data established and measured by timber concessions; (2) assess uncertainties of AGB estimates using various allometric models; (3) analyse the increment, growth, recruitment and mortality of aboveground biomass in logged-over dipterocarp forests; (4) analyse AGB stocks and emission factors in tropical dipterocarp ecosystems.

### 7.2 Materials and Methods

#### 7.2.1 Study Sites

Data compilation focused on timber concessions in East Kalimantan, North Kalimantan and West Kalimantan provinces, covering an area of about 200,000 square kilometres. The area extends between -3° 35’ and 3° 45’ latitude and 108° 15’ and 108° 25’ longitude. The timber concessions are managed under a selective logging system, where tree diameter and number per hectare cutting limits were applied. The forests are predominantly classified as lowland dipterocarp forest dominated by dipterocarp family from genus *Shorea, Dipterocarpus, Dryobalanops, Anisoptera* and *Hopea*. The altitudes of study sites range from 50 metres to 1000 metres, mean annual precipitation is between 2500 and 3500 mm and monthly temperature is between 26.4 and 27 °C. The soil type in the study site is mainly red-yellow Podzolik. This type of soil has a highly leached surface layer and low permeability, with a soil pH of between 4.2 and 4.8.
7.2.2 Data Collection

The data collection was conducted between February and May 2012 under the auspices of the FORCLIME-GIZ, a German–Indonesian cooperation in forestry and climate change. The datasets used in this study were compiled from timber concessions operating in project pilot provinces (West Kalimantan, East Kalimantan and North Kalimantan). Our interest was in collecting raw and digital data on PSP and OPTI datasets from the existing, active timber concessions operating in the study area.

First, we contacted all responsible government institutions, such as Forestry Services at province and district levels. Officially, all timber concessions must report all forest inventory and permanent sample data as a requirement for getting approval for their cutting plan proposal. Second, we sent official letters to the existing timber concessions to request related datasets. As some concessions are no longer operational, only active concessions were targeted for data compilation.
7.2.2.1 PSP Datasets

In each 1-ha plot of 100 m × 100 m, trees with diameter at breast height (DBH) ≥ 10 cm were measured, their scientific names, marked and labelled for long-term monitoring. The plot boundaries were clearly marked with poles in each corner. The circumference at breast height (CBH) or 20 cm above buttresses and total tree height (H) were measured for each tree in the plot. The DBH is CBH divided by phi value (3.14). Within the 1-ha plots, the trees were recorded in each subplot of 10 m × 10 m, allowing us to regroup the trees into smaller plots of 20 m × 20 m; 30 m × 30 m; 40 m × 40 m or 50 m × 50 m (Fig. 2). The smaller plots were used to evaluate the accuracy of AGB estimation at various plot size. However, we ignored the potential spatial autocorrelation between subplots, which may inflate the degree of freedom and slightly bias the estimates.

![Figure 2. Division of 1-ha plot into smaller plots, A: 20 m × 20 m; B: 30 m × 30 m; C: 40 m × 40 m and D: 50 m × 50 m](image)

We compiled digital files of PSP data from five timber concessions in East and North Kalimantan (Table 1). For this study we selected only datasets that had complete DBH and scientific name records. Only datasets from two companies out of five met the
requirements totalling 24 hectare plots, which were measured independently. For the first dataset, a total of 18 1-ha plots were established in logged-over forests. Out of these 18, six were established in 2003 and re-measured six times until 2010; six plots were established in 2005 and re-measured three times until 2010; and another six were established in 2011 without re-measurement. The second datasets consisted of six 1-ha plots established in 2006 and re-measured two times in 2007 and 2009 (only three plots).

Table 1. Compiled PSP datasets from timber companies in East, North and West Kalimantan. Each dataset consists of 6 1-ha plots.

<table>
<thead>
<tr>
<th>No.</th>
<th>Company Code (PSP Series)</th>
<th>Measurement</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>BR</td>
<td>2009 2010</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>IM</td>
<td>2001 2003</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>IK</td>
<td>1997 1998 1999 2000</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>KL</td>
<td>2003</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>MI</td>
<td>2003</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>PS</td>
<td>2002 2004 2005</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>RT</td>
<td>2005 2006 2007 2008</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>RM(2)</td>
<td>2003 2004 2005 2006 2008 2010</td>
<td>Complete tree identification</td>
</tr>
<tr>
<td>10</td>
<td>RM(3)</td>
<td>2007 2009 2011</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>RM(4)</td>
<td>2011</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>HA(1)</td>
<td>2005 2006 2009 2010 2011</td>
<td>No digital file</td>
</tr>
<tr>
<td>13</td>
<td>HA(2)</td>
<td>2009 2010 2011</td>
<td>No digital file</td>
</tr>
<tr>
<td>17</td>
<td>BK</td>
<td>2009 2010</td>
<td>Incomplete tree identification</td>
</tr>
<tr>
<td>18</td>
<td>KB</td>
<td>2006 2007 2008 2009 2010</td>
<td>No digital file</td>
</tr>
<tr>
<td>19</td>
<td>BF</td>
<td>2004 2006 2007</td>
<td></td>
</tr>
</tbody>
</table>

7.2.2.2 OPTI Datasets

For the purpose of allowable annual cut planning, each timber concession in Indonesia is required to conduct OPTI for the whole concession area (MoF, 2007). The OPTI collects only the DBH and commercial tree names of each recorded tree, in a nested plot of circular subplot, 10 m × 10 m subplot, 20 m × 20 m subplot and 20 m × 125 m for saplings, poles, trees d < 35 and large trees d ≥ 35 cm, respectively. Additionally, the physical
appearance and quality of trees were also recorded. The plots were systematically distributed with a distance of about 900–1000 metres, depending on the size of the concession.

We successfully compiled the OPTI datasets measured between 2009 and 2011 from 33 timber concessions in East, North and West Kalimantan provinces. The dataset consisted of 20,133 plots (Table 2). Duplicate plots from the same timber concessions and plots from a non-native timber plantation were excluded (3.7%) (Filter 1). Because each dataset was measured independently by the timber concession, data checking for quality assurance was essential. We removed plots with data inconsistency, such as large trees recorded in small subplots, redundant tree numbers within the same subplot or the occurrence of unexpectedly large trees (dbh≥200 cm). The unexpectedly large trees may occur because of measurement error of large buttress trees. Because of the difficulty validating each inconsistent tree record and very large basal area are unrepresentative of our targeted forest type, the plots in which inconsistencies and unrepresentativeness occurred were excluded from the analysis (10.3%) (Filter 2). To evaluate the AGB for each land cover class, only plots that provide coordinates were used for this analysis. After data screening on plot information, we found only 8,479 plots with coordinates (42.1%). Four different coordinate systems were used to define the location of the plots: geographic system, UTM 50N, UTM 50S and UTM 49N.

Table 2. Summary of the compiled OPTI datasets

<table>
<thead>
<tr>
<th>Timber Concessions</th>
<th>N Original</th>
<th>N Plot After Filter 1</th>
<th>N Plot After Filter 2</th>
<th>Plots with Coordinates</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>AHL</td>
<td>224</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Timber plantation</td>
</tr>
<tr>
<td>AKM</td>
<td>492</td>
<td>492</td>
<td>474</td>
<td>532</td>
<td></td>
</tr>
<tr>
<td>AW</td>
<td>69</td>
<td>69</td>
<td>64</td>
<td>64</td>
<td></td>
</tr>
<tr>
<td>BDK</td>
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<td>194</td>
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<td>113</td>
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</tr>
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<td>BNI</td>
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<td>972</td>
<td>956</td>
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<td></td>
</tr>
<tr>
<td>BRT</td>
<td>918</td>
<td>918</td>
<td>913</td>
<td>-</td>
<td>No coordinates</td>
</tr>
<tr>
<td>BS</td>
<td>58</td>
<td>58</td>
<td>58</td>
<td>58</td>
<td></td>
</tr>
<tr>
<td>DT</td>
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<td>527</td>
<td>519</td>
<td></td>
</tr>
<tr>
<td>HM</td>
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<td>160</td>
<td>-</td>
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<td>-</td>
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<tr>
<td>IAT</td>
<td>602</td>
<td>602</td>
<td>602</td>
<td>-</td>
<td>No coordinates</td>
</tr>
<tr>
<td>INK</td>
<td>1210</td>
<td>1210</td>
<td>1080</td>
<td>-</td>
<td>No coordinates</td>
</tr>
<tr>
<td>INL</td>
<td>1109</td>
<td>1109</td>
<td>922</td>
<td>-</td>
<td>No coordinates</td>
</tr>
</tbody>
</table>
### Table 3. Summary of AGB models used for the analysis

<table>
<thead>
<tr>
<th>AGB Model</th>
<th>Equations</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>0.125D^{2.533}</td>
<td>Manuri et al. (2016)</td>
</tr>
<tr>
<td>D2</td>
<td>0.118D^{2.585} (heavy timber)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.099D^{2.585} (medium heavy timber)</td>
<td>Manuri et al., in press</td>
</tr>
</tbody>
</table>

7.2.3 Uncertainty Assessment Resulting from Differences in AGB Equations

Using the selected PSP datasets—which have complete measurements including tree diameter, tree height and scientific name at tree level—we compared the allometric equations when applied to various plot sizes (i.e., 400, 900, 1600, 2500 and 10,000 m²). For evaluating the uncertainties of AGB estimates, we computed the tree AGB of the 24 PSP datasets using various AGB equations for dipterocarp forests in Kalimantan (Manuri et al., 2016) and species group equations for lowland forests (Manuri et al. in press) that have different predictor variables (Table 3).
Due to the occlusion of tree canopies, measuring tree height accurately in tropical forests is difficult. Figure SM1 showed a low precision of tree height measurement in the plots. In the case of canopy occlusion, the tree height was often estimated using a local D-H model. The overlay between the tree height data with the regional D-H model for lowland forests in Indonesia (Manuri et al. in press) showed strong agreement. We performed outlier analysis based on the studentised residuals of the regression between the measured and modelled tree heights. Residual values larger than 2 and smaller than -2 were outliers (Sileshi, 2014). We estimated the tree height of the outliers using the regional D-H model (Manuri et al. in press):

\[ H = 73.9 \times \exp(-0.03D^{0.765}) \]

We compared the AGB estimates at tree (kilogram) and plot (Mg.ha\(^{-1}\)) levels. To define the bias of the model estimates, we computed mean relative errors (MREs) between the estimates. MRE was calculated as \(\sum((\text{AGB}_p - \text{AGB}_b)/\text{AGB}_b)\), where AGB\(_p\) and AGB\(_b\) are the predicted and the best-predicted AGB, respectively. Another way to characterise model bias is by assessing the departures of slope and intercept of the linear regression between AGB\(_b\) and AGB\(_p\) (Piñeiro \textit{et al.}, 2008; Peacock \textit{et al.}, 2007). For assessing the precision of the AGB estimates, we computed the RMSE and the coefficient of determination (\(r^2\)).

\subsection*{7.2.4 Development of AGB-BA Models}

Assuming the AGB estimates using complete variables are the most accurate, we developed an AGB model based on BAs, which was found to be simple but with relatively high precision (Burrows \textit{et al.}, 2002; Slik \textit{et al.}, 2010). We assessed the performance of the AGB-BA models at individual tree and plot levels (0.04 ha, 0.09 ha, 0.16 ha, 0.25 ha and 1 ha plots) using the first measurement of 24-ha PSP data sets.

\subsection*{7.2.5 Assessing AGB Dynamics in Logged-Over Dipterocarp Forests}

We used the selected PSP dataset, which has complete measurement of DBH, tree height, species identification and long measurement (more than five years). Net annual AGB increment (\(I_{AGB}\)) was calculated as the net annual AGB change due to growth (\(G_{AGB}\)).
recruitment ($R_{AGB}$), mortality ($M_{AGB}$) and shrinkage ($S_{AGB}$) of trees that annually averaged across the monitoring period, assessed using the following equations Alder (1995) and Sheil (1995):

Annual growth = $G_{AGB} = \frac{1}{t} \frac{\Delta G}{AGB_1} \times 100$

Annual mortality = $M_{AGB} = (1 - \left(1 - \frac{\Delta M}{AGB_1}\right)^\frac{1}{t}) \times 100$

Annual recruitment = $R_{AGB} = \left(1 + \frac{\Delta R}{AGB_1}\right)^\frac{1}{t} \times 100$

Annual shrinkage = $S_{AGB} = \frac{1}{t} \frac{\Delta S}{AGB_1} \times 100$

$AGB_1$ is AGB stock in the beginning. $t$ is years between measurements. $\Delta G$, $\Delta M$, $\Delta R$ and $\Delta S$ are AGB differences due to growth, mortality, recruitment and shrinkage, respectively. Annual AGB increment was calculated as $I_{AGB} = G_{AGB} + R_{AGB} - M_{AGB} - S_{AGB}$.

### 7.2.6 Estimating AGB Stocks of Logged-over and Primary Dipterocarp Forests

For logged-over forests we used an OPTI and PSP dataset compiled from existing timber concessions in the study area. We used the D1 and DGH AGB model (Table 3) for estimating tree AGB of OPTI and PSP dataset, respectively. For comparison, we used the AGB-BA model, which uses information of BA per plot for estimating the plot-level AGB. For primary forests, we estimated using BAs from published research, updated using the best equations. Data sets from the literature (Rutishauser et al., 2013; Paoli et al., 2008; Slik et al., 2013; Hoshizaki et al., 2004) were used for estimating primary LDFs.

### 7.3 Results

#### 7.3.1 Testing Allometric and Biometric Models for Estimating AGB of Logged-over Forests

We analysed the regression between the best-predicted AGB (using the DGH model) and the predicted AGB values (using a model with fewer predictor variables) (Figure 3). As expected, the DG model performed similarly with the DGH model at tree level. The DG model was still relatively unbiased in small plots, but tended to be larger in larger plots. A similar trend occurred with D2 models, which used diameter and wood density class as
predictor variables. The D1 model, which used only diameter as a predictor variable, tended to be unbiased, aggregating the estimates at larger plots (e.g., 2500 m$^2$).

