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## Tree height integrated into pantropical forest biomass estimates

T. R. Feldpausch<sup>1</sup>, J. Lloyd<sup>1,2</sup>, S. L. Lewis<sup>1,3</sup>, R. J. W. Brienen<sup>1</sup>, E. Gloor<sup>1</sup>, A. Monteagudo Mendoza<sup>4</sup>, G. Lopez-Gonzalez<sup>1</sup>, L. Banin<sup>1,5</sup>, K. Abu Salim<sup>6</sup>, K. Affum-Baffoe<sup>7</sup>, M. Alexiades<sup>8</sup>, S. Almeida<sup>9,†</sup>, I. Amaral<sup>10</sup>, A. Andrade<sup>10</sup>, L. E. O. C. Aragão<sup>11</sup>, A. Araujo Murakami<sup>12</sup>, E. J. M. M. Arets<sup>13</sup>, L. Arroyo<sup>12</sup>, G. A. Aymard C.<sup>14</sup>, T. R. Baker<sup>1</sup>, O. S. Bánki<sup>15</sup>, N. J. Berry<sup>16</sup>, N. Cardozo<sup>17</sup>, J. Chave<sup>18</sup>, J. A. Comiskey<sup>19</sup>, E. Alvarez<sup>20</sup>, A. de Oliveira<sup>10</sup>, A. Di Fiore<sup>21</sup>, G. Djagbletey<sup>22</sup>, T. F. Domingues<sup>23</sup>, T. L. Erwin<sup>24</sup>, P. M. Fearnside<sup>10</sup>, M. B. França<sup>10</sup>, M. A. Freitas<sup>9</sup>, N. Higuchi<sup>10</sup>, E. Honorio C.<sup>1</sup>, Y. Iida<sup>25</sup>, E. Jiménez<sup>26</sup>, A. R. Kassim<sup>27</sup>, T. J. Killeen<sup>28</sup>, W. F. Laurance<sup>29</sup>, J. C. Lovett<sup>30</sup>, Y. Malhi<sup>31</sup>, B. S. Marimon<sup>32</sup>, B. H. Marimon-Junior<sup>32</sup>, E. Lenza<sup>32</sup>, A. R. Marshall<sup>33,34</sup>, C. Mendoza<sup>35</sup>, D. J. Metcalfe<sup>36</sup>, E. T. A. Mitchard<sup>37</sup>, D. A. Neill<sup>38</sup>, B. W. Nelson<sup>39</sup>, R. Nilus<sup>40</sup>, E. M. Nogueira<sup>10</sup>, A. Parada<sup>12</sup>, K. S.-H. Peh<sup>41</sup>, A. Pena Cruz<sup>42</sup>, M. C. Peñuela<sup>26</sup>, N. C. A. Pitman<sup>43</sup>, A. Prieto<sup>44</sup>, C. A. Quesada<sup>10</sup>, F. Ramírez<sup>17</sup>, H. Ramírez-Angulo<sup>45</sup>, J. M. Reitsma<sup>46</sup>, A. Rudas<sup>47</sup>, G. Saiz<sup>48</sup>, R. P. Salomão<sup>9</sup>, M. Schwarz<sup>1</sup>, N. Silva<sup>49</sup>, J. E. Silva-Espejo<sup>50</sup>, M. Silveira<sup>51</sup>, B. Sonké<sup>52</sup>, J. Stropp<sup>53</sup>, H. E. Taedoum<sup>52</sup>, S. Tan<sup>54</sup>, H. ter Steege<sup>55</sup>, J. Terborgh<sup>43</sup>, M. Torello-Raventos<sup>2</sup>, G. M. F. van der Heijden<sup>56,57</sup>, R. Vásquez<sup>42</sup>, E. Vilanova<sup>58</sup>, V. A. Vos<sup>59,60</sup>, L. White<sup>61,62,63</sup>, S. Willcock<sup>1</sup>, H. Woell<sup>64</sup>, and O. L. Phillips<sup>1</sup>

<sup>1</sup>School of Geography, University of Leeds, Leeds, LS2 9JT, UK

<sup>2</sup>School of Earth and Environmental Science, James Cook University, Cairns, Qld 4870, Australia

<sup>3</sup>Department of Geography, University College London, UK

<sup>4</sup>RAINFOR/Jardín Botánico de Missouri, Peru

<sup>5</sup>School of Environmental Sciences, University of Ulster, Cromore Road, Coleraine, BT52 1SA, UK

<sup>6</sup>Biology Programme, Faculty of Science, Universiti Brunei Darussalam, Tungku Link Road BE1410, Brunei Darussalam

<sup>7</sup>Resource Management Support Centre, Forestry Commission of Ghana, P.O. Box 1457, Kumasi, Ghana

<sup>8</sup>New York Botanical Garden, New York City, New York 10458, USA

<sup>9</sup>Museu Paraense Emilio Goeldi, Av. Magalhães Barata, 376, São Braz, 66040-170, Belém, PA, Brazil

<sup>10</sup>National Institute for Research in Amazonia (INPA), C.P. 478, Manaus, Amazonas, 69011-970, Brazil

<sup>11</sup>Geography, College of Life and Environmental Sciences, University of Exeter, Rennes Drive, Exeter, EX4 4RJ, UK

<sup>12</sup>Museo de Historia Natural Noel Kempff Mercado, Universidad Autonoma Gabriel Rene Moreno, Casilla 2489, Av. Irala 565, Santa Cruz, Bolivia

<sup>13</sup>Centre for Ecosystem Studies, Alterra, Wageningen University and Research Centre, P.O. Box 47, 6700 AA Wageningen, The Netherlands

<sup>14</sup>UNELLEZ-Guanare, Programa de Ciencias del Agro y el Mar, Herbario Universitario (PORT), Mesa de Cavacas, Estado Portuguesa 3350, Venezuela

<sup>15</sup>IBED, University of Amsterdam, POSTBUS 94248, 1090 GE Amsterdam, The Netherlands

<sup>16</sup>School of GeoSciences, University of Edinburgh, Edinburgh, EH9 3JN, UK

<sup>17</sup>Universidad Nacional de la Amazonía Peruana, Iquitos, Loreto, Perú

<sup>18</sup>Université Paul Sabatier, Laboratoire EDB, bâtiment 4R3, 31062 Toulouse, France

<sup>19</sup>Mid-Atlantic Network, Inventory and Monitoring Program, National Park Service, 120 Chatham Lane, Fredericksburg, VA 22405, USA

<sup>20</sup>Jardin Botanico de Medellin, Colombia

<sup>21</sup>Department of Anthropology, University of Texas at Austin, 1 University Station, SAC 5.150 Mailcode C3200, Austin, TX 78712, USA

<sup>22</sup>Ecosystem and Climate Change Division (ESCCD) Forestry Research Institute of Ghana (FORIG), U.P. Box 63, KNUST-Kumasi, Ghana

<sup>23</sup>Instituto de Astronomia, Geofísica e Ciências Atmosféricas, Universidade de São Paulo, 05508-090, Brazil

<sup>24</sup>Department of Entomology, Smithsonian Institute, P.O. Box 37012, MRC 187, Washington, DC 20013-7012, USA

<sup>25</sup>Graduate School of Environmental Science, Hokkaido University, Sapporo, 060-0810, Japan

- <sup>26</sup>Universidad Nacional de Colombia, Kilómetro 2 Via Tarapacá, Leticia, Amazonas, Colombia
- <sup>27</sup>Forest Research Institute Malaysia (FRIM), 52109 Kepong, Selangor Darul Ehsan, Malaysia
- <sup>28</sup>Conservation International, 2011 Crystal Drive, Suite 500, Arlington, VA 22202, USA
- <sup>29</sup>Centre for Tropical Environmental and Sustainability Science (TESS) and School of Marine and Tropical Biology, James Cook University, Cairns, Queensland 4878, Australia
- <sup>30</sup>CSTM, University of Twente, P.O. Box 217, 7500 AE Enschede, The Netherlands
- <sup>31</sup>Environmental Change Institute, School of Geography and the Environment, University of Oxford, UK
- <sup>32</sup>Universidade do Estado de Mato Grosso, Campus de Nova Xavantina, Caixa Postal 08, 78.690-000, Nova Xavantina, MT, Brazil
- <sup>33</sup>CIRCLE, Environment Department, University of York, York, UK
- <sup>34</sup>Flamingo Land Ltd., Kirby Misperton, YO17 6UX, UK
- <sup>35</sup>FOMABO (Manejo Forestal en las Tierras Tropicales de Bolivia), Sacta, Bolivia
- <sup>36</sup>CSIRO Ecosystem Sciences, Tropical forest Research Centre, P.O. Box 780, Atherton, QLD 4883, Australia
- <sup>37</sup>School of GeoSciences, University of Edinburgh, Drummond St, Edinburgh, EH8 9XP, UK
- <sup>38</sup>Universidad Estatal Amazónica, Facultad de Ingeniería Ambiental, Paso lateral km 2 1/2 via Napo, Puyo, Pastaza, Ecuador
- <sup>39</sup>Environmental Dynamics Department, National Institute for Research in Amazonia (INPA), C.P. 478, Manaus, Amazonas, CEP 69011-970, Brazil
- <sup>40</sup>Sabah Forestry Department, Forest Research Centre, Sandakan, 90715, Malaysia
- <sup>41</sup>Department of Zoology, University of Cambridge, Downing Street, CB2 3EJ, UK
- <sup>42</sup>Jardín Botánico de Missouri, Oxapampa, Pasco, Peru
- <sup>43</sup>Center for Tropical Conservation, Duke University, Box 90381, Durham, NC 27708, USA
- <sup>44</sup>Instituto de Ciencias Naturales, Universidad Nacional de Colombia
- <sup>45</sup>Universidad de Los Andes, Facultad de Ciencias Forestales y Ambientales, Mérida, Venezuela
- <sup>46</sup>Bureau Waardenburg bv, P.O. Box 365, 4100 AJ Culemborg, The Netherlands
- <sup>47</sup>Instituto de Ciencias Naturales, Universidad Nacional de Colombia, Colombia
- <sup>48</sup>Karlsruhe Institute of Technology, Garmisch-Partenkirchen, Germany
- <sup>49</sup>Universidade Federal Rural da Amazônia (UFRA), Brazil
- <sup>50</sup>Universidad Nacional San Antonio Abad del Cusco, Av. de la Cultura No. 733. Cusco, Peru
- <sup>51</sup>Universidade Federal do Acre, Rio Branco AC 69910-900, Brazil
- <sup>52</sup>Department of Biology, University of Yaoundé I, P.O. Box 047, Yaoundé, Cameroon
- <sup>53</sup>Institute for Environment and Sustainability, European Commission, DG Joint Research Centre, Via Enrico Fermi 274, 21010 Ispra, Italy
- <sup>54</sup>Sarawak Forestry Corporation, Kuching, Sarawak, Malaysia
- <sup>55</sup>Naturalis Biodiversity Center, P.O. Box, 2300 RA, Leiden, The Netherlands
- <sup>56</sup>Department of Biological Sciences, University of Wisconsin-Milwaukee, Milwaukee, Wisconsin, P.O. Box 413, 53201, USA
- <sup>57</sup>Smithsonian Tropical Research Institute, Apartado 2072, Balboa, Republic of Panama
- <sup>58</sup>Instituto de Investigaciones para el Desarrollo Forestal (INDEFOR), Universidad de Los Andes, Mérida, Venezuela
- <sup>59</sup>Programa Manejo de Bosques de la Amazonía Boliviana (PROMAB), Casilla 107, Riberalta, Beni, Bolivia
- <sup>60</sup>Universidad Autónoma del Beni, Campus Universitario, Av. Ejército Nacional, final, Riberalta, Beni, Bolivia
- <sup>61</sup>Agence National des Parcs Nationaux, Libreville, Gabon
- <sup>62</sup>Institut de Recherche en Ecologie Tropicale (CENAREST), Gabon
- <sup>63</sup>School of Natural Sciences, University of Stirling, UK
- <sup>64</sup>Sommersbergsestr. 291, 8990 Bad Aussee, Austria
- †deceased

*Correspondence to:* T. R. Feldpausch (t.r.feldpausch@leeds.ac.uk)

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**Abstract.** Aboveground tropical tree biomass and carbon storage estimates commonly ignore tree height ( $H$ ). We estimate the effect of incorporating  $H$  on tropics-wide forest biomass estimates in 327 plots across four continents using 42 656  $H$  and diameter measurements and harvested trees from 20 sites to answer the following questions:

1. What are the best  $H$ -model form and geographic units to include in biomass models to minimise site-level uncertainty in estimates of destructive biomass?
2. To what extent does including  $H$  estimates derived in (1) reduce uncertainty in biomass estimates across all 327 plots?
3. What effect does accounting for  $H$  have on plot- and continental-scale forest biomass estimates?

The mean relative error in biomass estimates of destructively harvested trees when including  $H$  (mean 0.06), was half that when excluding  $H$  (mean 0.13). Power- and Weibull- $H$  asymptotic models provided the greatest reduction in uncertainty, with regional Weibull- $H$  models preferred because they reduce uncertainty in smaller-diameter classes ( $\leq 40$  cm  $D$ ) that store about one-third of biomass per hectare in most forests. Propagating the relationships from destructively harvested tree biomass to each of the 327 plots from across the tropics shows that including  $H$  reduces errors from  $41.8 \text{ Mg ha}^{-1}$  (range 6.6 to  $112.4$ ) to  $8.0 \text{ Mg ha}^{-1}$  ( $-2.5$  to  $23.0$ ). For all plots, aboveground live biomass was  $-52.2 \text{ Mg ha}^{-1}$  ( $-82.0$  to  $-20.3$  bootstrapped 95 % CI), or 13 %, lower when including  $H$  estimates, with the greatest relative reductions in estimated biomass in forests of the Brazilian Shield, east Africa, and Australia, and relatively little change in the Guyana Shield, central Africa and southeast Asia. Appreciable different stand structure was observed among regions across the tropical continents, with some storing significantly more biomass in small diameter stems, which affects selection of the best height models to reduce uncertainty and biomass reductions due to  $H$ . After accounting for variation in  $H$ , total biomass per hectare is greatest in Australia, the Guyana Shield, Asia, central and east Africa, and lowest in east-central Amazonia, W. Africa, W. Amazonia, and the Brazilian Shield (descending order). Thus, if tropical forests span 1668 million  $\text{km}^2$  and store  $285 \text{ Pg C}$  (estimate including  $H$ ), then applying our regional relationships implies that carbon storage is overestimated by  $35 \text{ Pg C}$  (31–39 bootstrapped 95 % CI) if  $H$  is ignored, assuming that the sampled plots are an unbiased statistical representation of all tropical forest in terms of biomass and height factors. Our results show that tree  $H$  is an important allometric factor that needs to be included in future forest biomass estimates to reduce error in estimates of tropical carbon stocks and emissions due to deforestation.

## 1 Introduction

Accurate estimates of tropical tree biomass are essential to determine geographic patterns in carbon stocks, the magnitudes of fluxes due to land-use change, and to quantify avoided carbon emissions via mechanisms such as REDD+ (Reducing Emissions from Deforestation and forest Degradation). Global estimates of tree carbon in tropical forests vary between 40 to 50 % of the total carbon in terrestrial vegetation (Watson et al., 2000; Kindermann et al., 2008), indicating considerable uncertainty. Such uncertainty is the consequence of linking individual tree measurements to large-scale patterns of carbon distribution, as well as the definition as to what constitutes “forest”.

The estimation of tree-, plot-, regional-, or global-level mass of tropical trees requires first harvesting and weighing trees (Fittkau and Klinge, 1973), and subsequently estimating biomass on a larger population by measuring tree stem diameter ( $D$ ) and converting  $D$  to biomass based on allometric equations developed using the destructive harvest data (Brown et al., 1989; Overman et al., 1994; Ogawa et al., 1965). Biomass can also be estimated using active (e.g. radar and from light detection and ranging (LiDAR) remote sensing-based methods (e.g. Drake et al., 2002; Mitchard et al., 2011; Morel et al., 2011; Saatchi et al., 2011). Calibration of remotely-sensed biomass requires ground-based biomass estimates derived from stem diameter measurements and allometric equations (either calibrated “on-site” or from the literature to “ground-truth” data) (e.g. Lucas et al., 2002; Mitchard et al., 2009). Both ground- and spaceborne biomass estimates have uncertainty, and scaling from plots to regions introduces additional uncertainty. For example, carbon stock estimates for Amazonia based on spatial interpolations of direct measurements, relationships to climatic variables, and remote sensing data have an uncertainty of  $\pm 20$  % (Saatchi et al., 2007; Houghton, 2010). It is therefore necessary to generate accurate allometric models that reduce uncertainty in tree and plot-level estimates in order that remote sensing methods can provide biomass estimates more accurately over large spatial scales.

The most widely used allometric equation for tropical forest biomass ground-based estimates and validation of satellite-based estimates is based on  $\sim 1300$  harvested and weighed moist forest trees (Chave et al., 2005; Chambers et al., 2001), and include no destructive biomass samples from Africa. The small sample size and geographical limits of this dataset are due to the tremendous efforts required to work in remote forests dissecting and determining mass of trees, some of which may weigh over  $20 \text{ Mg}$ . Such a lack of data for calibration may bias estimates of carbon stocks in tropical forests (Houghton et al., 2000; Malhi et al., 2004). One major uncertainty in carbon stock estimates is related to architectural differences in tropical trees. For example, across plots, regions and continents there is significant and systematic variation in tropical forest tree height ( $H$ ) for a given

diameter (Feldpausch et al., 2011; Banin et al., 2012). This applies both to multispecies equations and to those restricted to individual species (Nogueira et al., 2008b). Hence, accounting for differences in  $H:D$  allometry may reduce uncertainty associated with tropical forest biomass estimates from plot to pantropical scales.