Figure 3. Regression between best-predicted total AGB and the predicted total AGB using less predictor models at tree individuals and plot levels. The dashed lines were the 1:1 lines. The thick lines were the fit lines. An outlier (asterisk) due to an individual tree with diameter of 200 cm with very low wood density (0.36 gr.cm$^{-3}$) was excluded.

Following the findings from Burrows et al. (2002) and Slik et al. (2010), we developed biometric models for estimating AGB using BA and wood density (WD) as variables. We
fitted both linear and non-linear models to the individual datasets and at various plot sizes (0.04, 0.09, 0.16, 0.25 and 1 ha.). We found that the non-linear models were better than the linear models, in terms of the normality of residuals distribution (result not shown). Models with additional WD as a predictor variable were only slightly better than the AGB model using only BA as a predictor variable (Figure 4). We decided to use the model with BA alone as a predictor variable, as it is also not practical to estimate average WD at plot level. We found that the best AGB-BA model is the model for 0.25-ha plot (adjusted $r^2=0.911$; RMSE: 27.8). The 0.25-ha plot is coincidently the same size as the OPTI plot.
Figure 4. Regression between the best-predicted AGB (best AGB_p) with predicted AGB using non-linear BA models (AGB_{BA})
7.3.2 Estimating AGB Stock of Logged-over Forests

We computed AGB of OPTI dataset using the D1 equation, which was tested to be less biased when applied to the 0.25 and 1 ha PSP plots (Figure 3). The result was compared to the AGB calculated in previous studies in primary forests using pan-tropical equations, and our study in PSP using the DGH equation. The AGB estimates of OPTI dataset using the D1 equation were still in agreement with the AGB estimates in logged-over forests and primary forests, where the plots have a BA less than 40 m$^2$/ha (Figure 5). However, the estimates using D1 equation tended to be lower than that of previous studies in primary forests, especially where the plots have a BA of more than 40 m$^2$/ha. In contrast, our predicted AGB using an AGB-BA model ($AGB = 6.37 \times BA^{1.206}$) developed from PSP dataset was in better agreement with the estimates from logged-over forests with BA less than 25 m$^2$/ha and primary forests that have BA more than 40 m$^2$/ha. The AGB estimates of AGB-BA model were lower than the studies in primary forests, especially in the plots that have BA between 25 – 40 m$^2$.

![Figure 5. Regression between BA (m$^2$/ha) and AGB (Mg/ha) per plot. The grey circles represent OPTI plots, while the crosses and stars were outliers due to duplicate records and unexpected large diameter trees, respectively. The green triangles and squares](image-url)
represent PSPs data in logged-over forests and from literature in primary forest studies, respectively. The solid line depicts the AGB-BA equation \((AGB = 6.37 \times BA^{1.206})\).

We compared our BA estimates using our datasets (OPTI and PSP) with BA estimates from previous studies in lowland tropical dipterocarp forests. Our estimates were lower than the estimates of previous studies in primary forests, but in accordance with the estimates from logged-over forests (Figure 6). The mean BA of OPTI and PSP dataset is comparable with the BA estimates of medium and high-impact logged-over forests, respectively (Sist and Nguyen-Thé, 2002). The results suggest that the OPTI dataset is generally consistent and reliable.

![Figure 6. BA distribution (mean and standard deviation) from PSP (logged-over forests), OPTI (mixed forest cover) and literature (primary and logged-over forests)](image)

We used forest cover type information recorded during the field measurement for estimating mean AGB. Primary dense forest had the highest mean AGB (371.2 Mg/ha) and non-forest had the lowest mean of AGB (148.2 Mg/ha). The mean AGB of other forest types ranged from 206.9 to 289.7 Mg/ha. Unexpectedly, the bush had a mean AGB higher than the secondary dense forests (Table 4). About 45% of the plots did not have information on forest cover type.
Based on the Tukey test on least square mean differences, only mean AGB from primary dense forest and non-forest were significantly different to other forest cover types. Other forest cover types, ranging from primary medium forest to bush, were not significantly different from each other.

**Table 4. Mean AGB estimates and standard deviation of forest cover classes determined during field measurement.**

<table>
<thead>
<tr>
<th>Forest Cover Types from Field Measurement</th>
<th>N</th>
<th>Mean AGB (Mg/Ha)</th>
<th>Std Dev</th>
<th>Std Error</th>
<th>Tukey's LSM Difference Test*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary dense forest</td>
<td>368</td>
<td>371.2</td>
<td>176.1</td>
<td>9.2</td>
<td>A</td>
</tr>
<tr>
<td>Primary medium forest</td>
<td>2480</td>
<td>289.7</td>
<td>131.5</td>
<td>2.6</td>
<td>B</td>
</tr>
<tr>
<td>Primary low forest</td>
<td>602</td>
<td>274.0</td>
<td>128.0</td>
<td>5.2</td>
<td>B</td>
</tr>
<tr>
<td>Secondary medium forest</td>
<td>3950</td>
<td>243.6</td>
<td>129.7</td>
<td>2.6</td>
<td>C</td>
</tr>
<tr>
<td>Secondary low forest</td>
<td>1272</td>
<td>239.9</td>
<td>127.2</td>
<td>3.6</td>
<td>C</td>
</tr>
<tr>
<td>Bush</td>
<td>209</td>
<td>227.0</td>
<td>151.0</td>
<td>10.4</td>
<td>C D</td>
</tr>
<tr>
<td>Secondary dense forest</td>
<td>1026</td>
<td>206.9</td>
<td>151.8</td>
<td>4.7</td>
<td>D</td>
</tr>
<tr>
<td>Non forest</td>
<td>206</td>
<td>148.2</td>
<td>94.7</td>
<td>6.6</td>
<td>E</td>
</tr>
<tr>
<td>Blank</td>
<td>7238</td>
<td>248.9</td>
<td>138.1</td>
<td>1.6</td>
<td></td>
</tr>
</tbody>
</table>

* Different letter denoted significant difference of the mean

We further overlaid the plots with geographical references with land cover map 2009 derived from satellite imagery classification (MoF, 2012). Only three land cover classes were represented by more than 100 plots, meaning they had high confidence level of the mean AGB estimates (i.e., primary dryland forest, secondary dryland forest and bush [Table 5]). The mean AGB of those three land cover classes were significantly different from the mean of other land cover classes, 251.8, 207.8 and 164.4 Mg/ha. Other land cover classes that were represented by a plot number less than 40 did not have a significantly different AGB. About 57% of the plots had no geographical references.

**Table 5. Mean AGB estimates and standard deviation of land cover classes from 2009 satellite image classification.**

<table>
<thead>
<tr>
<th>Land Cover Types from 2009 Satellite Image Classification</th>
<th>N</th>
<th>Mean AGB</th>
<th>Standard Deviation</th>
<th>Standard Error</th>
<th>Least Square Means Differences Tukey HSD Test*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary dryland forest</td>
<td>1775</td>
<td>251.8</td>
<td>135.6</td>
<td>3.2</td>
<td>A</td>
</tr>
<tr>
<td>Secondary dryland forest</td>
<td>5779</td>
<td>207.8</td>
<td>116.3</td>
<td>1.5</td>
<td>B</td>
</tr>
<tr>
<td>Bush</td>
<td>772</td>
<td>164.4</td>
<td>119.9</td>
<td>4.3</td>
<td>C</td>
</tr>
<tr>
<td>Pulp plantation</td>
<td>42</td>
<td>154.5</td>
<td>84.9</td>
<td>14.0</td>
<td>C</td>
</tr>
<tr>
<td>Mixed Agriculture</td>
<td>77</td>
<td>185.1</td>
<td>98.6</td>
<td>11.2</td>
<td>BC</td>
</tr>
</tbody>
</table>
The estimate of each land cover class was lower than the estimate based on similar forest cover classes derived from the field. This is because the land cover classification used a visual delineation method, which classifies several pixels close to each other as one entity, based on the majority of pixels. If the resolution is low, small portions of different pixels will likely be classified as different classes of majority pixels. Therefore, the mean AGB of forest classes will be lower than the forest classes based on plot identification, potentially due to the inclusion of small patches of low-density forest or logging-effected areas.

7.3.3 AGB Dynamics in Selectively-logged Dipterocarp Forests

Six 1-ha PSP datasets were used to analyse AGB dynamics after logging. The datasets have the longest measurement period: six time measurements from two to nine years after logging. At first measurement (two years after logging) the mean total AGB was 258.3 Mg/ha. At the second measurement (three years after logging), this was reduced to 240.72 Mg/ha due to the mortality of large and medium trees (Figure 7). The mean AGB continued to decline towards 229.45 Mg/ha at the fourth measurement (five years after logging) before it finally increased at the fifth (seven years after logging) and the sixth (nine years after logging) measurements (Table 6).

Table 6. Mean annual AGB dynamics of 24 PSP plots.

<table>
<thead>
<tr>
<th></th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2008</th>
<th>2011</th>
<th>Total</th>
<th>Annual rate (Mg/ha)</th>
<th>Annual rate %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Growing</td>
<td>258.30</td>
<td>235.73</td>
<td>223.52</td>
<td>219.82</td>
<td>214.55</td>
<td>233.46</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shrinkage</td>
<td>-0.58</td>
<td>-0.29</td>
<td>0.00</td>
<td>-1.69</td>
<td>-3.36</td>
<td>-5.92</td>
<td></td>
<td>-0.74</td>
<td>-0.29</td>
</tr>
<tr>
<td>Recruitment</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>3.75</td>
<td>0.17</td>
<td>3.92</td>
<td></td>
<td>0.49</td>
<td>0.19</td>
</tr>
<tr>
<td>Total AGB</td>
<td>258.30</td>
<td>240.72</td>
<td>231.21</td>
<td>229.45</td>
<td>240.11</td>
<td>247.92</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Mortality and growth have negative correlation. The mortality rate was 3.09%, with the highest rate at three years after logging (21.98 Mg/ha/year), while growth was the lowest (4.99 Mg/ha). The annual mortality was high in the earlier measurement period, and decreased towards the end of measurement. In contrast, the annual growth in the earlier measurement was very low, then continued to increase to 10.9 Mg/ha/year at seven years after logging.

At nine years after logging, the mean AGB was still lower than the first measurement two years after logging, because the growth rate was still lower than the mortality rate. Also, recruitment did not occur until seven years after logging, which contributed only 0.49 Mg/ha annually. Surprisingly, the shrinkage was higher than the recruitment (0.74 Mg/ha/year).

7.4 Discussions
There have been few attempts to evaluate the potential use of existing forest inventory for assessing historical forest carbon stocks and biomass growth in Indonesia. This study explores the potential of existing forest inventory plots for quantifying carbon stocks and growths in logged-over forests. We successfully compiled data from 20,133 OPTI plots. After data filtering for consistency and outlier checks, we found that about 17,301 plots (85.9%) were reliable. Most of the removed plots had unrealistically large total BAs or AGB, because of frequent recording errors or unexpected existence of very large trees in the plots. A validation process must be conducted to address this issue. The current
process for validating the OPTI result is performed only if there is a discrepancy between the plan and the implementation, mostly due to administrative matters (MoF, 2009). The selection of plots for field validation should also be based on the outlier plots.

Our analysis of the distribution of AGB based on the forest cover information from the field found that they were not consistent, so the mean AGB values among forest cover types were mostly not significantly different. It seems the definition of each forest cover type overlapped and were hard to distinguish in the field, thus confusing field crews when defining forest cover. We also found that 57.3% of the OPTI plots did not record geographical position. Because of Indonesia’s large geographical size, it is suggested that a geographic coordinate system be used for easy compilation and comparison among OPTI databases. Also, it seems that the coordinate positions of the plots do not represent the actual plot position, as can be observed from the fully systematic distribution of the plots. In relatively difficult terrain with limited accessibility, reaching a plot or placing a plot as the plan is often problematic. Therefore, 100% similarity between the planned and actual plot position seems to be unrealistic. The actual location of the plot using GPS in the field is not only useful for documentation and revisiting for field validation, but also for validating estimation of forest metrics based on remote sensing imageries.

The number of existing forest inventory plots measured by timber concessions are exceptionally large. Out of 265 timber concessions operating in Indonesia in 2016, 250 concessions completed and reported the OPTI (MoF, personal communication). This could potentially be used to fill the NFI gap in estimating forest metrics, including timber and biomass stock in Indonesian tropical forests. Several existing initiatives for database management could be integrated and maintained at district, national and global levels (Harja et al., 2011; Sist et al., 2015; Manuri and Susanto, 2012).

A relationship model between AGB and BA could be used for estimating AGB stock from historical forest inventory plot summaries. Our finding suggests that the AGB-BA non-linear model is better than the linear model for estimating a wide range of BA values representing areas with scarce trees to dense forests, with very large trees in tropical dipterocarp forests. This is different from a study on eucalyptus forests, where a linear model of AGB-BA achieved similar accuracy (Burrows et al., 2002). The main reason is that tree diameter and height ranges in tropical dipterocarp forests are much higher than in eucalyptus forests.
Similar to OPTI, the PSP datasets were utilised in a limited manner within the timber concession for yield and annual allowable cut regulation. Twelve out of the compiled 19 PSP series were not in digital format. Only four series were in digital format, with botanical identification at least at genus level. The mortality rate is still higher than the accumulation of growth and recruitment rate nine years after logging. A study in dipterocarp forests in East Kalimantan found that the highest mortality rate occurred one to three years after logging (Suszanty et al., 2015), which is in agreement with our study. Mortalities in selectively-logged forests occurred even after eight to 17 years after logging (Cannon et al., 1994), due to damage from logging (Nguyen-The et al., 1998) and wind disturbance after fragmentation (Laurance et al., 1998). This implies the need for managing long-term forest plot monitoring database in logged over forests, which established and measured by timber concessions in Indonesia since 1995 (Tata et al., 2010). Unfortunately, since 2009 development and measurement of PSP is no longer a requirement for timber concessions when applying for cutting permits in Indonesia.