Improving the accuracy of such estimates is important as almost all tropical forest regions of the world are currently undergoing major changes which alter biomass and carbon stocks. For example, it is now apparent that many remaining intact tropical forests are not at carbon equilibrium, but rather are accumulating biomass (Lewis et al., 2009; Phillips et al., 1998). An accurate quantification of this apparent pantropical sink hinges on, amongst other factors, unbiased biomass estimates for individual trees. Similarly, quantifying changes in global carbon stocks and emissions where much of the active deforestation occurs (e.g. arc of deforestation in Brazil, INPE, 2009) can be overestimated when ignoring the effect of tree  $H$  on biomass estimates, because trees tend to be shorter for a given  $D$  in transitional forests where the most active deforestation fronts often occur (Nogueira et al., 2008b). As a result, carbon emissions from tropical deforestation (INPE, 2009) may be biased. More generally, incorporation of  $H$  in biomass estimates may help to account for variation in carbon stocks and could represent potential changes in calculated carbon emissions under deforestation (INPE, 2009), selective logging (Pinard and Putz, 1996; Feldpausch et al., 2005), sinks caused by forest regrowth (Uhl and Jordan, 1984; Feldpausch et al., 2004) and carbon valuation under REDD+ (Aragao and Shimabukuro, 2010; Asner et al., 2010; Gibbs et al., 2007).

Along with wood specific gravity ( $\rho_W$ ) (Baker et al., 2004b), tree  $H$  has already been incorporated into some regional and pantropical forest biomass allometric models (Brown et al., 1989; Chave et al., 2005). Biomass estimation is then based on a four-step process:

1. measure individual tree  $D$ ;
2. estimate  $\rho_W$  at the finest taxonomic level available from  $\rho_W$  databases (Chave et al., 2009; Fearnside, 1997);
3. measure or estimate  $H$  from allometric models based on the relationship between  $H$  and  $D$  alone (Brown et al., 1989) or with additional forest structure and climate variables to parameterise  $H$  estimates (Feldpausch et al., 2011);
4. use these data to calculate biomass for individual trees from allometric equations based on  $D$ ,  $\rho_W$ , and  $H$ .

Despite the early recognition of the importance of  $H$  in biomass estimates (Crow, 1978; Ogawa et al., 1965), in practice  $H$  has less frequently been accounted for in pantropical biomass estimates due to lack of data. Nevertheless, where data have been available, inclusion of  $H$  has been shown to appreciably reduce errors in the estimation of destructively

sampled biomass. For example, the standard error in estimating stand biomass for a destructively sampled dataset of trees  $\geq 10$  mm  $D$  was 12.5 % if an equation including  $H$  was used, but 19.5 % when an equation derived without  $H$  (but calibrated on the same dataset) was applied (Chave et al., 2005). This same study showed that  $H$  was more important than a precipitation-based forest categorisation (dry, moist, wet) in more accurately estimating biomass.

Thus, allometric model choice, rather than sampling error or plot size, may then be the most important source of error in estimating biomass (Chave et al., 2004). With the pantropical destructive biomass dataset sample size restricted by sampling cost and effort,  $H$  estimates from regional or continental-scale  $H:D$  models may provide a simple way to improve aboveground biomass estimates. Selection of the “best” model form to represent  $H$  in biomass models is not straightforward, however, with numerous statistical forms, geographical and environmental parameterisations, and separations by growth form having been tested (e.g. Fang and Bailey, 1998; Feldpausch et al., 2011; Rich et al., 1986; Thomas and Bazzaz, 1999; Banin et al., 2012). In a global tropical analysis using multi-level models to examine the relationship between  $H$  and diameter, Feldpausch et al. (2011) grouped plots into regions and found that after taking into account the effects of environment (annual precipitation coefficient of variation, dry season length, and mean annual air temperature) and forest basal area, there were two main regional groups differing in their  $H:D$  relationships. Forests in Asia, east, west, and central Africa and the Guyana Shield are all similar in their  $H:D$  allometry, but with trees in the forests of much of the Amazon Basin and tropical Australia typically being shorter at any given diameter. Using a similar dataset, but excluding drier forests, Banin et al. (2012), conducted a continental-scale analysis and showed significantly different asymptotic maximum  $H$  and allometry among continents after accounting for differences in environment, forest structure and wood specific gravity. These results suggest that either continental or sub-continental geographic  $H:D$  patterns may, in addition to model form, be important in reducing error in biomass estimates.

Here, using a large dataset of tree  $H$ , destructive biomass data (i.e. actual tree biomass is known) and pantropical permanent plot data (where information on  $H$  and  $D$  is known, but not the true biomass of a plot), we provide a first pantropical evaluation of the effects of  $H$  on biomass estimates, including by geographical location (plot, region, and continent). Specifically, we address the following questions:

1. Which is the best  $H$ -model form and geographic scale for inclusion in biomass models to minimise site-level uncertainty in estimates of *destructive* biomass?
2. What is the reduction in uncertainty in plot-level biomass estimates based on census data from *permanent plots* across the tropics when including  $H$ ?

3. How does inclusion of  $H$  in biomass estimation protocols modify plot- and continental-level biomass estimates across the tropics?

## 2 Methods

We developed aboveground forest biomass estimates and evaluated biases using tree diameter ( $D$ ), wood specific gravity ( $\rho_w$ ) and tree height  $H$  based on destructive sampling and permanent-plot census data. This assessment was completed through the following process: (1) compiled pantropical destructive biomass, tree  $H$ , and permanent sample plot census data; (2) computed new pantropical biomass models that included or excluded tree  $H$ ; (3) developed models to estimate  $H$  from  $D$ ; (4) using the destructive data, evaluated the effect of inclusion or exclusion of actual or simulated  $H$  in biomass estimates; (5) applied the new biomass models and error estimate from destructive biomass estimates to pantropical plot-based tree census data to (6) determine how biomass estimates change when including  $H$ ; (7) determined the error associated with biomass estimates for pantropical permanent plots; and (8) assessed regional and continental changes in biomass estimates due to  $H$  integration in biomass estimates.

Destructive biomass data were compiled from published and non-published data from 20 plots in nine countries (described below).  $H$  and  $D$  measurements are identical to those in Feldpausch et al. (2011). The tree census data reported here (Fig. 1; Supplement Table S1) are from permanent sample plots, primarily from the RAINFOR (Peacock et al., 2007; Baker et al., 2004a; Phillips et al., 2009) and AfriTRON (Lewis et al., 2009) networks across South America and Africa, respectively, the TROBIT network of forest-savanna transition sites (Torello-Raventos et al., 2012), the CSIRO network in Australia (Graham, 2006), and data from Asia (Banin, 2010) curated in the [www.forestplots.net](http://www.forestplots.net) data repository (Lopez-Gonzalez et al., 2011). In addition, for each plot, mean annual precipitation, annual precipitation coefficient of variation, and dry season length were obtained from WorldClim global coverage at 2.5-min resolution based on meteorological station data from 1950–2000 (Hijmans et al., 2005).

### 2.1 The destructive dataset

To determine the efficacy of biomass models to predict biomass, we assembled a destructively sampled tree biomass dataset based on actual cut and weighed tropical forest trees (Chave et al., 2005; Nogueira et al., 2008a; Hozumi et al., 1969; Araújo et al., 1999; Mackensen et al., 2000; Brown et al., 1995; Lescure et al., 1983; Yamakura et al., 1986; Djomo et al., 2010; Henry et al., 2010; Deans et al., 1996; Ebuy et al., 2011; Ketterings et al., 2001; Samalca, 2007). We hereafter refer to this dataset as the “destructive data”. The destructive data are pantropical but with relatively few samples from

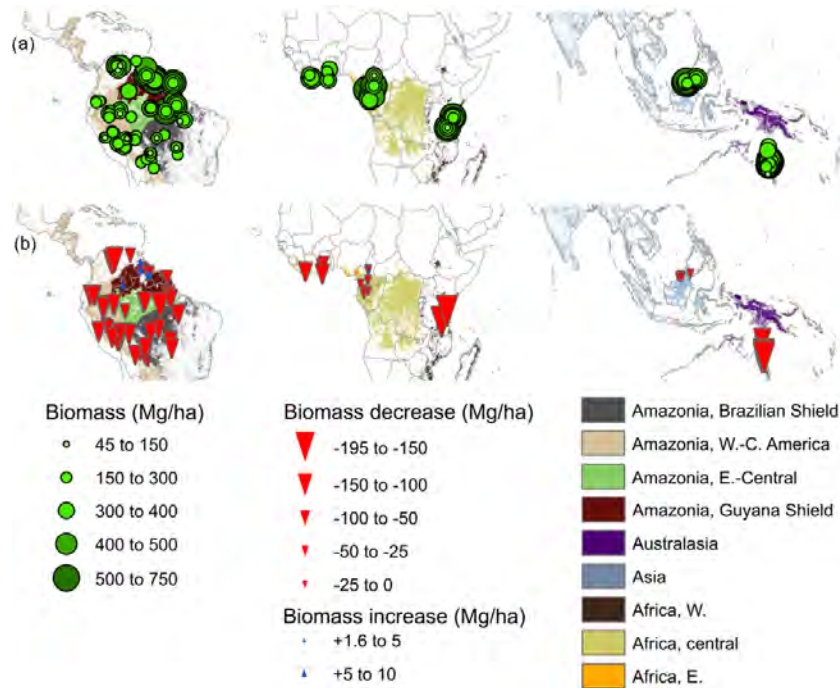
Africa ( $n = 116$ ). The main differences between the dataset used by Chave et al. (2005) and our dataset are that we excluded mangrove and dry forest biomass data from Chave et al. (2005), and we included recently published destructive biomass datasets from Africa (Ghana, the Democratic Republic of Congo, and Cameroon) (Djomo et al., 2010; Henry et al., 2010; Deans et al., 1996; Ebuy et al., 2011), Kalimantan, Indonesia (Samalca, 2007), and Brazil (Nogueira et al., 2008a). To classify sites, climate data for the destructive dataset were extracted from the WorldClim data based on plot coordinates. For the destructive site data, mean annual precipitation ranged from 1520 to 2873 mm, dry season length 0 to 6 months,  $D$  from 1.2 to 1800 mm, and  $H$  from 1.9 to 70.7 m.

### 2.2 Tree height measurements

Tree height ( $H$ ) had been previously measured at many of the permanent census plots from each of the four continents. Methodology and sites are specified in Feldpausch et al. (2011). To summarise the methods, in general a minimum of 50 trees per plot were sampled for  $H$  (total tree  $H$  above the ground) from 100 mm binned diameter classes (i.e. 100 to 200, > 200 to 300, > 300 to 400 mm, and > 400 mm). For some plots every tree was measured for  $H$ . Tree  $H$  was measured using Vertex hypsometers (Vertex Laser VL400 Ultrasonic-Laser Hypsometer III, Haglöf Sweden), laser range-finders (e.g. LaserAce 300, LaserAce Hypsometer, Leica Disto-5), mechanical clinometers, physically climbing the tree with a tape measure, or by destructive methods. To examine how tree architectural properties related to stem  $D$  independent of external factors such as trees damaged by treefalls, trees known to be broken or with substantial crown damage were excluded from analyses. A recent comparison of ground-based methods found that trigonometric methods resulted in no systematic bias (non-laser method), or resulted in a small underestimate of actual tree height (ground laser-based methods) compared to heights measured from an observational tower (Larjavaara and Muller-Landau, 2012). A second study reported a Pearson correlation of  $r^2 = 0.977$  for trigonometry versus laser rangefinder estimates of height (Marshall et al., 2012).

### 2.3 Biomass calculations

Aboveground biomass of trees for each destructively sampled site or permanent sample plot was calculated from a combination of variables. Wood specific gravity,  $\rho_w$ , was extracted from a global database (<http://datadryad.org/handle/10255/dryad.235>; Zanne et al., 2010; Chave et al., 2009). Where species-specific values were unavailable, we applied genus-level values. Likewise where genus-level values were missing, we applied family-level values. Where tree identification was lacking, we applied the mean  $\rho_w$  from all stems in the plot. Based on the moist forest biomass model form



**Fig. 1.** Location of the pantropical permanent plots, including (a) biomass stocks ( $\text{Mg ha}^{-1}$ ), and (b) change in biomass ( $\text{Mg ha}^{-1}$ ) due to inclusion of  $H$  in biomass estimates ( $B$ ) (relative to exclusion of  $H$ ) for forests ( $B_H - B_{\text{No-Ht.}}$ ) in Africa, Asia, Australia, and South America. Symbols indicate an increase (blue) or decrease (red) in biomass estimates after including  $H$  compared to our biomass model Eq. (1) that excludes  $H$ . See Supplement Table S1 for plot details. Biomass estimated from the moist forest pantropical models (Table 1) based on tree diameter and wood density, and  $H$  (where applicable), with  $H$  estimated from Weibull region-specific tree  $H$  models (Eq. 5) based on the pantropical tree  $H$ - $D$  database shown in Feldpausch et al. (2011). Coloured shading indicates forest cover and different regions used in Figs. 3 and 4.

proposed by Chave et al. (2005), we developed bootstrapped biomass model (1), as described below, to estimate biomass ( $B$ ) based on just the measured diameter ( $D$ ) and estimated  $\rho_W$  (i.e. excluding tree  $H$ ) using the model form:

$$B = \exp \left( a + b \ln(D) + c(\ln(D))^2 - d(\ln(D))^3 + e \ln(\rho_W) \right). \quad (1)$$

Alternatively, using the  $H:D$  database developed by Feldpausch et al. (2011), we inferred  $H$  using a range of  $H:D$  allometric models, and then used that inferred value in bootstrapped biomass model (2) based on the form proposed by Chave et al. (2005) as described below. The model parameterisation, which includes  $H$  in addition to diameter and  $\rho_W$  is:

$$B = \exp(a + b \ln(\rho_W D^2 H)). \quad (2)$$

## 2.4 Biomass error estimation with and without height

From the destructive dataset, we evaluated the ability of a range of models to estimate biomass (kg) from a combination of  $D$  and  $\rho_W$ , or  $D$ ,  $\rho_W$  and  $H$ , also examining error distributions across diameter classes and sites. To develop the

$H:D$  allometric relationships for inclusion in biomass models, we used  $H$  measurements for individual trees made in 283 plots in 22 countries representing 42 656 individual concurrent  $H$  and  $D$  measurements. Because the global destructive tree biomass dataset was small compared to this and with the distribution of trees in the destructive dataset not necessarily similar in biomass/size distribution of a natural forest, we applied a three-step approach to scale biomass estimates and their associated errors from the destructive dataset to permanent plots and landscape.

1. When biomass models included  $H$ , we recomputed the regional and continental  $H$  models of Feldpausch et al. (2011) to test for their efficacy to reduce error in biomass estimates. These  $H$  models were either a non-linear 3-parameter exponential (Pinheiro et al., 1994; Banin et al., 2012) viz:

$$H = a - b(\exp(-cD)), \quad (3)$$

or, a model where  $H$  scales with  $D$  according to a simple power function as in:

$$H = aD^b, \quad (4)$$

or, alternatively a Weibull function (Bailey, 1979), which takes the form of:

$$H = a(1 - \exp(-bD^c)). \quad (5)$$

As there is good evidence of a large difference between different geographical areas in  $H:D$  allometry (Feldpausch et al., 2011; Banin et al., 2012), we derived region- and continent-specific parameterisations for each  $H:D$  equation and report the residual standard error and Akaike Information Criterion for the selected models (Akaike, 1974). We then tested how these parameterisations of  $H$  increased or decreased biomass estimates.

2. To test the effect of the inclusion of  $H$  estimates on biomass estimates, we computed a biomass model of all sites with destructively harvested trees, except the site which we wished to estimate. We then estimated the biomass of the trees in the site that was excluded from the model. We then dropped each individual site until all sites were excluded once from model development. The mean relative error in estimated biomass was calculated for each dropped site, where relative error was represented as:  $(B_P - B_M)/B_M$ , where  $B_P$  is the predicted biomass of a tree (with or without  $H$  model) and  $B_M$  is the biomass measured by destructive sampling of individual trees.
3. To evaluate how the error from the destructive dataset related to the distribution of trees found in pantropical forests, we estimated biomass for 327 plots from the forest permanent-plot database as described above by locale for tree-diameter classes, providing a biomass distribution by diameter class for each geographic locale (note that the destructive data came from “sites” – sample areas that may not have defined boundaries – while the permanent plot data come from defined-area sample “plots”). We then propagated error from Eqs.(1) and (2) from the destructive dataset to each diameter bin by geographical location and reported the mean relative error for each region. The log-transformation of tree  $D$  and biomass data produces a bias in final biomass estimation so that uncorrected biomass estimates are theoretically expected to underestimate the real value (Sprugel, 1983; Baskerville, 1972). This effect can be corrected by multiplying the estimate by a correction factor:

$$C_F = \exp\left(\frac{RSE^2}{2}\right), \quad (6)$$

which is always a number greater than 1, and where RSE is the residual standard error of the regression model.

## 2.5 Permanent plot tree census data

To determine how  $H$  integration alters biomass estimates and affects error in biomass estimates, we compiled a pantropical dataset of permanent sample plots (Supplementary Table S1). All plots occurred in intact (minimal recent direct anthropogenic influence) forest, with a minimum plot size of 0.2 ha (mean = 0.95; max = 9 ha) area using standardised sampling methodologies across all sites. Diameters of all live trees and palms ( $\geq 100$  mm diameter at breast height ( $D$ )) were measured to the nearest 1 mm at 1.3 m above the ground or 0.5 m above any buttresses or stilt-roots following international standards of permanent sampling plot protocol (Phillips et al., 2010). Trees were identified by local botanists. For unknown species, vouchers were collected, later identified and archived.

### 2.5.1 Africa

African permanent sample plots ( $n = 62$ ) were grouped into three geographical regions: western, eastern and central Africa. Measurements were made in western Africa in Ghana and Liberia (Lewis et al., 2009; Feldpausch et al., 2011). Central African sites were sampled in central and southern Cameroon, and Gabon (Lewis et al., 2009; Feldpausch et al., 2011). Eastern African sites were established in the Eastern Arc Mountains of Tanzania (Marshall et al., 2012). The number of months with precipitation  $< 100$  mm per month, based on the estimated average monthly evapotranspiration of a tropical forest (Shuttleworth, 1988) and a widely used index of dry season length (Malhi and Wright, 2004), varies from 1 to 7 months across all sites.

### 2.5.2 Asia

We classified forests in Asia ( $n = 14$ ) as one region for this study, with the division between Asian and Australasian plots according to Lydekker’s line (Lohman et al., 2011). Wet and moist forests were sampled in Brunei and Malaysian Borneo (Banin, 2010; Banin et al., 2012). These sites have zero months with mean precipitation  $< 100$  mm per month.