7.5 Conclusions

Using existing OPTI datasets, we are able to estimate mean AGB stock with high confidence, as well as using them for estimating AGB based on land cover map. In this study we developed models using BA per plot as a predictor variable for estimating AGB with high precision and low bias. Our estimates of AGB in primary forests were calculated based on forest cover information from field plots, and land cover maps derived from satellite imagery classification, which were useful for estimating emission factors from the land and forest cover types.

This study compiled and explored the existing datasets of timber concessions for assessing historical forest carbon stocks and biomass growth. Most of the existing forest inventory datasets are difficult to access because of unstandardised database management systems within companies and the relevant government institutions. It is also important to control the quality of measurements and improve procedures for data checking for inconsistencies. There is a need for a standardised database platform at various levels of management for data repository and sharing. This would improve the accuracy and transparency of forest monitoring in Indonesia.

References

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Chapter 8

Advanced Land Cover Mapping of Tropical Peat Swamp Ecosystems using Airborne Discrete Return Lidar

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Authors: Solichin Manuri, Hans-Erik Andersen, Cris Brack, Bruce Doran

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ADVANCED LAND COVER MAPPING OF TROPICAL PEAT SWAMP ECOSYSTEM USING AIRBORNE DISCRETE RETURN LIDAR

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Abstract: The ability to better understand tropical peat ecosystems for restoration and climate change mitigation is often hampered by the lack of availability accurate and detailed data on vegetation cover and hydrology, which is typically only derived from detailed and high-resolution imaging or field-based measurements. The aim of this study was to explore the potential advantage of airborne discrete-return lidar for mapping of forest cover in peat swamp forests. We used 2.8 pulse.m−1 lidar and the associated 1-m DTM derived from an airborne platform. The lidar dataset fully covered a 120 thousand hectare protection forest in Central Kalimantan. We extracted maximum vegetation heights in 5-m grid resolution to allow detailed mapping of the forest. We followed forest definition from FAO for forest and non-forest classification. We found that lidar was able to capture detail variation of canopy height in high-resolution, thus provide more accurate classification. A comparison with existing maps suggested that the lidar-derived vegetation map was more consistent in defining canopy structure of the vegetation, with small standard deviations of the mean height of each class.

1. INTRODUCTION

The importance of tropical peat swamp forests as carbon sinks and sources is well recognized (Murdiyarso, Hergoualc’h, & Verchot 2010). The organic soil of the peat swamp forest, formed by the accumulation of dead vegetation, stores a huge amount of carbon (Jaenicke et al., 2008). On the other hand, there has been a long history of deforestation and forest degradation of peat swamp forests in South East Asia (Miettinen, Shi, & Liew, 2012). In addition, recurring fires in this region, boosted by El Nino-driven prolonged drought, continues to release carbon into the atmosphere at an alarming rate (Page et al., 2002).

Given the relationships between ecological, hydrological conditions and fire occurrence in tropical peat swamp ecosystems (Wösten et al., 2006), more accurate and detailed baseline information on vegetation cover is needed to support restoration activities designed to mitigate the ecological impact of climate change (Jaenicke et al., 2010). Remote sensing techniques have been deployed for large area mapping of tropical regions, including with high-resolution products (Asner et al., 2012). In peat swamp forest of Central Kalimantan, small-scale illegal logging activities can only be detected using high-resolution (1 – 5 meter resolution) optical imagery, due to their low impact to the existing stands (Franke et al., 2012). Airborne light detection and ranging (Lidar) has emerged as a tool to characterize detailed forest structures, providing more accurate ground elevation measurements under canopy and covering a large area (Wulder et al., 2012).
Lidar has been applied in tropical peat swamp forests for estimating aboveground biomass (Jubanski et al., 2013; Kronseder et al., 2012). However, according to our knowledge, no previous study in tropical peat swamp forests has been carried out for land and forest classification using lidar. Lidar has proven to be an accurate tool for measuring canopy height (Takahashi et al., 2005). Given the advantages of high-resolution airborne lidar in providing highly accurate forest measurements, previous studies have successfully explored the effect of ecological and topographic factors on tree height variations (Saremi et al., 2014) as well as the use of lidar to improve the classification of vegetation structures (Dowling & Accad, 2003).

According to the FAO definition, “Forest is a land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ” (FAO, 2010a). Formally, the forest and land cover maps produced by the government of Indonesia followed correspondingly the definition used by the FAO (FAO, 2010b). Due to technical limitation and the unavailability of high-resolution data, a so-called working definition was used for forest classification and mapping throughout Indonesia (MoEF, 2015).

In this study, we were interested in the utilization of lidar metrics for forest and land cover mapping in a tropical peat swamp ecosystem following the definition of ‘forest’ by FAO. According to our knowledge, no study has been carried out related to vegetation classification mapping using lidar in tropical peat swamp ecosystem in Indonesia. The aim of this study was to explore the potential advantage of airborne discrete lidar for mapping of forest and land cover in a peat swamp ecosystem. The specific objectives were (1) to classify forest and land cover types based on vegetation heights and (2) to compare with existing forest and land cover maps. This research provides an alternative technique for accurate mapping of peat swamp forest and land cover which is useful for the implementation of land use and spatial planning policies related to restoration of degraded peat land and moratorium oil palm development in high density peat swamp forests.

2. DATA AND METHODS

2.1 Study Site

Our study site was located at a protection forests, ex Kalimantan Forest Carbon Partnership (KFCP) project area (114° 23.5’ – 114° 40.3’ E; 1° 56.0’ to 2° 30.1’ S) in Kapuas District, Central Kalimantan Province, Indonesia (Figure 1). The study site encompasses 119,737 ha of tropical peat swamp ecosystem with a range of degradation levels due to conversion for agriculture, timber extraction and fires.

![Figure 1. Study site in peat swamp forest of Central Kalimantan, Indonesia (ESRI and KFCP)](image)

2.2 Lidar Data

Lidar data sets were provided by the KFCP project. The calculated pulse density was 2.8 pulse.m². All datasets were captured using Optech ALTM 3100 and Optech Orion M200 instruments mounted in Pilatus Porter fixed wing aircraft. The vendor provided a 1- meter resolution lidar-derived digital terrain model (DTM) for the KFCP area. The lidar point data was stored in LAS format and split into 1618 tiles. An accuracy assessment carried out after data acquisition found that the vertical accuracy of the lidar data was 0.14 m (Ballhorn et al., 2014).
2.3 Pointcloud Data Processing

We used FUSION 3.4 LTK Processor to extract lidar metrics from the tiles of pointcloud data and converted into lidar metrics. The 1-m resolution DTM was used for normalizing the terrain effect on the vegetation height. We generated 5-m resolution lidar metrics including the canopy height model in raster format. All relevant lidar metrics were converted to a raster format for further processing.

2.4 Existing Land and Forest Cover Maps

Due to the capability in covering a large area, satellite-derived imageries were commonly used for producing land and forest cover maps in Indonesia, such as Landsat and Alos Palsar imageries. Three existing and relevant forest and land cover maps were identified and compiled for the comparison analysis, i.e. produced by Ministry of Forestry (MoF) (Ministry of Forestry, 2012), KFCP (Siegert et al., 2013) and JAXA (Shimada et al., 2014).

The MoF map utilized a mosaic of Landsat imageries from 2010 to 2012. Operators were trained and familiarized with the MoF classification system. The classification was carried out using visual interpretation. KFCP forest and land cover map were clipped from the original file that covered the whole district. The map was produced using object-based classification from a Landsat mosaic. The JAXA map was generated based on Alos Palsar imageries derived from 2010. Only two classes, i.e. forest and non-forest, were produced.

2.5 Land and Forest Cover Classification

In this study, we interpreted the vegetation cover based on the canopy height model derived from airborne lidar. Instead of “land use”, we used the “land cover” as a basic term for the classification of forest (Lund, 2002). Furthermore, the Land Cover Classification System (LCCS) requires information on vegetation structures, including tree height (Di Gregorio, & Jansen, 1998). Therefore, for detailed classification of forest and land cover, we further classified the canopy height model into several height classes, i.e. 1, 2, 5, 10, 20 and 30 meters (Table 1). For visualization and comparison purposes, we generalized the classified lidar map (Figure 2). We used ArcGIS 11 Desktop software for the data classification and visualization.

Table 1. Vegetation structures and classification used in this study
(modified from Dowling & Accad (2003))

<table>
<thead>
<tr>
<th>Vegetation Height (m)</th>
<th>Description</th>
<th>Class</th>
<th>Generalized Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 – 1</td>
<td>An open land or bareland, dominated by grasses, ferns and herbaceous plants</td>
<td>Grassland</td>
<td>Non Forest</td>
</tr>
<tr>
<td>1 – 2</td>
<td>An area covered by shrubs or a mixed between tall grasses and low woody vegetation, including tree seedlings</td>
<td>Shrub</td>
<td>Non Forest</td>
</tr>
<tr>
<td>2 – 5</td>
<td>An area covered by tall shrubs and poles</td>
<td>Bush</td>
<td>Non Forest</td>
</tr>
<tr>
<td>5 – 10</td>
<td>An area covered with trees with height more than 5 m</td>
<td>Low forest</td>
<td>Forest</td>
</tr>
<tr>
<td>10 – 20</td>
<td>An area covered with trees with height more than 10 m</td>
<td>Medium tall forest</td>
<td>Forest</td>
</tr>
<tr>
<td>20 up</td>
<td>An area covered with trees with height more than 20 m</td>
<td>Tall forest</td>
<td>Forest</td>
</tr>
</tbody>
</table>

We compared the result with the existing forest cover maps and computed the mean and standard deviation of canopy height within the various land and forest cover classes of each map. To assess the significances of the means height difference, we extracted the canopy height values from a set of point samples, which were systematically distributed. As each point represented 1 ha area (100 m × 100 m), the total number of sample was 119,616 points. We performed the Tukey Honesty Significant Difference test for each class in each map. The significantly different classes were depicted by the different in the mean canopy height. We used JMP 12 for the statistical analysis.
Figure 2. Flow chart of generating forest cover map using canopy height lidar ESRI (ESRI, 2015).

3. RESULTS AND DISCUSSION

3.1 Lidar-derived Land and Forest Cover Map

A vegetation-height profile showed that detailed variation of the canopy from low vegetation to tall trees can be captured using lidar (Figure 3). Trees along the canals remained after large fires were also detected. This suggested that mapping vegetation structures with high accuracy using lidar was sensible. A forest cover map of the study area was produced using lidar-derived canopy height model, which included forest and non-forest classes with three sub-classes each. More than 65 % of the study site was covered by forest, dominated by medium-tall forest (height between 10 – 20 m) (Table 2). About 35% of the study site was not forested, which predominantly covered by grasslands and ferns. Open peatlands such as this are the result of repeated fires (Hoscio et al., 2011; Langner, Miettinen, & Siegert, 2007).

Table 2. Summary of vegetation classes covering study site (Own Analysis, 2016)

<table>
<thead>
<tr>
<th>Vegetation Classes</th>
<th>Size (ha)</th>
<th>Size (%)</th>
<th>Ha forest</th>
<th>% Forest and Non-Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grassland</td>
<td>25,162</td>
<td>21.0</td>
<td>41,413</td>
<td>34.6</td>
</tr>
<tr>
<td>Shrub</td>
<td>5,923</td>
<td>5.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bush</td>
<td>10,328</td>
<td>8.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Forest</td>
<td>11,164</td>
<td>9.3</td>
<td>78,235</td>
<td>65.4</td>
</tr>
<tr>
<td>Medium Tall Forest</td>
<td>67,054</td>
<td>56.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tall Forest</td>
<td>17</td>
<td>0.0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
3.2 Comparison with Existing Land and Forest Cover Maps

We carried out a mean canopy height comparison between the lidar-derived map and the existing maps. We computed the mean canopy height and its standard deviation of the classes of each map. Most of the secondary forest classes from the existing maps were in agreement with our medium tall forest class, which had canopy height ranging between 10 m – 20 m and mean canopy height about 13 meters (Figure 4). However, none of the forest classes of existing maps were equivalent to our low forest classes, which had height range between 5 m – 10 m. The KFCP bush/shrub/regrowth class was equivalent to our low forest class, with the mean canopy height of 7.5 m. The MoF bush/shrub class had lower mean canopy height (4.8 m) than the KFCP bush/shrub class, although it was extremely closed to the threshold of the FAO forest definition (5 m). None of the class in the existing maps represented the high canopy forests similar to our tall forest class. Surprisingly, the KFCP primary forest class had an even lower mean height than its secondary forest. In contrast, the MoF settlement class had the mean height of 9.3 m, much higher than the lowest height threshold of FAO forest definition. Furthermore, most of the KFCP and MoF non-forest classes had insignificant differences in mean heights (Figure 4).

Figure 4. Mean canopy height of vegetation classes and their standard deviation. Different letters depicted significant differences of the mean values within each map (Tukey’s HSD test).

Figure 5 illustrated the significantly-different mean heights between forest and non-forest classes of each map. This suggested that the existing forest/non-forest maps had better accuracy in defining the classes than the detailed forest and land classification maps. Regarding size of the area, the Jaxa forest/non-forest map had better agreement with our result. However, regarding the spatial distribution of the forests, we found that the KFCP forest/non-forest map was in better agreement with the lidar-derived forest/non-forest map (Figure 6).

Figure 5. Mean canopy height of each forest and non-forest classes and their standard deviation (Own Analysis, 2016)
Mapping of vegetation structures with high accuracy using lidar is sensible. This approach will support more detailed and accurate vegetation mapping, and in particular, will allow the use of a classification system based on physiognomy and canopy height structures (Ellenberg & Mueller-Dombois, 1966; Woodwell, 1984). On the other hand, existing forest and land cover maps, which relied on optical and active sensor imageries, tend to be inconsistent in identifying the spatial distribution of detail forest and land classes, due to their lower resolution. However, high-resolution optical imagery may also have a similar limitation (Nagendra & Rocchini, 2008).