### 2.5.3 Australasia

Trees were sampled in tropical forest permanent plots ( $n = 26$ ) in northern Australia (Graham, 2006; Torello-Raventos et al., 2012). Precipitation varies over a very short distance from coastal to inland sites, with the dry season length ranging from 4 to 10 months.

### 2.5.4 South America

Tree censuses conducted in plots ( $n = 225$ ) (Baker et al., 2009; Feldpausch et al., 2011; Nogueira et al., 2008b) in South America are grouped here into four regions based on geography and substrate origin (e.g. Fittkau, 1971;



Schobbenhaus and Bellizzia, 2001): Western Amazonia (Colombia, Ecuador and Peru), with soils mostly originating from recently weathered Andean deposits; Southern Amazonia, encompassing the Brazilian Shield (Bolivia and Brazil); on the opposite side of the Basin to the north, the Guyana Shield (Guyana, French Guiana, Venezuela); and eastern central Amazonia (Brazil), which is mostly comprised of old sedimentary substrates derived from the other three regions (Quesada et al., 2012; Schargel, 2011; Schargel et al., 2001). The number of months with precipitation < 100 mm per month ranges from 0 to 9 months.

## 2.6 Patterns and revision of biomass and carbon stocks

We used a Monte Carlo approach to quantify uncertainty in biomass estimates with and without  $H$ , and to extrapolate biomass estimates from plots to the landscape. We accounted for the uncertainty in wood specific gravity ( $\rho_W$ ) and  $H$  measurements in biomass estimates. For our analysis, we calculated a mean biomass (or carbon) estimate and a 95 % confidence interval for each plot, region, and continent from 1000 realisations of biomass estimates for individual plots. These estimates were based on 1000 realisations of biomass estimates for individual trees in each plot based on the normal distribution of values of the standard error drawn from a random sample for each tree. To estimate biomass for each tree, we used our new biomass models and generated 1000 realisations for each tree by adding error to the  $\rho_W$  and  $H$  where applicable. The  $\rho_W$  of each tree including the error terms was estimated as  $\hat{\rho}_W = \rho_W + \chi_{\rho_W} \sigma_{\rho_W}$ , and  $H$  for each tree including the error terms was estimated as  $\hat{H} = H + \chi_H \sigma_H$ , where the “” symbol indicates estimates that necessarily include some error,  $\chi$  represents a random value sampled from a distribution with mean = 0 and standard deviation = 1, and  $\sigma$  represents the standard error of  $\rho_W$  or  $H$  for a plot. For the realisations of biomass stocks based on forest area, we drew 1000 times from the sample plots for each region. The 95 % confidence interval was calculated as the 2.5th and 97.5th percentiles of the 1000 realisations of each estimate.

Spatial patterns in plot-level biomass estimates with and without  $H$  were examined by region and continent. Based on the regional tropical forest area estimates of broadleaf deciduous open and closed and evergreen tree cover classification from GLC2000 (Global Land Cover Map 2000) (Bartholomé and Belward, 2005) reclassified in ArcGIS® (ESRI, 2010), we scaled bootstrapped regional biomass estimates and uncertainty tropics-wide. Our estimates of tropical forest area are lower than those reported by Mayaux et al. (2005) since we excluded the more open vegetation classes. Biomass was converted to carbon values using a conversion factor of 0.5 (Chave et al., 2005). Statistical analyses were conducted using the R statistical platform (R Development Core Team 2011). Biomass and  $H$  models were developed using the lme and nlme functions of R (Pinheiro et al., 2011).

## 3 Results

Using our expanded pantropical destructive biomass dataset (Fig. 2a), we first examine how estimates of real (destructive) biomass data using bootstrapped biomass models (Table 1) are affected by different  $H$  model forms and regional or continental parameterisations by examining the relative error by diameter bin (Fig. 2b) and overall bias in biomass estimates by destructively sampled site (Table 2). We next examine how the selected  $H$  models (Table 3) affect biomass estimates (Fig. 3) and uncertainty (Fig. 4) as a result of regional variation in forest structure (Supplement Table S2) and distribution of biomass among diameter classes for trees measured in pantropical permanent sample plots (Supplement Table S1). Finally, we extrapolate our results to assess the influence of incorporating variations in  $H:D$  allometry on regional/continental and global biomass estimates (Tables 4 and 5).

### 3.1 How much does the inclusion of height reduce uncertainty in destructive biomass estimates?

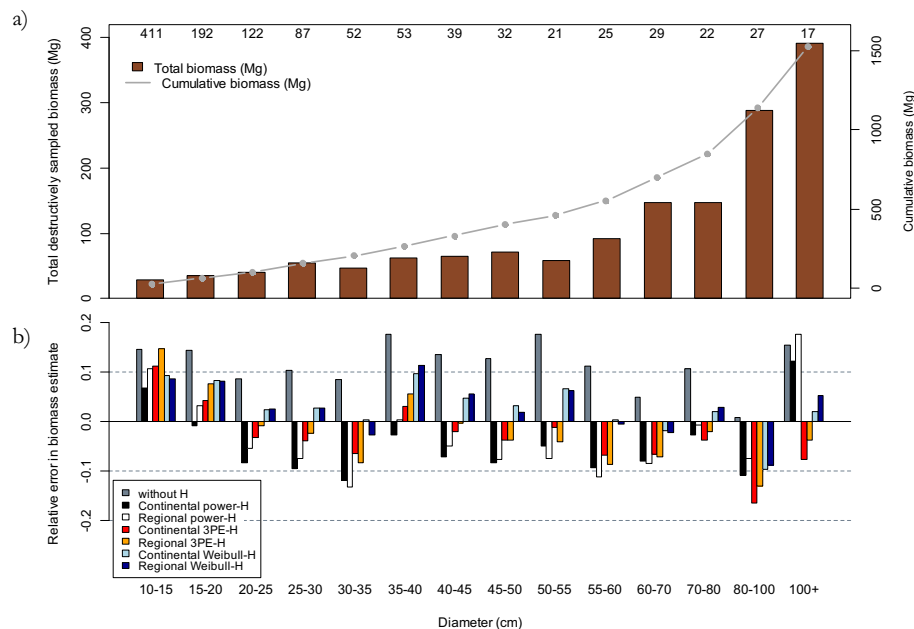
The distribution of destructively sampled aboveground tree dry mass from the available pantropical dataset was roughly equally sampled across the 50 mm increment diameter classes from 250 mm <  $D$  ≤ 500 mm but, although involving many more individual trees, somewhat less for  $D$  < 250 mm (Fig. 2a). Although relatively few trees had been sampled for large diameter classes (e.g. 17 trees ≥ 1000 mm diameter), these larger trees clearly accounted for a significant proportion of the total biomass to be simulated within the dataset. The cumulative biomass in Fig. 2a represents the nearly 1500 Mg of biomass destructively sampled to date in moist tropical forest which we use to assess the effect of  $H$  in biomass estimates. Most of these data have been used in the parameterisation of currently used pantropical biomass models (e.g. Chave et al., 2005), but with newly published data from Africa, Asia, and Brazil included in our analysis.

#### 3.1.1 Measured heights

The effect of the inclusion of  $H$  using the biomass model forms of Chave et al. (2005) as applied to our dataset are presented in Table 1, where our allometric equations both with and without  $H$  included (i.e. Eqs. 1 and 2) are compared. This shows that applying Eq. (1) (which excludes  $H$ ) resulted in considerably higher residual standard error (RSE) and Akaike information criteria (AIC) estimates than for when  $H$  was included (Eq. 2).

#### 3.1.2 Simulated heights

The effects of substituting estimates of  $H$  from Eqs. (3–5) into Eq. (2) are shown in Table 2. The inclusion of  $H$  improved site-level estimates of aboveground biomass, bringing them closer to the known destructive harvest values, with



**Fig. 2.** (a) Distribution of destructively sampled aboveground tree dry mass (bars) by diameter class (cm) and cumulative biomass (line) on the second axis. Numbers above the bars indicate the number of trees sampled. The dataset represents the pantropical destructive data to date used to form biomass allometric models, including additional data from Africa, Asia, and South America. (b) Relative error associated with estimating the true (destructively) sampled aboveground tree dry mass  $((B_{\text{estimated}} - B_{\text{measured}})/B_{\text{measured}})$  for the same dataset estimated with and without estimated  $H$  in the biomass model by diameter class (cm). Height estimated by three model forms and either a continental or regional parameterisation. Positive values indicate the biomass model overestimates true destructively sampled mass.

**Table 1.** Pantropical models to estimate dry biomass (kg) from Eq. (1), diameter ( $D$ , cm) and wood specific gravity ( $\rho_W$ ,  $\text{g cm}^{-3}$ ), and Eq. (2), also including tree height ( $H$ , m) for trees in pantropical forests; including the residual standard error (RSE), Akaike information criterion (AIC) and number of trees ( $n$ ) based on destructively sampled moist forest tree data from Africa, Asia, and South America.

Model	$a$	$b$	$c$	$d$	$e$	RSE	$R^2$	AIC	$n$
Eq. (1): $\ln(B) = a + b \ln(D) + c (\ln(D))^2 + d (\ln(D))^3 + e \ln(\rho_W)$	-1.8222	2.3370	0.1632	-0.0248	0.9792	0.3595	0.973	1444	1816
Eq. (2): $\ln(B) = a + b \ln(D^2 \rho_W H)$	-2.9205	0.9894	–	–	–	0.3222	0.978	1044	1816

a relative error of 0.06 for both the Weibull- $H$  region and continent-specific  $H$  models (Table 2). Excluding  $H$  tended to produce overestimated aboveground biomass estimates, with a relative error of 0.13. Regionally derived  $H$  estimates were non-significantly better than continental scale derived  $H$  estimates at predicting site-level biomass (Table 2).