Compared to the aerial photos, lidar offers great advantages in accuracy and fully automated digital processing in vegetation mapping (Dowling & Accad, 2003). Lidar also advanced in the identification of inundated wetland areas using the pulse intensity (Lang & McCarty, 2009). Floristic classification remains a practical limitation in tropical vegetation mapping using lidar, which is also a common problem with other optical sensors. To overcome this limitation, several studies successfully integrated lidar with hyperspectral
sensor for species identification in temperate regions (Holmgren, Persson, & Söderman, 2008; Jones, Coops, & Sharma, 2010), although it was less successful in mangrove vegetation (Hirano, Madden, & Welch, 2003) and highly diverse tropical forests (Clark et al., 2011).

4. CONCLUSION

The goal of this study was to explore the potential advantage of airborne discrete lidar for vegetation cover mapping in peat swamp forests. Lidar was able to capture detail variation of canopy height in high-resolution, thus provide more accurate classification. A comparison with existing maps, suggested that the lidar-derived vegetation map was more consistent in defining canopy structure of the vegetation.

5. ACKNOWLEDGMENTS

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Chapter 9

Assessing the influence of return density on estimation of lidar-based aboveground biomass in tropical peat swamp forest of Kalimantan, Indonesia

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Authors: Solichin Manuri, Hans-Erik Andersen, Robert J. McGaughey and Cris Brack

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Assessing the influence of return density on estimation of lidar-based aboveground biomass in tropical peat swamp forests of Kalimantan, Indonesia

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ABSTRACT

The airborne lidar system (ALS) provides a means to efficiently monitor the status of remote tropical forests and continues to be the subject of intense evaluation. However, the cost of ALS acquisition can vary significantly depending on the acquisition parameters, particularly the return density (i.e., spatial resolution) of the lidar point cloud. This study assessed the effect of lidar return density on the accuracy of lidar metrics and regression models for estimating aboveground biomass (AGB) and basal area (BA) in tropical peat swamp forests (PSF) in Kalimantan, Indonesia. A large dataset of ALS covering an area of 123,000 ha was used in this study. This study found that cumulative return proportion (CRP) variables represent a better accumulation of AGB over tree heights than height-related variables. The CRP variables in power models explained 80.9% and 90.5% of the BA and AGB variations, respectively. Further, it was found that low-density (and low-cost) lidar should be considered as a feasible option for assessing AGB and BA in vast areas of flat, lowland PSF. The performance of the models generated using reduced return densities as low as 1/9 returns per m² also yielded strong agreement with the original high-density data. The use model-based statistical inferences enabled relatively precise estimates of the mean AGB at the landscape scale to be obtained with a fairly low-density of 1/4 returns per m², with less than 10% standard error (SE). Further, even when very low-density lidar data was used (i.e., 1/49 returns per m²) the bias of the mean AGB estimates was still less than 10% with a SE of approximately 15%. This study also investigated the influence of different DTMs resolutions for normalizing the elevation during the generation of forest-related lidar metrics using various return densities point cloud. We found that the high-resolution digital terrain model (DTM) had little effect on the accuracy of lidar metrics calculation in PSF. The accuracy of low-density lidar metrics in PSF was more influenced by the density of aboveground returns, rather than the last return. This is due to the flat topography of the study area. The results of this study will be valuable for future economical and feasible assessments of forest metrics over large areas of tropical peat swamp ecosystems.

1. Introduction


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Chapter 9

9.2 Materials and methods

9.2.1 Study site

Due to a combination of factors, including limited studies at the landscape scale, reliance on low-resolution remotely-sensed data and the absence of locally-developed tree biomass models, global-scale aboveground biomass (AGB) estimates for tropical forests have generally had high levels of uncertainty (Houghton et al., 2012). A review of previous studies showed high levels of variability in the AGB estimates within Indonesian PSF mainly due to limited sample sizes (MoEF, 2015). Establishing plots within PSF of Indonesia is logistically difficult and labour intensive; thus, field studies are expensive and spatially limited. Consequently, there has been strong interest in the use of remote sensing to decrease the costs and increase the efficiency of forest assessments and monitoring in Indonesian PSF.

Tools such as radar and high-resolution optical satellite imagery have been used to support forest inventory in PSF; however, the results of previous studies, particularly, in terms of predictive power, were not favourable (Enghart et al., 2011; Hirata et al., 2014; Schlund et al., 2015). For example, the coefficients of determination ($R^2$) (a statistical measure of the strength of the regression relationship between remote sensing metrics and AGB measurements) have been found to range from 0.5 to 0.65. Conversely, studies using airborne lidar system (ALS) yielded significantly more precise estimates of AGB in PSF with $R^2$ values of lidar derived metrics and AGB that range from 0.77 to 0.88 (Enghart et al., 2013; Jabanski et al., 2012).

However, compared to satellite-based remote sensing technologies, the costs associated with ALS acquisitions are relatively high; for example, at a small scale, the overall cost of ALS can approach that of ground measurements for a forest stand assessment (Hummel et al., 2011). Given that the largest component of the costs of a lidar acquisition is aeroplane flight time, it is more economical to acquire lidar by having an aircraft fly higher and faster; however, all other things being equal, this results in a lidar point cloud that has a lower return density (and thus poorer spatial resolution). Flying at a higher altitude not only affects reduced return density and intensity, but also increases footprint size. Footprint size may affect the accuracy of individual tree measurements (Andersen et al., 2006); however, it has an insignificant effect on area-based forest metrics assessments (Goodwin et al., 2006; Nassset, 2004).

Studies assessing the effect of return density on the accuracy of lidar derived forest metrics have mostly been conducted in temperate and boreal regions (Gabakken and Nassset, 2008; Jakubowski et al., 2013; Magnusson et al., 2007; Singh et al., 2015; Watt et al., 2014), but have been limited to tropical regions (Hansen et al., 2015). In mountainous regions, the use of low-density lidar should be avoided due to potentially large errors in the terrain model that can have deleterious effects on the accuracy of canopy height metrics (Leitold et al., 2015). However, it should be noted that other studies conducted in areas of complex topography have shown that highly accurate inventory estimates can be obtained using relatively low return densities (i.e., 1–2 returns per m$^2$ for biomass (Jakubowski et al., 2013) and 2–3 returns per m$^2$ for timber volume (Watt et al., 2014)). Further, Ruiz et al. (2014) found that reducing return density to 1/4 returns per m$^2$ continued to provide good estimates of AGB in a steep terrain, suggesting that the size of field plots was crucial to the development of lidar metric models.

The majority of previous lidar studies have used direct canopy height metrics (Drake et al., 2003; Jabanski et al., 2012) and canopy height-related statistical metrics (d’Oliveira et al., 2012; Singh et al., 2015) to develop predictive models for forest inventory parameters. Such models have been shown to be more accurate in less-diverse temperate forests (Lefsky et al., 2005) than tropical forest regions (Andersen et al., 2014; Asner and Mascaro, 2014). A number of recent studies have explored the use of return proportion-related parameters (Joki et al., 2014; Sheridan et al., 2014) and developed multivariate models that include the return proportion at 20–25 m height as an independent variable; however, the performance of these models was no better than that obtained using mean aboveground height parameters (Joki et al., 2014). This type of model could be suitable for areas dominated by less disturbed forests, but is not suitable for areas characterised by a wide range of degraded conditions and succession levels.

The overall objective of this study was to demonstrate the ability of ALS in AGB estimation and mapping in large area of degraded tropical PSF in Central Kalimantan, Indonesia. The specific objectives of the study were to: identify the best AGB and basal area (BA) models using canopy height-related and return proportion parameters at various return density levels; assess the sensitivity of lidar metrics associated with reduced return densities; and estimate AGB levels for a large peat swamp area, using a model-based estimation/inferential framework. It appears that this study was the first to assess the effect of lidar return density on the estimation of AGB in tropical PSF.

2. Materials and methods

2.1. Study site

The study site was the former Kalimantan Forest Carbon Partnership (KFCP) project area, located in the Ex-Mega Rice Project (EMRP) in peat land of Central Kalimantan Indonesia (114°23.5’–114°40.3’ E; 1° 56.0’ to 2° 30.1’ S) (see Fig. 1). The KFCP boundary encompasses 123,608 ha of tropical PSF with a range of degradation levels. The topography of the area is very flat with elevations of 1–20 m above sea level and slope less than 0.1%. Peat dome fringes have their lowest elevations near riverbanks, but these elevations slowly increase as they approach the center of the dome.

From 2003 to 2010, the mean annual rainfall was 2900 mm (Ichsan et al., 2013) and the dry seasons (in which the monthly rainfall was less than 200 mm) were from June to September; From the 1970s to the 1990s, large concessionaires selectively logged the forest and small scale illegal logging continues today. Forests with a high variation of succession and high degradation levels dominated the northern part of the study site. The forests were dominated by non-dipterocarp species, including Combretocarpus rotundatus, Campnosperma coriacum, Tectaria obovatum and Palauquium cochleiformifolium. The dominant tree species from dipterocarp family included Shorea teysmaniana and Shorea balangeran. Conversely, as a result of logging, land clearing and frequent fires, the southern part of the study site was covered by shrubs, ferns or grasslands (Graham et al., 2014) (see Fig. 2).

The tropical PSFs in Borneo occur in peat soil which developed from the accumulation of dead vegetation in a waterlogged environment since more than 30,000 years ago (Page et al., 2004). PSFs are considered to be the highest carbon stock ecosystem but lower in biodiversity and productivity, than the neighbouring lowland dipterocarp forests. The soil nutrient deficiency and acidity are increased toward the center of the dome, where the peat is deeper, providing a limiting factors for vegetation to grow. Thus, only low pole trees could grow in the peat dome center, commonly dominated by Combretocarpus sp and Dacyrydium sp (Morley, 1981). In contrast, primary PSFs grow in the fringe of the dome harbour large emergent and commercial trees such as Shorea spp from dipterocarp family, Agathis sp, Koompassia sp, Palauquium sp and Gongylodes bancanus with maximum tree height between 40 and 45 m (Anderson, 1963; Page et al., 1999) (see Fig. 2).
2.2. Ground measurements

The KFCP project established permanent plots for vegetation monitoring that were systematically placed in eight randomly selected zones representing land cover classes and disturbance levels (Graham et al., 2014). Five zones were located near large canals and in highly degraded areas, while the other three zones were located in closed-canopy forests. Within each zone, three transects, spaced 150 m apart, were placed perpendicular to the canals or in an east to west direction from randomly located starting points.
Four plots were established on each transect at a distance of 50, 100, 400 and 700 m from the canals or the starting points. The scientific names of the species, the diameters at breast height (DBH) or above buttress and the height of all the trees within the plot were recorded. Square nested-plots of 1 m x 1 m, 8 m x 8 m, 16 m x 16 m and 32 m x 32 m were established for seedlings (less than 1.5 m in height), saplings (with a height greater than 1.5 m and DBH less than 10 cm), poles (with a DBH greater than 10 cm but less than 20 cm) and trees (with a DBH greater than 20 cm), respectively. A total of 88 plots were measured in mid-2011 and at the beginning of 2012. The other eight plots were measured in 2013, two years after lidar acquisition, and thus excluded from the analysis.

2.3. Lidar data sets

Lidar data sets were provided by the KFCP project. Lidar data of KFCP areas were captured with an intended density of 2 returns per m². Due to a 30% overlapping swath area, the calculated return density was 2.8 returns per m². All datasets were captured using Optech ALTM 3100 and Optech Orion M200 instruments mounted on a Pilatus Porter fixed wing aircraft (Table 1). The same vendor collected data from 15 August to 2 October 2011. The vendor provided a 1 m resolution lidar derived digital terrain model (DTM) for the KFCP area. The vendor also classified ground and non-ground points. The vertical accuracy of the raw lidar data and the DTM products were 0.14 m and 0.18 m, respectively (Ballhorn et al., 2014).

2.4. Field plot data analysis

AGB and BA were calculated for 88 and 72 plots, respectively. There were fewer plots for the BA because there were no saplings or trees in 16 plots. Mixed species AGB equations for PSFs were used to estimate AGB for trees with DBH greater than 2 cm. Two multi-parameter AGB equations were selected. The first used DBH, wood density (WD) and height (see Eq. (1)) and the second used DBH and height (see Eq. (2)) (Manuri et al., 2014).

\[
AGB = 0.15D^{0.69}WD^{0.66}H^{0.52}
\]

(1)

\[
AGB = 0.081D^{2.04}W^{0.672}
\]

(2)

Where AGB is in kg, D is DBH or above buttress in centimetres, WD is in g cm⁻³ and H is tree height in metres. The models were developed from relatively large sample size (n = 148), more than the minimum sample size suggested by Roxburgh et al. (2015) for developing generic allometric models. The samples were collected using destructive sampling in PSF in Sumatra and West Kalimantan, covering a wide range of tree size, with maximum tree diameter and height of 176 cm and 49.5 m, respectively. These models predicted AGB better than other local models in a PSF in Central Kalimantan through a validation using destructive sampling data (Manuri et al., 2015).

To calculate AGB, WD values for each species were derived from the WD global database (Zanne et al., 2009) using values associated with related tree species names or genus names. WD values were not assigned for unidentified tree species. Eq. (2) was used to estimate the AGB of unidentified trees. The average AGB for seedlings less than 1.5 m in height were estimated as 0.10 kg, as there was no destructive sampling data from seedlings and undergrowth. AGB and BA were calculated in Mg ha⁻¹ and m² ha⁻¹, respectively and summarised to the plot level.

2.5. Lidar processing

Data processing flows and the associated specific objectives were presented in Fig. 3. FUSION v3.42 was used to process all point cloud lidar data (McGaughey, 2014). To compute products over the entire acquisition area, the Lidar Toolkit (LTK) Processor tool was used in FUSION to create and manage the processing workflow.

The lidar return densities were reduced from the original density to simulate different acquisition specifications for the lidar data. We used ThinData utility in FUSION to reduce the lidar returns from 2.8 returns per m² to 1 return per 100 m². The points were selected randomly in cell sizes of 25 m². The return density of lidar data was reduced from 2.8 to 2, 1, 1/1, 1/3, 1/5, 1/10, 1/100 returns per m² that were equivalent to a return spacing of 1/2, 1–10 m, respectively. A similar approach has been applied in other studies (Letfolt et al., 2015; Magnusson et al., 2007; Ruiz et al., 2014; Strunk et al., 2012).

Ground points were filtered using the GroundFilter utility with a grid size of 16 m. Two scenarios were applied to assess the effect of point density on the regression models. In the first scenario, each thinned dataset was normalised using the original DTM delivered by the lidar provider to remove terrain influence on vegetation height. In the second scenario, the thinned dataset was normalised using the corresponding DTM created from the thinned point data. In relation to all return densities, a 1 m resolution of DTM was created using the TINSurface utility. This utility created a triangular irregular network (TIN) surface and then interpolated a regular grid at the desired resolution.

Using the original and thinned point cloud data, lidar metrics were computed for each plot area so that they could be used as predictor variables in the regression models. Ground points and low vegetation (less than 1 m) returns were excluded from the metric computation. Several lidar metrics were calculated in relation to vegetation heights (i.e. mean aboveground height (MAH), quadratic mean aboveground height (QM AH), variance of aboveground height (VAR) and height percentiles (P1) and return proportions (i.e. density of return points (RD), cumulative return proportion (CRP), quadratic cumulative return proportion (QCRP), return proportion of certain height stratum (Str) and cumulative return proportion of height strata (CStr)) (see Table 2). Several authors have used different terminologies to describe return proportion, including laser penetration (Ioki et al., 2014) and point frequency or density (Sheridan et al., 2014). This paper defined return density as the total number of returns per area and return proportion as the ratio of the number of returns above a certain height and the total number of returns (Table 2 and Fig. 4).

2.6. Regression analysis of aboveground biomass models

Regression modelling of field-measured AGB data was used to evaluate lidar metrics at the plot level and determine the best-fitting AGB (Mg ha⁻¹) and BA (m² ha⁻¹) models. All metrics (including aboveground height-related metrics, height percentiles and return proportions) that had previously been reported to be correlated with AGB were tested for significance using ordinary least square (OLS) regression. Models with insignificant variables (i.e., p-values larger than 0.05) were excluded. Collinearity in the multivariate regression models was evaluated using the variance inflation factor (VIF). Models with VIFs greater than five were...
Fig. 3. Flowchart of lidar analysis in this study. The grey boxes represent the specific objectives.

Fig. 4. Boxplot of mean total returns per plot (32m x 32m) above various height at different thinning levels.
Table 2
Summary of the lidar forest structure variables derived from the lidar point cloud for each ground plot used in this study.

<table>
<thead>
<tr>
<th>Metric symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAH</td>
<td>Mean height of aboveground canopy</td>
</tr>
<tr>
<td>QM AH</td>
<td>Quadratic value of MAH = (MAH)^2</td>
</tr>
<tr>
<td>V AH</td>
<td>Height variance of aboveground canopy</td>
</tr>
<tr>
<td>P1, P5, P10, P20, P25, P30, P40, P50, P60, P70, P75, P80, P90, P95, PP99</td>
<td>Percentile height values of the aboveground returns</td>
</tr>
<tr>
<td>R D1, R D5, R D10, R D15, R D20, R D25 and R D30</td>
<td>Density of return points above 1, 5, 10, 15, 20, 25 and 30 m heights, derived by dividing total number of returns above specific height with area size. Return proportion above 1, 5, 10, 15, 20, 25 and 30 m heights, are the ratio of return number above specific height and total number of returns.</td>
</tr>
<tr>
<td>CR P</td>
<td>Cumulative return proportion is the sum of all RP values</td>
</tr>
<tr>
<td>QC RP</td>
<td>Quadratic cumulative return proportion is the quadratic value of CRP = (CRP)^2</td>
</tr>
<tr>
<td>Str1-5; Str5-10; Str10-15; Str15-20; Str20-25 and Str25-30</td>
<td>Return proportion of canopy height strata (Str) is the ratio of return number at specific height strata/bin and total number of returns</td>
</tr>
<tr>
<td>C Str</td>
<td>Cumulative number of return proportion of canopy height strata (Str)</td>
</tr>
</tbody>
</table>

excluded (Sileshi, 2014). The relationship between AGB and lidar metrics was modeled using simple and multivariate linear model forms. When residuals of a linear model did not depict a normal distribution, the variable was then fitted using a non-linear model form. The linear models were fitted using OLS regression, while the power models were fitted using non-linear regression. The best and the most parsimonious models were selected based on the significant parameter estimates, highest R^2 and the lowest root mean square errors (RMSE) while still having a normal distribution of residuals. We validated the models using the 10-fold cross-validation technique (Kohavi, 1995). We used JMP 11 software (SAS, 2015) for the regression modelling and R statistical package (R-Development-Core, 2013) for 10-fold cross validation and full coverage AGB estimation using variance estimator.

2.7. Comparing lidar metrics to assess the effect of return density

Lidar derived metrics generated from four different return densities (i.e., 1/4, 1/16, 1/49 and 1/100) were compared with the original lidar metric. Different terrain models were also generated for each density level. A total of 1,192 sampling points were selected across the KFCP area using a systematic grid of sample points spaced 1 km apart. All lidar metrics for the sample locations were extracted from raster layers covering the entire acquisition area. Scatter plots were produced for each metric and compared. The R^2, RMSE, intercept and slope deviation of the fitted line between lidar metrics were generated using the reduced density data and original high return data. An intercept of 0 and a slope of 1 indicated unbiased.

2.8. AGB estimates using variance estimator

To assess the influence of lidar return density on the precision of mean biomass estimates, a model-based approach was used to estimate the mean biomass and the variance of this estimate for different thinning levels (2.8, 1/4, 1/16, 1/49 and 1/100 returns per m^2) covering whole study site. We generated lidar metrics for different thinning levels with 30-m resolution. As stated above, the KFCP site was approximately 123,608 ha and thus resulting in 1,330,748 30-m pixels. Adopting the approach of (McRoberts, 2010), if y represents the random variable of AGB with a mean $\mu$ and standard deviation $\sigma$, the observed AGB at the i-th pixel ($y_i$) was represented as: $y_i = \mu_i + e_i$, where $e_i \sim N(0, \sigma^2)$. The mean AGB at the i-th pixel was then given by $\hat{\mu}_i = f(\bar{X}; \hat{\beta})$ (as estimated by $\hat{\mu}_i = f(\bar{X}; \hat{\beta})$).

Where $X_j$ is the lidar-based predictor variable at the i-th pixel and $\hat{\beta}$ is the vector of p predicted regression coefficients ($p=2$, in this case). The model-based estimate of mean AGB over the entire area was $\frac{1}{N} \sum_{i=1}^{N} \hat{\mu}_i$. The variance of the model-based mean AGB estimate was given by:

$$\hat{\sigma}^2 \left[ \frac{1}{N} \sum_{i=1}^{N} \hat{\mu}_i \right] = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \text{Cov}(\hat{\beta}_0, \hat{\beta}_1) = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} X_{ij} \mathbf{V}_{ij} Z_j$$

Where $\mathbf{V}_{ij}$ is the variance-covariance matrix for the regression model parameter estimates. For the case of $p=2$ (and for this study), $\mathbf{V}_{ij}$ was given by:

$$\begin{bmatrix} \text{Cov}(\hat{\beta}_0, \hat{\beta}_0) & \text{Cov}(\hat{\beta}_0, \hat{\beta}_1) \\ \text{Cov}(\hat{\beta}_1, \hat{\beta}_0) & \text{Cov}(\hat{\beta}_1, \hat{\beta}_1) \end{bmatrix}$$

$$z_j = \frac{\partial (X; \hat{\beta})}{\partial \beta_j}$$

As shown by the above variance formula, the calculation of an exact variance would entail a computationally difficult double summation over a total of $N \times p$ pixels ($1,330,748 \times 1,330,748 = 1.7$ trillion pixels). (McRoberts, 2010) demonstrated that the variance could be closely approximated by using a sample of the pixels in which sampled pixels were on an equally-spaced, two-dimensional, perpendicular grid over the entire area:

$$\hat{\sigma}^2 \left[ \frac{1}{N} \sum_{i=1}^{N} \hat{\mu}_i \right] = \frac{1}{n_{grid}^2} \sum_{i=1}^{n_{grid}} \sum_{j=1}^{n_{grid}} Z_{ij} \mathbf{V}_{ij} Z_j$$

Further, McRoberts et al. (2013) showed that any detrimental effects of using the gridded sample to calculate the variance estimate were negligible for grid widths (i.e., spacing) up to $n_{p} = 100$ population units (pixels).

3. Results

3.1. Regressions models for BA and AGB estimation

The 10 best models were selected for BA and AGB estimation from linear, multivariate linear and non-linear regressions based on their residual distribution, $R^2$ and RMSE. The selected BA and AGB models had $R^2$ of more than 0.70 and 0.85, respectively (see Tables 3 and 4). All return density and height percentiles metrics failed to fulfill good model requirements due to insignificant parameters, low $R^2$, high RMSE and non-normal residual distribution. The best percentile parameters for the models were $a + b \times P_{40}$ and $a + b \times P_{25} + c \times VAR$ (see Models No. 1 and 8 in Tables 3 and 4).

Other linear models also had similar trends in their residual distributions (i.e., the $a + b \times MAH$ and $a + b \times CRP$). Similar to Sheridan...
Chapter 9

9.3.2 Influence of return density on model performance

9.3.3 Return density effects on lidar metrics

Table 3
Parameter estimates of BA models using full density data (2.8 returns per m²). Significance is indicated by *** for p < 0.001; ** for p < 0.01; * for p < 0.05 and ns for not significant.

<table>
<thead>
<tr>
<th>Model No</th>
<th>BA Model</th>
<th>Parameter estimates</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>R²</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>a+b × P40</td>
<td>-5.722***</td>
<td>4.065***</td>
<td></td>
<td></td>
<td></td>
<td>0.754</td>
<td>7.04</td>
</tr>
<tr>
<td>2</td>
<td>a+b × MAH</td>
<td>-9.591**</td>
<td>3.983***</td>
<td></td>
<td></td>
<td></td>
<td>0.729</td>
<td>7.37</td>
</tr>
<tr>
<td>3</td>
<td>a+b × CRP</td>
<td>-8.656**</td>
<td>12.541***</td>
<td></td>
<td></td>
<td></td>
<td>0.777</td>
<td>6.70</td>
</tr>
<tr>
<td>4</td>
<td>a+b × QMAH</td>
<td>4.312***</td>
<td>0.238***</td>
<td></td>
<td></td>
<td></td>
<td>0.701</td>
<td>7.75</td>
</tr>
<tr>
<td>5</td>
<td>a+b × Cstr</td>
<td>2.373***</td>
<td>2.878***</td>
<td></td>
<td></td>
<td></td>
<td>0.809</td>
<td>6.19</td>
</tr>
<tr>
<td>6</td>
<td>a+b × Str15+c × Str20 + Str25</td>
<td>5.320**</td>
<td>57.028***</td>
<td></td>
<td></td>
<td></td>
<td>0.780</td>
<td>6.65</td>
</tr>
<tr>
<td>7</td>
<td>a+b × Str15+c × Str20 × Str25</td>
<td>5.281**</td>
<td>60.145***</td>
<td>57.902***</td>
<td>32.078***</td>
<td></td>
<td>0.790</td>
<td>6.60</td>
</tr>
<tr>
<td>8</td>
<td>a+b × P25 + c × Var</td>
<td>-3.532</td>
<td>4.691***</td>
<td>0.15***</td>
<td></td>
<td></td>
<td>0.752</td>
<td>7.11</td>
</tr>
<tr>
<td>9</td>
<td>a × MAH</td>
<td>1.008</td>
<td>1.433***</td>
<td></td>
<td></td>
<td></td>
<td>0.733</td>
<td>7.43</td>
</tr>
<tr>
<td>10</td>
<td>a × CRP</td>
<td>15.516</td>
<td>2.212***</td>
<td></td>
<td></td>
<td></td>
<td>0.802</td>
<td>6.20</td>
</tr>
</tbody>
</table>

Table 4
Parameter estimates of AGB models using full density data (2.8 returns per m²). Significance is indicated by *** for p < 0.001; ** for p < 0.01; * for p < 0.05 and ns for not significant.

<table>
<thead>
<tr>
<th>Model No</th>
<th>AGB Model</th>
<th>Parameter estimates</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>R²</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>a+b × P40</td>
<td>-46.351***</td>
<td>27.639***</td>
<td></td>
<td></td>
<td></td>
<td>0.891</td>
<td>38.3</td>
</tr>
<tr>
<td>2</td>
<td>a+b × MAH</td>
<td>-67.710***</td>
<td>26.484***</td>
<td></td>
<td></td>
<td></td>
<td>0.857</td>
<td>44.0</td>
</tr>
<tr>
<td>3</td>
<td>a+b × CRP</td>
<td>-29.625***</td>
<td>77.254***</td>
<td></td>
<td></td>
<td></td>
<td>0.858</td>
<td>43.9</td>
</tr>
<tr>
<td>4</td>
<td>a+b × QMAH</td>
<td>-5.174***</td>
<td>1.831***</td>
<td></td>
<td></td>
<td></td>
<td>0.883</td>
<td>39.8</td>
</tr>
<tr>
<td>5</td>
<td>a+b × Cstr</td>
<td>-1.405***</td>
<td>20.328***</td>
<td></td>
<td></td>
<td></td>
<td>0.907</td>
<td>35.5</td>
</tr>
<tr>
<td>6</td>
<td>a+b × Str15+c × Str20</td>
<td>7.640**</td>
<td>425.758***</td>
<td></td>
<td></td>
<td></td>
<td>0.890</td>
<td>38.6</td>
</tr>
<tr>
<td>7</td>
<td>a+b × Str15+c × Str20 + Str25</td>
<td>10.090**</td>
<td>371.409***</td>
<td>529.170***</td>
<td>502.928***</td>
<td></td>
<td>0.888</td>
<td>37.5</td>
</tr>
<tr>
<td>8</td>
<td>a+b × P25 + c × Var</td>
<td>-43.230***</td>
<td>32.161***</td>
<td>0.546***</td>
<td></td>
<td></td>
<td>0.882</td>
<td>40.3</td>
</tr>
<tr>
<td>9</td>
<td>a × MAH</td>
<td>1.038</td>
<td>1.998***</td>
<td></td>
<td></td>
<td></td>
<td>0.884</td>
<td>39.7</td>
</tr>
<tr>
<td>10</td>
<td>a × CRP</td>
<td>15.516</td>
<td>2.212***</td>
<td></td>
<td></td>
<td></td>
<td>0.802</td>
<td>35.2</td>
</tr>
</tbody>
</table>

et al. (2014), this study also confirmed the heteroscedasticity of the residuals using these parameters. These models were thus excluded in the next step of the analysis.