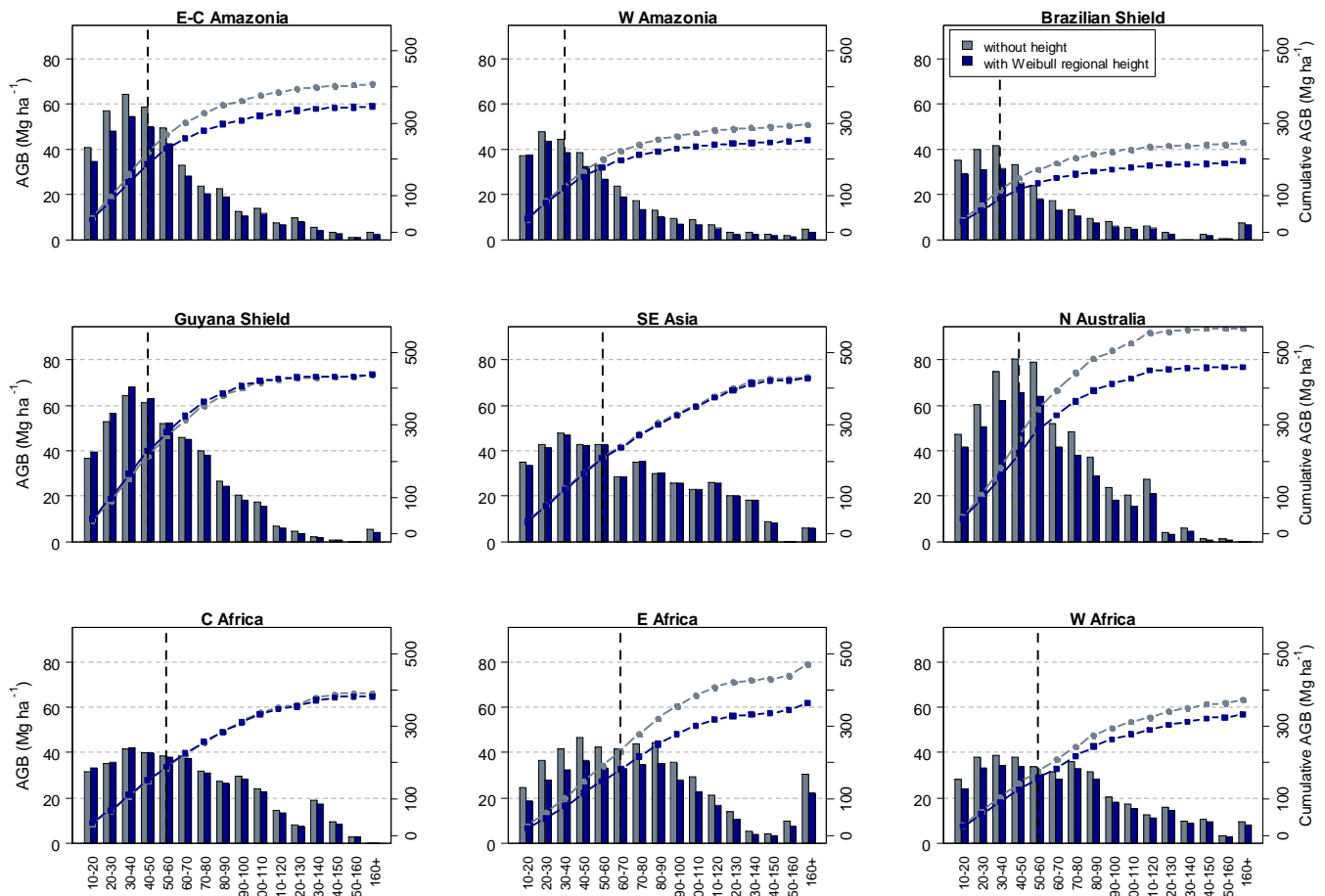
Specifically, the Weibull- $H$  (Eq. 5) (Table 3) consistently reduced the relative error in biomass estimates over all diameter classes as compared to the non- $H$  estimates. This contrasted with the power- $H$  model (Eq. 4), which although reducing error even further in some diameter classes, had greater error for other diameter classes, even greater than those derived from Eq. (1) which excludes  $H$  (Fig. 2b). The power model also had greater error for small diameter classes. Hence, overall, we consider that the Weibull model

modestly outperformed the other two function forms of  $H:D$  relationships, and utilise this relationship (Table 2).

### 3.2 Improving biomass estimates from permanent sample plots

#### 3.2.1 Effect of including height in biomass estimates

Integration of the region-specific Weibull- $H$ , on average, reduced estimated biomass per plot ( $B$ ) relative to excluding  $H$  in biomass estimates by  $-52.2$  ( $-82.0$  to  $-20.3$  Mg dry mass  $\text{ha}^{-1}$  bootstrapped 95 % CI) (Figs. 1b and 3, Table 4). As shown by the cumulative biomass curves in Fig. 3, including  $H$  in biomass estimates did not affect all regions equally. For South America, including  $H$  significantly reduced biomass estimates for all regions (by



**Fig. 3.** Biomass ( $\text{Mg ha}^{-1}$ ) distribution (bars) among diameter class (cm) by region with cumulative aboveground biomass (AGB) ( $\text{Mg ha}^{-1}$ ) on the second axis (lines) for trees in pantropical permanent plots. Tree-by-tree biomass was estimated by model (1) without  $H$ , or model (2) with Weibull (Eq. 5) region-specific  $H$ . The vertical dashed line represents the mid-point in biomass storage above and below the indicated diameter bin. See Table 4 for differences in biomass estimates due to  $H$  integration.

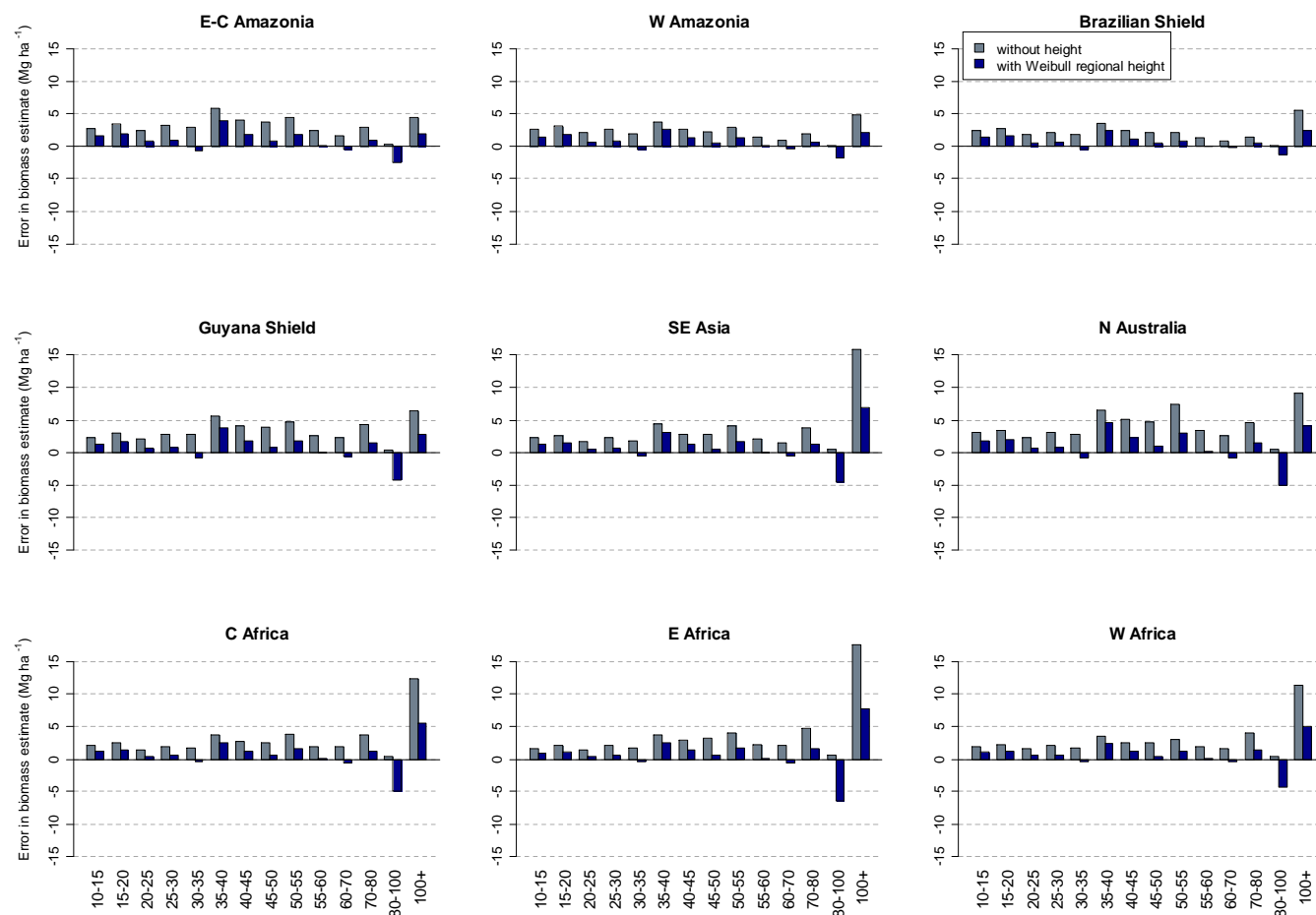
–55.9, –66.6, and –48.0  $\text{Mg ha}^{-1}$  for the Brazilian Shield, east-central Amazonia and western Amazonia, respectively) (paired t-test,  $p < 0.001$ ). East and west Africa, and northern Australia also had significantly lower biomass estimates when including  $H$  (–107.9, –44.2, –116.5  $\text{Mg ha}^{-1}$ , respectively). Southeast Asia, central Africa, and the Guyana Shield of South America had small but significant reductions in biomass estimates when including  $H$  (paired t-test,  $p < 0.001$ ). No region had significantly higher biomass estimates after including  $H$  (see Supplement, Table S1, for  $\Delta$  biomass estimates for all plots).