The power models using CRP variable explained 80.9% and 90.9% of the BA and AGB variations, respectively. These fits were similar or slightly better than those of squared CRP (QCRP) linear models. However, the regressions between predicted and observed values from all linear models had better-fitted lines than power models with slopes not significantly different from 1 and intercepts not significantly different from 0. A 10-fold cross-validation confirmed the lowest RMSE for all CRP-related models (Fig 5.).

Most of the return proportion models demonstrated normal residual plots except the linear CRP model. The models’ errors were distributed near zero. However, all models tended to have low precision in estimating small AGB. This may be attributable to the exclusion of AGB measurement from shrubs or grases in the plots. The majority of the heavily degraded peat swamps were dominated by lower vegetation such as grasses, shrubs, sedges or ferns (Riley and Ahmad-Shah, 1996). Only tree species were recorded on the plots. Thus, the biomass values of highly degraded PSF did not completely represent the actual biomass in the plots. These models also tended to under-estimate lower biomass and over-estimate large biomass (see Fig 5.). There are two potential reason for this trend: first, similar to Magnusson et al. (2007), we found in these large AGB plots, understory vegetation are abundant (small trees occupying second layer canopy). The other reason could be due to the model form. Similar trend was found by Engeltart et al. (2013) when applying power model. They further suggested to use 2 equations: i.e. power model for low AGB and linear for high AGB values.

3.2. Influence of return density on model performance

Overall, the R² of BA and AGB models, where the point clouds were normalised using the original high-resolution DTM, declined by 12–30% as return density decreased to 0.01 or 1/100 returns per m² (see Fig 6). The R² and RMSE of the models remained stable until 1/9 returns per m². Below this point, the performance of the models decreased slightly until 1/49 density. Then, they either remained stable or declined further. The decreases of R² were comparable to a previous study by (Singh et al., 2015) of an urban forest in a relatively flat area.

As expected, the performance of the models that had been built with data in which the elevations were normalised using the thinned DTM data, declined more drastically than the performance of the models, which normalised using the high-resolution DTM, especially the models with return density lower than 1/9 returns per m² (see Fig. 6A2 and B2). The difference in R² varied from 25 to 60%. The R² of the lowest density power CRP model that used high-resolution DTM, declined by only 12% from the model with the highest return density. The performance of these models was similar between 2 and 1/9 returns per m².

The CRP power models performed similarly to the QCRP linear models until 1/9 returns per m² in estimating the AGB (see Fig. 6). Below this density, the CRP power model outperformed the QCRP linear models. Most of the BA and AGB models with reduced DTM depicted unstable declines except the linear model of Cstr. The performance of the Cstr model was similar to the CRP power model and QCRP linear model in estimating BA until density declined to 1/4 returns per m². After which, the performance of the model decreased sharply to its lowest level.

3.3. Return density effects on lidar metrics

The lidar derived metrics of four different return densities (i.e., 1/4 1/16, 1/49 and 1/100) were compared with the original lidar metric. Three lidar metrics were considered in the comparative analysis (i.e., maximum height (H max), QMAH and QCRP). All of the lidar metrics derived from the 1/4 return density data had a high correlation with the metrics derived from the original, higher-density data with a R² of more than 0.96 and slopes very close to 1. Further reductions in return density produced a poorer correlation with the original data and led to an underestimation of the metrics.
Fig. 5. Scatterplot of observed against predicted AGB per plot from the best models as shown in Table 4. Cross-val RMSE is the root mean square error from 10-fold cross validation.
Table 5
QCRP linear regression models and their variance-covariance for different lidar densities.

<table>
<thead>
<tr>
<th>Lidar density</th>
<th>Parameter estimates</th>
<th>$R^2$</th>
<th>Variance Intercept</th>
<th>Variance QCRP</th>
<th>Covariance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$a$</td>
<td>$b$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.8</td>
<td>1.405</td>
<td>20.328</td>
<td>0.91</td>
<td>45.59</td>
<td>0.49</td>
</tr>
<tr>
<td>1/4</td>
<td>7.52</td>
<td>36.3</td>
<td>0.91</td>
<td>42.55</td>
<td>1.58</td>
</tr>
<tr>
<td>1/16</td>
<td>15.29</td>
<td>37.229</td>
<td>0.86</td>
<td>60.80</td>
<td>2.59</td>
</tr>
<tr>
<td>1/49</td>
<td>6.487</td>
<td>37.114</td>
<td>0.82</td>
<td>83.95</td>
<td>3.37</td>
</tr>
<tr>
<td>1/100</td>
<td>70.98</td>
<td>25.372</td>
<td>0.48</td>
<td>176.49</td>
<td>8.42</td>
</tr>
</tbody>
</table>

Fig. 6. AGB (A) and BA (B) models performance at various return densities.

The DTM effects on the reduced density lidar metrics were also assessed. Specifically, the metrics that had been normalised using the original high-resolution DTM were compared with the metrics that had been normalised using the thinned DTM data. The lidar metrics calculated using the thinned DTM had a similar correlation to the ones calculated using high-resolution DTM (see Fig. 7). However, reducing the return density had the greatest effect on the $H$ max metric compared to the other metrics. An underestimation of the $H$ max was clearly observed in low return density metrics as indicated by larger intercepts of the fitted lines (see Fig. 7c). QMAH and QCRP tended to be similar in their responses to reductions in return densities (see Fig. 6a and b). There were underestimations of the metrics towards lower-density data; however, the slope and the intercepts of the fitted lines remained close to 1 and 0, respectively. The correlation with the original resolution metrics was still high with $R^2$ of more than 0.9 at a return density of 1/16. At the density of 1/5 returns per m$^2$, the slope and $R^2$ were very close to 1. Further sharp declines in accuracy occurred at the return density of 1/100. However, QMAH metrics were unable to detect most of the low vegetation areas at a return density lower than 1/16.

3.4. Return density effects on model-based estimates of mean AGB

To assess the effect of decreasing the lidar return density on the precision of the AGB estimates at landscape scale, the (model-based) mean AGB estimate was calculated over the study area ($\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \beta_i V_j Z_j$) for the original density (2.8 returns per m$^2$) and densities corresponding to four thinning levels (1/4, 1/16, 1/49, and 1/100 returns per m$^2$) (see Table 5). The standard deviation was reported; thus, the units were the same as the mean estimate. In this case, the variance was calculated using a gridded sample with a spacing of $n_p = 50$ (30 m x 50 m = 1500 m$^2$), resulting in $n_{pix} = 525$. The mean AGB was calculated using all ($N = 1,330,748$) pixels for each density level.

The model-based estimated mean AGB using the highest density dataset was 202.41 Mg ha$^{-1}$ with a relative standard error (SE) of only 3.1% (see Table 6). The relative error (RE) of the estimates from reduced density datasets ranged from -1.9% to -6.7%. The precision of the model-based estimate of mean AGB decreased as the return density decreased. However, at the study site, the relatively precise estimates of the mean AGB (13.7% relative SE) were still obtained with a fairly low-density of 1/49 returns per m$^2$.

4. Discussions

This study showed that models with return proportion metrics appeared to better predict AGB in PSF than models with height-related metrics. Our analysis suggested that the cumulative value of return proportions better represents the accumulation of biomass.
along the canopy height bins than the height-related statistics. The models with return proportion metrics not only provided the highest $R^2$ and the lowest RMSE, but also had normal distribution of errors. Loki et al. (2014) used return proportions below a height of 12 m as a predictor variable and found that it explained more than 70% of AGB variation in tropical Bornean forests. Sheridan et al. (2014) also analysed the return proportions above certain heights to estimate AGB in conifer-dominated forests of Oregon. Both studies concluded that the best model was the model with the return proportion variable. Those studies used return proportion or return number at certain height bins as a single variable, rather than the cumulative return proportion (CRP) as used in this study.

Several authors have suggested using linear models by using a square root transformation for the dependent variables and then back transforming the prediction using correction factors (d’Oliveira et al., 2012; Sheridan et al., 2014). However, this study found the use of quadratic (squared) terms for independent variables; that is, QCRP was more parsimonious than transforming the dependent variables, as it did not require a back transformation. In this study, the models with square root transformed dependent
variables had higher $R^2$ values. However, the back-transformed models were slightly worse than the models with squared independent variables.

Similar to previous research (Gobakken and Nasset, 2008), this study showed that reducing return density had the greatest effect on the H max metric and led to biased estimates of the forest metrics. As the return density was reduced, the probability of the lidar pulse hitting the highest point of the vegetation canopy decreased. Thus, it appeared that H max is sensitive to decreases in low return density and should not be used as an independent variable for developing models for forest metrics, particularly, in relation to low-density lidar datasets.

This study suggested that using a thinned DTM provided similar accuracies to those obtained using the original DTM to normalize the lidar point elevations in PSF. However, other studies conducted on relatively complex terrain (Leitold et al., 2015; Watt et al., 2014) showed that DTM from lower-density datasets had lower precision, as the percentage of classified ground points increased as return density fell. The study area was very flat, with slope less than 0.1%; thus, a lack of complex topography may explain this contradiction. However, Hansen (Hansen et al., 2015) found that low return density of up to 1/4 returns per m² had little effect on DTM in tropical mountainous regions and further suggested that the accuracy in ground point classification was crucial.

Reducing return density to approximately 1/4–1/9 returns per m² yielded model accuracies comparable to those obtained with higher return densities. A relatively precise estimate (with relative SE less than 10%) of the mean AGB at landscape scale were still obtained with a fairly low-density of 1/4 returns per m² using model-based statistical inference. Thus, it appears that potentially acceptable biomass and carbon estimates can be obtained in very flat regions using low-density ALS. Further, by using very low-density ALS data (1/49 returns per m²), the bias of the mean AGB estimates remained less than 10% and had a SE of less than 14%. In relation to reducing return density in PSF, the results were much more promising than those of previous studies in areas with relatively complex topography (Jakobowski et al., 2013; Leitold et al., 2015) and their accuracy was similar to that of a study in relatively flat areas in temperate forests (Gobakken and Nasset, 2008). However, it should be noted that these conclusions should not be extended to more mountainous areas, as the deleterious effects of lower return density on the quality of biomass estimates may be much more evident (see the discussion above). These findings suggest that high-density ALS is not required for forests and AGB monitoring in flat tropical PSF. Thus, the costs of remote sensing assisted forest monitoring could be reduced if less expensive, lower-density ALS data were used.

For area-based forest monitoring, (e.g. for AGB, BA, timber volume) such approach using low density lidar might be appropriate with consideration of the terrain factor. In flat terrain, model-based inference using return density of 0.02–0.05 would still yield 85% accuracy, as suggested from this study and Strunk et al. (2012). In a relatively steep and complex terrain, a 0.25 return density still provides a similar level of accuracy (for forest metric estimates) as high density lidar (Gobakken and Nasset, 2008; Ruiz et al., 2014). However in very steep terrain and mountainous region, high density lidar seems to be required to avoid error in DTM (Leitold et al., 2015).

5. Conclusions

This study demonstrated that low-density ALS is a feasible option for assessing AGB in vast areas of flat, lowland PSF. Notably, this study showed that return proportion-related variables (i.e., CRP, QCRR and Cstr) were able to estimate AGB and BA better than height-related variables. Those variables represent better accumulation of AGB over tree heights. This study provided strong evidence that the accuracy of the models generated using data with lower return densities of 1/9 returns per m² still yielded strong agreement with models generated using the original, higher-density data. Using variance estimator approach, the bias and standard error of the mean AGB at the landscape level, estimate using 1/49 returns per m² data were less than 10% and 15%, respectively. This study also showed that a high-resolution DTM had little effect on the accuracy of the calculated lidar metrics for areas with terrain similar to that examined in this study. Consequently, the acquisition and processing costs could be reduced if large areas of tropical PSF were monitored with ALS while maintaining relatively good accuracy.

Acknowledgements

This study was funded by the United States Government’s Silvacarbon programme. The authors are grateful to the KFCP project, a bilateral project between Indonesia and Australia governments and the Ministry of Forestry of Indonesia for providing the lidar and plot measurement datasets and to Pavla Graham and Laura Graham for their guidance in accessing plot measurement data. We would also like to acknowledge the support of Professor Monika Mosial and the team from Remote Sensing and Geospatial Analysis Laboratory of the University of Washington, United States who provided resources and suggestions during data processing. We thank Julie Watson for their critical reading of the previous manuscript, Elite Editing for proof reading of the draft manuscript and the two anonymous reviewers for their insightful comments and suggestions to improve the manuscript. We also thank Clive Hilliker for the support in graphic editing. Solichin Manuri gratefully acknowledges the support of Australia Award Scholarship from 2013 to 2017.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jag.2016.11.002.

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Chapter 10

Synthesis

To better understand the role of tropical forests in climate change and to quantify the impact of climate change mitigation efforts, such as REDD+, accurate estimation of forest AGB is essential (Herold and Skutsch, 2009). Many studies have demonstrated the importance of allometric equations for converting easily measured tree metrics into tree AGB (Chave et al., 2014; Basuki et al., 2009; Pelletier et al., 2012), ground measurements for filling the gap of NFI grid using an existing forest inventory (MoEF, 2015) and the reliability of remote sensing technology for biomass mapping (Rosenqvist et al., 2003; Asner, 2011).