### 3.2.2 Differences in biomass distribution among regions

Forests store a large fraction of total biomass in smaller diameter stems, with appreciable differences in the biomass distribution among diameter classes reflecting strong regional patterns (Fig. 3). For example, forests of the four regions of South America had a significantly ( $p < 0.05$ ) larger fraction of total biomass in smaller size classes ( $\leq 40$  cm

$D$ ) compared to the three regions of Africa and Asia. This is shown graphically in Fig. 3 by the cumulative biomass curves, where forests of some regions approach an asymptote in cumulative biomass at larger diameter classes. The vertical dashed line in Fig. 3 represents the mid-point in biomass storage above and below the indicated diameter bin.

It is because of the skewed biomass distributions of Fig. 3 with a concentration of biomass in smaller diameter classes (e.g.  $\leq 40$  to  $60$  cm  $D$ ) that in Sect. 3.1 we chose the Weibull- $H$  model, which has lower relative error in small diameter classes (in contrast to the power- $H$  model and three-parameter exponential model), and therefore has the greatest plot-level effect in reducing uncertainty. After accounting for regional tree  $H$  differences, total biomass per hectare is thus estimated to be greatest in Australia, the Guyana Shield, and Asia and lowest in west Africa, west Amazonia, and the Brazilian Shield (descending order) (Table 4).



**Fig. 4.** Error in biomass estimates ( $\text{Mg ha}^{-1}$ ) for trees in pantropical permanent plots due to biomass model inputs excluding or including  $H$  (relative error propagated from destructive data). Tree-by-tree biomass was estimated by model (1) without  $H$ , or model (2) with Weibull (Eq. 5) region-specific  $H$ .

### 3.2.3 Estimating effects of $H$ on errors in permanent sample plot biomass estimates

To estimate error in permanent plots due to error in destructive measurements, we multiplied the relative error from the diameter bin from the small sample of destructive measurements for the Weibull- $H$  model (Eqs. 2 and 5), as shown in Fig. 2b, by the biomass of the equivalent size class in each of the pantropical permanent plots. This relative error in field-based plots was greater when the same procedure was undertaken for the “no- $H$ ” Eq. (1) (Fig. 4). Specifically, by including  $H$ , the error in estimates is reduced in small diameter classes but not large diameter classes. This is because of the increasing absolute errors of the Weibull- $H$  model for the larger trees. The mean error in biomass estimates for all regions when including Weibull- $H$  in biomass estimates was an overestimate of  $8.0 \text{ Mg ha}^{-1}$ , a value considerably less than the calculated overestimate of  $41.8 \text{ Mg ha}^{-1}$  when  $H$  was excluded (Fig. 4). The alternative two  $H$  models of Eqs. (3) and (4) were also tested and found to underestimate

biomass by  $-8.2$  and  $-5.5 \text{ Mg ha}^{-1}$ , respectively. Overall, inclusion of Weibull- $H$  (Eq. 5) in biomass estimates for tropical forest plots resulted in a smaller mean bias in biomass estimates compared to when  $H$  was omitted. Specifically the bias with  $H$  included ranged from  $6$  to  $9.5 \text{ Mg ha}^{-1}$  (South America),  $10.1$  to  $10.6 \text{ Mg ha}^{-1}$  (Asia and Australia), and  $5.3$  to  $7.3 \text{ Mg ha}^{-1}$  (Africa), as compared to estimation without  $H$  which had biases of  $28.6$  to  $47.2 \text{ Mg ha}^{-1}$  (South America),  $48.9$  to  $63.2 \text{ Mg ha}^{-1}$  (Asia and Australia), and  $40.5$  to  $49.4 \text{ Mg ha}^{-1}$  (Africa) (Fig. 4).

### 3.3 Effect on pantropical carbon estimates

Based on published estimates of tropical forest area (GLC2000), and biomass and carbon estimated in our permanent plot networks, we calculated the change in regional and continental aboveground live tree carbon stocks due to integration of  $H$  in biomass models. Using GLC2000 (Bartholomé and Belward, 2005) tropical forest categories and mean carbon storage in each region from the plot data,

**Table 2.** Efficacy of biomass models including or excluding tree  $H$  to predict true (destructively) sampled biomass for trees  $\geq 10$  cm  $D$  for individual sites excluded from model formulation. Values represent bootstrapped mean relative error, or bias ( $(B_{\text{predicted}} - B_{\text{measured}})/B_{\text{measured}}$ ), for a site, in dry biomass estimated from a biomass model excluding  $H$  (Eq. 1), and biomass including  $H$  (Eq. 2) using various  $H$  models (Eqs. 3–5) based on region- and continent-specific  $H$  models. Values in bold indicate the model with the lowest mean relative error (bias) for a site (this excludes the power model, which although it has the lowest overall bias and standard deviation, fails to reduce error in the small diameter classes).\*

Dropped Site**	Location	Region	$n$	3PE		Weibull		Power		No Ht	Data source
				Continent	Region	Continent	Region	Continent	Region		
BraCot	Cotriguaçu, Pará, Brazil	Brazilian Shield	151	<b>0.01</b>	−0.02	<b>0.01</b>	−0.09	−0.04	−0.07	0.09	Nogueira et al. (2008a)
BraJuruena	Juruena, Mato Grosso, Brazil	Brazilian Shield	49	<b>−0.04</b>	−0.06	−0.05	−0.13	−0.08	−0.11	0.05	Nogueira et al. (2008a)
BraMan1	Manaus, Amazonas, Brazil	E.-Central Amazonia	315	<b>0.01</b>	−0.07	−0.05	−0.14	−0.05	−0.13	−0.01	Chave et al. (2005)
BraMan2	Manaus, Amazonas, Brazil	E.-Central Amazonia	123	0.05	<b>−0.03</b>	0.04	−0.06	0.00	−0.09	0.13	Chave et al. (2005)
BraNPro	Novo Progresso, Mato Grosso, Brazil	Brazilian Shield	64	−0.22	−0.23	−0.25	−0.30	−0.25	−0.28	<b>−0.20</b>	Nogueira et al. (2008)
BraPara1	Tomé Açu, Pará, Brazil	Brazilian Shield	127	−0.04	−0.12	<b>−0.02</b>	−0.10	−0.08	−0.16	0.07	Araujo et al. (1999)
BraPara3	Belem, Pará, Brazil	Brazilian Shield	21	−0.14	−0.21	−0.09	−0.16	−0.18	−0.25	<b>0.01</b>	Chave et al. (2005)
BraRond	Rondonia, Brazil	Brazilian Shield	8	−0.50	−0.53	−0.46	−0.53	−0.52	−0.54	<b>−0.39</b>	Brown et al. (1995)
FrenchGu	Piste St. Elie, French Guiana	Guyana Shield	360	0.48	0.77	<b>0.37</b>	0.53	0.40	0.73	0.47	Chave et al. (2005)
Llanosec	Llanos secondary	Western Amazonia	24	0.47	0.79	<b>0.45</b>	0.66	0.40	0.73	0.61	Chave et al. (2005)
Llanosol	Llanos old-growth	Western Amazonia	27	<b>0.10</b>	0.35	0.17	0.35	0.07	0.35	0.32	Chave et al. (2005)
CamCampo-Ma'an	Campo-Ma'an, Cameroon	Central Africa	71	0.15	0.34	<b>−0.01</b>	0.22	0.03	0.24	0.13	Djomo et al. (2010)
CamMbalmayo	Mbalmayo, Cameroon	Central Africa	4	<b>0.09</b>	0.11	0.15	0.29	0.04	0.05	0.33	Deans et al. (1996)
DRCYangambi	Yangambi, Democratic Republic of Congo	Central Africa	12	−0.07	−0.04	<b>−0.01</b>	0.12	−0.13	−0.11	0.13	Ebuey et al. (2011)
GhaBoiTano	Boi Tano, Ghana	Western Africa	41	−0.18	−0.14	−0.13	−0.13	−0.14	−0.10	<b>−0.01</b>	Henry et al. (2010)
Kaliman1	Kalimantan, Balikpapan, Indonesia	South-east Asia	23	−0.04	−0.04	−0.02	−0.02	−0.07	−0.07	<b>0.01</b>	Chave et al. (2005)
Kaliman2	Kalimantan, Sebulu, Indonesia	South-east Asia	69	<b>−0.11</b>	<b>−0.11</b>	−0.18	−0.18	−0.15	−0.15	−0.13	Yamakura et al. (1986)
Kaliman3	PT Hutan Labanan Sanggam Lestari, Kalimantan, Indonesia	South-east Asia	40	−0.08	−0.08	−0.07	−0.07	−0.12	−0.12	<b>−0.03</b>	Samalca (2007)
Pasoh-01	Pasoh, Malaysia	South-east Asia	139	<b>−0.07</b>	<b>−0.07</b>	−0.13	−0.13	−0.11	−0.11	−0.09	Chave et al. (2005)
Sumatra	Sepunggur, Sumatra, Indonesia	South-east Asia	29	0.27	0.27	<b>0.26</b>	<b>0.26</b>	0.22	0.22	0.33	Ketterings et al. (2001)
Relative error				0.03	0.05	0.06	0.06	−0.01	0.02	0.13	
Std. Dev.				0.25	0.33	0.22	0.29	0.23	0.32	0.25	