This study explored ways to improve the accuracy of forest AGB estimates in Indonesia. The results provide essential foundations to improve the estimation of forest AGB at the tree scale through development of new AGB equations for several major forest types in Indonesia. This study also adds to our knowledge on the potential use of existing forest inventory and permanent sample plot datasets to be integrated into the carbon accounting system. Lastly, this study explored cutting-edge lidar technologies (both airborne and terrestrial) for non-destructive sampling techniques of mangrove trees and wide area mapping of forest biomass and land cover.

The assessment at various scales provided an overview of whether the errors cancelled out or aggregated at the larger scale. I found that the use of single variable equation to estimate tree AGB had similar results to the AGB estimation using complex variables, as the error at tree scale was cancelled out at plot scale. However, species composition and forest type may play important roles. For instance, in a pioneer-dominated forest, bias may occur due to different means of community WD or different tree diameter-height relationships. For substantial differences in forest type or tree communities, the use of WD-grouping allometric equations could reduce bias and improve precision.

10.1 Major Findings and Contribution to the Body of Knowledge

Component 1: Development of allometric equations for estimating tree AGB in various forest types.
Component 1 provides a basis for estimating tree AGB of major tropical forest types in Indonesia, including peat swamp forests, dipterocarp forests and lowland forests. I wrote three papers in relation to the development of allometric equations to achieve the objective of Component 1:

- Chapter 3: ‘Tree biomass equations for tropical peat swamp forest ecosystem in Indonesia’ (published in *Forest Ecology and Management*).
- Chapter 4: ‘Improved allometric equations for tree aboveground biomass estimation in tropical dipterocarp forests of Kalimantan, Indonesia’ (published in *Forest Ecosystems*).
- Chapter 5: ‘The effect of species grouping and site variables on aboveground biomass models for lowland tropical forests in Indo-Malay region’ (accepted in *Annals of Forest Science*).

Chapter 3 was the first published paper on allometric equations in peat swamp forests in a tropical region. Using a large dataset (148 trees, with a maximum diameter of 176) compiled from peat swamp forests of Sumatra and Kalimantan, the models we developed outperformed existing equations. The best model involved tree diameter, WD and height as predictor variables. In addition, I found that WD classes and major taxon (i.e., dipterocarp vs non-dipterocarp) were significant variables in explaining the variation of AGB, especially for the models using only tree diameter as a predictor variable. In evaluating the use of WD values from global database, I found that only 70% of tree species used in this study were available in the global database. The database was even more unreliable considering the minimal relationship between the measured WD values and global WD dataset ($r^2 = 0.169$).

In Chapter 4 I presented my new allometric equations, which are more accurate than previously published equations for dipterocarp forests. I contested the accuracy of previously published equations and compared the estimates using independent datasets (different to the datasets I used for the equation development), which were used in part for developing the previous equations. I found that previous local equations were systematically biased and imprecise, possibly because of the small range of tree diameters used for the samples and different assumptions made for fresh weight and dry weight measurements of large trees.
In Chapter 5, I used destructive sampling datasets, some from direct measurement and others from a literature review (for a total of 1,201 trees). Of all studies on allometric equations in the Indo-Malay region, this study used the largest dataset. This paper presented a region-scale analysis of allometric equations for tropical lowland forests in the Indo-Malay region. Apart from traditional variables, I also assessed additional variables, including climate and biogeographical variations, for estimating tree AGB. I found that climatic and major taxon-based variables (dipterocarp vs non-dipterocarp) were not significant in explaining AGB variations. Biogeographical zones were a significant variable explaining AGB variation, but they made only a minor contribution to the accuracy of AGB models. This suggests that generic equations should be able to estimate tree AGB from various ecological and climatic gradients. In accordance with Chapter 3, I found that the integration of wood-density classes in lowland forests improved the models significantly. In contrary to the result of Chapter 3, where species grouping based on dipterocarp and non-dipterocarp families was a significant and influential variable in explaining tree AGB variation in PSF, I concluded that over larger geographical ranges and ecological gradients, the influence of major taxon to tree allometry may diminish, to be replaced by the limiting factors for a tree to grow, such as climate and soil characteristics.

This study also emphasised the importance of standardised methods for destructive sampling to reduce sampling error, which could lead to bias in the regression models, especially in determining the WD of each tree section based on wood samples. Due to the variation of WD within species and individuals, more samples representing different parts and sizes of tree components are required. Further, because of the heteroscedasticity of the AGB data, where large trees have large variation of errors, it is crucial to include as much as possible large-diameter trees representing the ecosystem that we want to assess.

Component 2: Testing a non-destructive method for measuring tree AGB using a TLS

As demonstrated by Component 1, many samples from large-diameter trees are required for developing accurate AGB equations. Component 2 (Chapter 6) explored a non-destructive approach for calculating tree AGB using TLS for 3D volume and an AV measurement tool for estimating WD. This is also useful for measuring tree AGB in a cutting-restricted area, such as national parks.
This study demonstrated the capability of TLS in generating 3D point clouds of trees in mangrove ecosystems. Using two different software programmes for comparison, I found that QSM reconstructed the trees more realistically than CompuTree. However, CompuTree provided straightforward and automatic parameter optimisation, which was much easier for defining the best parameter than QSM. In addition, CompuTree was able to reconstruct the large trees with prop roots with better results than QSM, while noting that QSM was able to reconstruct prop roots separately. Most errors of volume estimated using TLS were high in small (4<D<10 cm) and medium (10<D<20 cm) branches of large trees, due to lower point density and occlusion in the canopy higher than 20 m. Overall, by excluding these branches in large trees, the accuracy of AGB estimates using TLS and AV was less than 4%.

This study also explored the potential use of AV for estimating WD with a non-destructive approach. I found that the AV measurement had a low correlation with WD values of logs from mixed species. However, when species was integrated into the variable, it showed that AV could explain the variation of WD within species. This may provide a better way to understand the variation of WD within species and individuals. However, I suggest integrating with other non-destructive tools for more accurate estimation of WD, regardless of the species.

Component 3: Synthesizing existing forest inventory datasets for estimating historical AGB stocks and growth in logged over tropical dipterocarp forests

In Component 3 (Chapter 7), I examined the potential use of existing permanent sample plots and timber inventory datasets measured by timber companies in Kalimantan, Indonesia. I compiled and evaluated more than 20,133 OPTI datasets measured between 2009–2011 and 24 1-ha PSP datasets. I found that 13% of compiled OPTI datasets could not be used for analysis due to data inconsistency in plot and tree data. Only 40% of the compiled OPTI datasets had geographical coordinates, which are useful for validating land cover maps and estimating AGB at landscape scale. The mean AGB of primary dryland forest, secondary dryland forest and bush classes was 281.1 ± 4.0 Mg/ha, 231.5 ± 1.7 Mg/ha and 179.0 ± 5.0 Mg/ha, respectively. I found that the average mortality rate (3.1%) was higher than the average growth rate (2.5%) 9 years after logging, thus resulting in a negative AGB increment. This is in agreement with previous
studies in East and West Kalimantan (Cannon et al., 1994; Susanty et al., 2015).
However, 7 years after logging the trend was reversed and the forests started to gain more biomass. This suggests the need for maintaining long-term measurement plots from timber concessions, which partly already established and measured since 1990s.

The results of this study also suggest that the use of allometric equations with fewer variables still provide comparable results when compared to the best allometric equations that involve all traditional variables, including tree diameter, height and WD, when applied at plot levels. The errors of AGB estimation at tree scale tend to cancel out at plot scale. In addition, in the absence of a raw dataset of forest inventories, I found that AGB-BA models can be used to estimate mean AGB at plot scale.

Component 4: Potential use of airborne lidar for AGB and land cover mapping at landscape scale

In Component 4 (Chapters 8 and 9) I explored the use of airborne lidar for assessing land cover and AGB at landscape scale, for which I wrote and published two papers:


Chapter 8 demonstrated the capability of airborne lidar for forest and land cover classification in 120,000 hectares of peat swamp forest in Central Kalimantan. I extracted maximum vegetation heights in 5-m grid resolution from the 2.8 pulse.m⁻¹ lidar point cloud and the associated 1-m DTM, to follow the criteria of minimum tree height used for the definition of forest. I found that lidar was able to capture detailed variations in canopy height in high-resolution, thus providing a more accurate classification. A comparison with existing maps suggested that the lidar-derived vegetation map was more consistent when defining the canopy structure of the vegetation.

In Chapter 9, I further utilised the same airborne lidar point cloud data to develop a model for estimating AGB and for assessing the optimal lidar density in relation to the resolution and accuracy of the AGB estimation. I found that the performance of the models
generated using reduced return densities as low as 1/9 returns per m$^2$ also yielded strong agreement with the original high-resolution data. These results suggest that low-density (and low-cost) lidar should be considered as a feasible option for assessing AGB and BA in vast areas of flat, lowland PSF. These results will be valuable for future economic and feasibility assessments of forest metrics over large areas of tropical peat swamp ecosystems.

### 10.2 Recommendations

The findings of this study suggest that the selection of AGB equations used to estimate tree AGB in tropical forests should be based on the representativeness of the samples used for the allometric equation development. As it is commonly agreed that the best existing models or datasets should be used, I suggest that the allometric equations developed locally from a limited number of samples or small range of diameter classes should not be used to estimate tree AGB outside the area or forest types where the equations were developed. Our newly developed equations outperform existing local equations. I further recommend the use of reliable generic allometric equations developed from this study to estimate forest AGB in Indonesia. This study provides a wide range of options of allometric models that use different variables or a combination, as well as an option to select forest-type-specific or generic equations.

This study also recommends that the selection of equations should be based on validation using field measurements, especially for large trees. In suggesting this option, the results of this study offer an alternative for non-destructive sampling of large trees. Several initiatives have been conducted to develop and improve software for fast and automatic 3D reconstruction of tree point cloud data derived from TLS. This option will be suitable to collect more AGB data of large-diameter trees. This information is needed to fill the gap of sample representativeness in some forest types and in the eastern region. I therefore recommend forestry research institutions in Indonesia to invest in TLS technology for filling the gaps and implementing accurate and verifiable measurement of their field sample plots.

To estimate forest AGB at landscape scale, it is essential to collect a large number of plots from ground measurements to reduce the uncertainty. However, the quality of existing ground measurements for forest monitoring program in the production forests remains uncertain. Based on this study, I also recommend the development of an integrated database that includes all existing forest inventory measurements conducted by timber
Chapter 10

10.2 Conclusions

Concessions or forest-related projects. Relevant initiatives have been tested at district, province and national levels. An integrated and standardised database platform will enable quality control and quality assurance of each database before their use for any application. The results of this study can be used to improve the estimation of emission factors from deforestation and forest degradation, at least for East Kalimantan and North Kalimantan. In addition, this could be used to emphasise the importance of the long term monitoring plots and to shape the policy that encourage logging concessions to maintain and measure existing permanent plots.

At landscape scale, this study demonstrates the capability of airborne lidar for forest monitoring and forest cover classification in peat swamp ecosystems. Based on this study, I recommend further utilising airborne lidar for large area mapping and monitoring of peat swamp forests. To reduce the cost of lidar acquisition, the density of lidar return can be reduced to at least 1 return per 4 m². For mapping of forest and land cover, airborne lidar allows more accurate and precise mapping compared with mapping using optical and active sensors. Overall, this study provides a number of new or improved methods to improve the accuracy of forest AGB estimates, thus providing a better understanding of emission factors from deforestation and forest degradation. These methods should be integrated into the forest monitoring and MRV system for assessing the emission reduction target and measuring the impact of REDD+ implementation, in particular, in the forested areas that experienced rapid deforestation, e.g. Kalimantan and Sumatra.

10.3 Limitations and Future Research

Because of limitations in research funding, time allocation for data collection and some technical and non-technical difficulties with data collection and processing, this study has some limitations in relation to the compiled datasets. For instance, more tree samples from various forest types and ecological gradients are required to understand the allometric relationship in explaining AGB variation in tropical forests. The distribution of the dataset used for this study on allometric equations was skewed, with more data compiled from the western part of Indonesia (Kalimantan and Sumatra) than from the eastern regions. The allometric study in PSF used datasets collected only from Sumatra and Kalimantan and none from Papua island, which harbours 38% of Indonesia’s peatlands (Ritung S. et al., 2011). For the lowland forest study, I included some datasets from the eastern part of Indonesia, including Maluku, Nusa Tenggara and Papua. However, the proportion was relatively low compared with the datasets compiled from
the western region. Most of the samples were collected from dipterocarp forests, reducing the emphasis on other lowland forests that dominate the middle and eastern region of Indonesia.

The study on non-destructive sampling was conducted in mangrove forests using a limited number of samples. Because of equipment limitations, only two trees were scanned, felled and weighed. More samples are required to develop allometric equations, especially for the trees that have prop roots. Another important aspect of research that was not adequately addressed in this study is how to estimate WD without destructive sampling. This study found that the AV measurement failed to estimate WD of mangrove trees accurately. Further studies using other forms of non-destructive portable equipment, such as pylodins, torsimeters or resistographs (Gao et al., 2012) are recommended. Alternatively, small cores at appropriate locations could be used to estimate WD, without damaging or killing the trees (Williamson and Wiemann, 2010).

This study on allometric equations focused on forest type-specific equations, such as for peat swamp forests, dipterocarp forests and lowland forests. Although this study developed generic equations for the Indo-Malay region, the samples were collected from the lowland forests in mineral soils, excluding wetland and mountainous forest ecosystems. Further research is necessary on how forest type influences tree allometry and to understand the variables that could be included to estimate forest AGB using generic equations.
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Appendix 1. Supplementary Materials for Chapter 4

Improved allometric equations for tree aboveground biomass estimation in tropical dipterocarp forests of Kalimantan, Indonesia

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Table 1. Number of trees, their dimensions and their mean wood density by family used in this study.
<table>
<thead>
<tr>
<th>No</th>
<th>Family</th>
<th>N trees</th>
<th>N species</th>
<th>Min D</th>
<th>Max D</th>
<th>Min H</th>
<th>Max H</th>
<th>Mean G</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Anacardiaceae</td>
<td>12</td>
<td>6</td>
<td>18.5</td>
<td>104.0</td>
<td>19.0</td>
<td>44.6</td>
<td>0.597</td>
</tr>
<tr>
<td>2</td>
<td>Annonaceae</td>
<td>5</td>
<td>4</td>
<td>18.0</td>
<td>61.5</td>
<td>17.8</td>
<td>37.5</td>
<td>0.562</td>
</tr>
<tr>
<td>3</td>
<td>Apocynaceae</td>
<td>4</td>
<td>1</td>
<td>35.3</td>
<td>105.3</td>
<td>16.2</td>
<td>48.2</td>
<td>0.451</td>
</tr>
<tr>
<td>4</td>
<td>Bombiaceae</td>
<td>1</td>
<td>1</td>
<td>97.0</td>
<td>97.0</td>
<td>47.1</td>
<td>47.1</td>
<td>0.624</td>
</tr>
<tr>
<td>5</td>
<td>Burseraceae</td>
<td>3</td>
<td>3</td>
<td>45.2</td>
<td>54.9</td>
<td>27.8</td>
<td>31.8</td>
<td>0.692</td>
</tr>
<tr>
<td>6</td>
<td>Celastraceae</td>
<td>2</td>
<td>1</td>
<td>52.0</td>
<td>77.0</td>
<td>37.8</td>
<td>38.2</td>
<td>0.920</td>
</tr>
<tr>
<td>7</td>
<td>Clusiaceae</td>
<td>2</td>
<td>2</td>
<td>27.9</td>
<td>67.0</td>
<td>25.9</td>
<td>30.2</td>
<td>0.412</td>
</tr>
<tr>
<td>8</td>
<td>Dilleniaceae</td>
<td>2</td>
<td>2</td>
<td>54.7</td>
<td>64.0</td>
<td>32.1</td>
<td>32.2</td>
<td>0.765</td>
</tr>
<tr>
<td>9</td>
<td>Dipterocarpaceae</td>
<td>33</td>
<td>23</td>
<td>13.2</td>
<td>172.0</td>
<td>10.3</td>
<td>75.0</td>
<td>0.644</td>
</tr>
</tbody>
</table>

|            |                |         |          |       |       |       |       |       |
|            | *Anisoptera laevis* Ridl. | 1       | 76.0    | 76.0   | 37.8  | 37.8  | 0.666 |
|            | *Anisoptera* sp | 2       | 67.3    | 110.0  | 29.3  | 36.9  | 0.646 |
|            | *Dipterocarpus gracilis* Blume | 2       | 73.5    | 106.7  | 30.0  | 44.6  | 0.660 |
|            | *Dipterocarpus hasseltii* Blume | 1       | 32.3    | 32.3   | 28.9  | 28.9  | 0.730 |
|            | *Dipterocarpus stellatus* Vesque | 1       | 45.0    | 45.0   | 31.8  | 31.8  | 1.372 |
|            | *Dryobalanops beccarii* Dyer | 1       | 126.0   | 126.0  | 41.9  | 41.9  | 0.714 |
|            | *Hopea dyeri* F. Heim | 1       | 13.2    | 13.2   | 10.3  | 10.3  | 0.630 |
|            | *Shorea atrinervosa* Symington | 1       | 95.3    | 95.3   | 39.9  | 39.9  | 0.530 |
|            | *Shorea bracteolata* Dyer | 2       | 81.5    | 93.7   | 45.8  | 50.0  | 0.525 |
|            | *Shorea dasypylly* Foxw. | 1       | 53.0    | 53.0   | 27.8  | 27.8  | 0.550 |
|            | *Shorea jochoensis* Foxw. | 1       | 22.0    | 22.0   | 16.4  | 16.4  | 0.400 |
|            | *Shorea laevoifolia* (Parijs) Endert | 2       | 71.0    | 107.0  | 31.7  | 47.9  | 0.910 |
|            | *Shorea lamellata* Foxw. | 1       | 82.7    | 82.7   | 29.6  | 29.6  | 0.660 |
|            | *Shorea leprosula* Miq. | 2       | 81.5    | 103.0  | 34.2  | 42.5  | 0.535 |
|            | *Shorea macrophylla* (de Vriese) | 1       | 96.2    | 96.2   | 36.6  | 36.6  | 0.490 |
|            | P.S.Ashton       |          |          |       |       |       |       |       |
|            | *Shorea parvifolia* Dyer | 2       | 38.6    | 65.1   | 32.3  | 34.4  | 0.420 |
|            | *Shorea pauciflora* King | 1       | 91.0    | 91.0   | 46.6  | 46.6  | 0.701 |
|            | *Shorea quadrirhervis* Slooten | 2       | 15.4    | 83.3   | 12.4  | 38.8  | 0.621 |
|            | *Shorea scabrida* Symington | 3       | 33.0    | 68.8   | 24.7  | 36.6  | 0.641 |
|            | *Shorea smithiana* Symington | 1       | 50.5    | 50.5   | 30.6  | 30.6  | 0.475 |
|            | *Shorea sp* | 2       | 58.4    | 87.7   | 18.1  | 42.3  | 0.745 |
|            | *Shorea virescens* Parijs | 1       | 172.0   | 172.0  | 75.0  | 75.0  | 0.588 |
|            | *Vatica rassak* Blume | 1       | 36.2    | 36.2   | 33.2  | 33.2  | 0.700 |
| 10 | Ebenaceae         | 4       | 3       | 19.2   | 54.0  | 16.8  | 23.7  | 0.702 |
| 11 | Euphorbiaceae     | 3       | 3       | 24.0   | 59.7  | 19.9  | 33.4  | 0.494 |
| 12 | Fabaceae          | 3       | 3       | 48.6   | 104.5 | 27.6  | 52.0  | 0.778 |
| 13 | Gutiferae         | 2       | 2       | 27.4   | 65.0  | 20.0  | 26.8  | 0.530 |
| 14 | Icacinaceae       | 1       | 1       | 26.0   | 26.0  | 15.6  | 15.6  | 0.520 |
| 15 | Lauraceae         | 3       | 2       | 18.3   | 54.3  | 13.0  | 18.3  | 0.691 |
| 16 | Lecythidaceae     | 1       | 1       | 29.0   | 29.0  | 21.8  | 21.8  | 0.487 |
| 17 | Lythraceae        | 1       | 1       | 21.2   | 21.2  | 17.5  | 17.5  | 0.360 |
| 18 | Moraceae          | 3       | 3       | 19.0   | 63.0  | 21.5  | 32.6  | 0.648 |
| 19 | Myristicaceae     | 3       | 2       | 13.1   | 71.1  | 11.3  | 32.4  | 0.603 |
| 20 | Myrtaceae         | 5       | 2       | 21.0   | 66.0  | 22.2  | 37.7  | 0.776 |
| 21 | Polygonaceae      | 1       | 1       | 17.2   | 17.2  | 14.3  | 14.3  | 0.770 |
| 22 | Rubiaceae         | 3       | 3       | 16.0   | 43.0  | 16.1  | 32.1  | 0.726 |
| 23 | Sapindaceae       | 3       | 3       | 24.5   | 60.3  | 16.0  | 31.8  | 0.870 |
| 24 | Sapotaceae        | 3       | 3       | 14.0   | 37.0  | 14.2  | 33.2  | 0.652 |
| 25 | Solanaceae        | 1       | 1       | 74.5   | 74.5  | 36.6  | 36.6  | 0.930 |
| 26 | Sterculiaceae     | 3       | 2       | 28.0   | 123.8 | 26.8  | 62.5  | 0.628 |
| 27 | Tetramelaceae     | 1       | 1       | 93.4   | 93.4  | 41.1  | 41.1  | 0.380 |

| 108 | 80 | 13.1 | 172.0 | 10.3 | 75 | 0.642 |
Table 2. Parameter estimates and indicators of model fit of the log-transformed AGB equations.

Values in parentheses are standard errors of parameter estimates.

<table>
<thead>
<tr>
<th>Model ID</th>
<th>Linear model form</th>
<th>Parameter estimates</th>
<th>n</th>
<th>REst</th>
<th>Adj. $R^2$</th>
<th>RMSE</th>
<th>AICc</th>
</tr>
</thead>
<tbody>
<tr>
<td>LN D1</td>
<td>$a' + b'(LN D)$</td>
<td>$(2.533, 0.241)$</td>
<td>108</td>
<td>1.037</td>
<td>0.940</td>
<td>0.385</td>
<td>104.7</td>
</tr>
<tr>
<td>LN D2</td>
<td>$a' + b'(LN D) + c'(LN D)^2 + d'(LN D)^3$</td>
<td>$(2.726, 0.122)$, $(0.094, 0.104)$, $(0.271, 0.141)$</td>
<td>108</td>
<td>1.071</td>
<td>0.941</td>
<td>0.382</td>
<td>105.2</td>
</tr>
<tr>
<td>DH3</td>
<td>$a' + b'(LN D) + c'H$</td>
<td>$(2.268, 0.215)$, $(0.483, 0.200)$</td>
<td>108</td>
<td>1.021</td>
<td>0.943</td>
<td>0.377</td>
<td>101.1</td>
</tr>
<tr>
<td>DH4</td>
<td>$a' + b'(LN D^2H)$</td>
<td>$(0.986, 0.024)$</td>
<td>108</td>
<td>1.010</td>
<td>0.940</td>
<td>0.386</td>
<td>105.3</td>
</tr>
<tr>
<td>DĤ5</td>
<td>$a' + b'(LN D) + c'H$</td>
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Appendix 2. Supplementary Materials for Chapter 5

Effect of species grouping and site variables on aboveground biomass models for lowland tropical forests of the Indo-Malay region

Solichin Manuri, Cris Brack, Teddy Rusolono, Fatmi Noor’an, Louis Verchot, Sandhi Imam Maulana, Wahyu Catur Adinugroho, Hery Kurniawan, Dian Wulansih Sukisno, Gita Ardia Kusuma, Arif Budiman, Rahmad Supri Angono, Chairil Anwar Siregar, Onrizal Onrizal, Dhany Yuniati, Emma Soraya

Appendix S1. Additional and detailed methods of destructive sampling and literature review to collecting AGB datasets

Destructive sampling

Three datasets were produced from our direct measurements in timber concessions in Malinau and Bulungan in East Kalimantan and Kapuas Hulu in West Kalimantan between March – November 2012. We felled a total of 68 trees from the current-year allocated cutting blocks. Trees were randomly selected to represent diameter classes. We excluded trees that their canopy were strongly affected by previous timber felling or clearing for road development activities. Before the felling, we measured D at 1.3 m from the ground or at 20 cm above tree buttress. All trees were felled and fractioned into tree compartments: stems, branches, twigs and leaves. All small stems and branches (D≤30 cm), twigs and leaves were weighed in the field using OCS L Crane digital scales with capacity of 100 kg and 50 kg. We estimated the volume of large stems and branches (D>30 cm) using Smalian formula. Heights were measured using cloth tapes after tree felling, giving a relatively accurate measurement than a standing tree measurement.

Samples of tree compartments (disc or wedge-shaped samples for stems and branches) were collected and weighted, before being packed and transported to the nearest wood laboratories (i.e. Mulawarman University in East Kalimantan and Tanjungpura University in West Kalimantan) for dry weight and specific gravity analysis. G was calculated by dividing wood sample dry weight with green volume (in gr.cm⁻³). Samples were dried in ovens at a temperature of 80° C or 105° C until achieving constant dry
weights. The laboratory of Tanjungpura University measured the green wood volume of the sample using the water displacement method while the lab of Mulawarman University measured the volume of cube-shaped samples. Leaf voucher specimens were collected and shipped to the Research Center for Biology, Indonesian Institute of Sciences (LIPI) for species identification.

A total of 68 sample data were collected from destructive harvesting in East and West Kalimantan (Table 1). The largest tree had a diameter of 172 cm, a total height of 75 m, and AGB of 45,947 kg. The dataset consisted of 36 genera from 22 families. Twenty-five percent of total felled trees were Dipterocarpaceae.

**Literature review**

To extend the coverage of our study, we systematically reviewed existing studies in Indonesia and Malaysia from published and unpublished literatures. A recent study on pantropical biomass equation included tree biomass data mostly from published studies, including research originated from western Indonesia and Malaysia (Chave et al., 2014). In addition, Krisnawati et al. (2012) and Anitha et al. (2015) systematically compiled lists and reviewed existing tree biomass studies across Indonesia, which were mostly from grey literature. Based on the lists of the studies, we compiled tree biomass data from lowland natural forests. In the case where the AGB data was not attached, we contacted the authors for data request.

We were able to compile raw datasets only from 22 studies out of 59 studies that were identified to be relevant to our study, which were mostly in the grey literature (Table S3 and S4). The reasons included the absence of destructive sampling method, incomplete AGB data and using small diameters of sample trees, which less than 5 cm. Nine studies used the same datasets from other five studies.

**Appendix S2.** The output for the heteroscedasticity tests. * is significant p-value, which means rejecting H0 of homoscedasticity

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<td>Abridged White</td>
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<td>&lt;.0001*</td>
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### Appendix S3. Linear model description and parameter estimates for tree AGB estimation.

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<th>RMSE</th>
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<th>Correction Factors</th>
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<td>1201</td>
<td>0.960</td>
<td>0.462</td>
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**Appendix S4. List of local allometric research compiled in this study.**

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<th>Annual Precipitation (P, in mm)</th>
<th>Elevation (in m)</th>
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Appendix S6. Comparison of MRE and MARE between the models back-transformed using MM and REst correction factors

A

B
Appendix S7. Relative error distribution of the developed equations against wood density. Dashed and solid lines are zero and fitted lines, respectively.
Figure SM1. Relationship tree height and DBH of PSP data showed a low precision of tree height measurement in the plots. The green line was the Weibull model line. The asterisks were the outliers.
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