\* Biomass estimated from models based on tree diameter, wood density (Eq. 1) and where applicable,  $H$  (Eq. 2). Height is estimated from models developed from the pantropical tree  $H$ - $D$  database of Feldpausch et al. (2011). \*\* Efficacy of the biomass model to predict biomass was independently assessed for each “dropped site” which was excluded from the development of the biomass model.

the tropical Americas had the largest reduction  $-17.1$  Pg C ( $-18.5$  to  $-15.6$  bootstrapped 95 % CI),  $-14$  % in estimated carbon storage due to  $H$ , and Asia,  $-1$  Pg C ( $-1.1$  to  $-0.8$  bootstrapped 95 % CI),  $-2$  %, the smallest. Inclusion of region-specific  $H$  models to estimate carbon reduced tropics-wide estimates of total carbon in tropical forests from  $320.5$  Pg C ( $282.4$ – $358.6$  bootstrapped 95 % CI) to  $285.1$  Pg C ( $251.8$ – $318.9$  bootstrapped 95 % CI), a reduction of  $-35.2$  Pg C ( $-39.4$  to  $-30.7$  bootstrapped 95 % CI), or 13 %, relative to when  $H$  was included (Table 5).

## 4 Discussion

We show that (1) including  $H$  significantly improves the accuracy of estimation of tropical forest aboveground biomass; (2) failing to include  $H$  usually causes an overestimate of biomass; (3) such overestimates may have globally significant implications – here we estimate that carbon storage in tropical forests may be overestimated by 13%; and finally we recommend that (4) continental or regional-specific asymptotic Weibull  $H$ : $D$  functions to be included in future estimates of biomass to reduce uncertainty in aboveground biomass estimates in tropical forests. Below, we discuss some of the sources of variability in biomass and  $H$

estimates, limitations of these models, and implications for pantropical scaling and carbon valuation under REDD+.

### 4.1 Compensating for imperfect biomass models

#### 4.1.1 Representing height in biomass estimates

In this study we selected the  $H$  model based on the region-specific parameterisation of the Weibull- $H$  (Eq. 5) model because it reduced error in estimating biomass for the smaller diameter classes (Fig. 2b), which constitute a large part of the plot-level biomass (Fig. 3). Although the Weibull- $H$  form is less than ideal for trees of 800–1000 mm diameter, the three-parameter exponential (Eq. 3) and power- $H$  models (Eq. 4) were not significantly better biomass estimators for the largest trees (Fig. 2b). This may be because the parameterisation of the Weibull- $H$  model should theoretically account for some of the asymptotic nature of tree growth more than the power- $H$  or 3-parameter exponential  $H$  models. In general, however, asymptotic  $H$  has not been detected as often as may be expected among species growing in tropical forest (Poorter et al., 2006; Chave et al., 2003; Davies et al., 1998; Thomas, 1996; Iida et al., 2011); only one-fourth of species in sites sampled in Bolivia reached an asymptote (Poorter et al., 2006). However, asymptote detection is likely to be, in part, sample size dependent. Unlike the power

**Table 3.** Coefficients for Weibull- $H$  region-, continent-specific and pantropical models ( $H = a(1 - \exp(-bD^c))$ ) to estimate tree height ( $H$ , m) from diameter ( $D$ , cm)  $\geq 10$  cm in pantropical forests, including the residual standard error (RSE), Akaike information criterion (AIC), and number of trees ( $n$ )\*.

Continent	Region	$a$	$b$	$c$	RSE	AIC	$n$
Africa		50.096	0.03711	0.8291	5.739	75 422	11 910
	C. Africa	50.453	0.0471	0.8120	6.177	16 671	2572
	E. Africa	43.974	0.0334	0.8546	5.466	10 343	1658
	W. Africa	53.133	0.0331	0.8329	5.165	47 020	7680
S. America		42.574	0.0482	0.8307	5.619	121 167	19 262
	Brazilian Shield	227.35**	0.0139	0.5550	4.683	20 639	3482
	E. C. Amazonia	48.131	0.0375	0.8228	4.918	39 688	6588
	Guyana Shield	42.845	0.0433	0.9372	5.285	32 491	5267
	W. Amazonia	46.263	0.0876	0.6072	5.277	24 201	3925
Asia	S. E. Asia	57.122	0.0332	0.8468	5.691	18 623	2948
Australia	N. Australia	41.721	0.0529	0.7755	4.042	48 073	8536
Pantropical		50.874	0.0420	0.784	5.479	266 169	42656

\* Models adapted from the pantropical tree  $H:D$  database of Feldpausch et al. (2011).

\*\* Although an unrealistic asymptotic maximum  $H$  coefficient ( $a$ ), trees of 10 and 160 cm diameter would have an estimated  $H$  of 11.1 and 47.2 m, respectively, with this model.

model, the 3-parameter exponential and Weibull functions for tree  $H$  have an additional biologically meaningful parameter with a term for maximum tree height ( $H_{\max}$ ) here being applied at the plot, regional, or continental (as opposed to species) level, and it is for this reason that the  $H_{\max}$  should be interpreted carefully. For example, when pooling the transitional forests from our study for the Brazilian Shield of Amazonia, the Weibull- $H$  model converged on a  $H_{\max}$  beyond the observable tree size range, and thus spurious, large  $H_{\max}$  parameters may be obtained (e.g.  $> 200$  m). This model, however, gives an estimate of 11 and 47 m for trees of 100 and 1600 mm diameter, respectively, demonstrating that although the model provides realistic values, use of  $H_{\max}$  alone to describe stand properties could give erroneous interpretations. For some forests, the power- $H$  model provides a better fit for large-diameter trees (Feldpausch et al., 2011), and in the current study the power model resulted in a lower mean error in estimating destructive tree biomass (Supplement Table S1). With a goal of reducing error in biomass estimates at the stand-level, the asymptotic model form – which reduces error in small-diameter trees – outperforms the power model because of the skewed distribution of stand-level biomass found in smaller-diameter trees, and was, therefore, chosen (Fig. 3).

Independent of  $H$  model form, no current regional-scale  $H$  models are parameterised to account for successional variation of tropical forest trees. Secondary forest trees are frequently taller for a given  $D$  (Montgomery and Chazdon, 2001). Mechanical effects can also modify small patches of forest over large areas, where, for example, bamboo can modify  $H:D$  relationships (Griscom and Ashton, 2006) and wind may alter forest structure (Laurance and Curran, 2008).

Our  $H$  models were developed from the most comprehensive dataset to date, which includes a range of forest types including bamboo and liana forests. Developing site- or forest-specific  $H$  models is one alternative to account for localised variations in forest structure but requires substantial cost and field time to develop. Development of plot-level basal area-weighted height estimates (i.e. Lorey's height) would also aid in validating remote sensing biomass estimates (e.g. Saatchi et al., 2011).

#### 4.1.2 Modelling destructive biomass data

Examination of Fig. 2b raises two questions: “Why does exclusion of  $H$  in biomass estimates largely overestimate true biomass?” and “Why are biomass models unable to reduce error in large trees?” It was previously noted that pantropical biomass models overestimate biomass in large trees (Chave et al., 2005). Some of this error was attributed to the lack of sampling in large trees (Chave et al., 2004); however, close inspection of Fig. 4 in Chave et al. (2005) shows that biomass of the smallest trees (e.g.  $< 100$  mm diameter) is also underestimated (with these trees having the largest sample size). This suggests a different biomass model functional form may be necessary to remove the positive bias of trees  $\geq 100$  mm diameter either with or without including  $H$ . Other studies have confirmed that the model functional form we use (Eqs. 1 and 2) provides a better fit than other parameterisations (e.g. Vieilledent et al., 2012).

The challenge to reduce uncertainty in biomass estimates of large-diameter trees (e.g.  $\geq 800$  mm diameter) can be understood by examining the destructively sampled trees. Trees from this diameter class have an enormous variation

**Table 4.** Pantropical live tree aboveground dry biomass ( $B$ ) estimates (mean ( $\text{Mg ha}^{-1}$ ) and bootstrapped 95 % CI) when calculated as column (a) biomass estimated as per most published studies excluding  $H$  using our recalculation of the Chave et al. (2005) model with new published data; (b) biomass estimated based on height ( $H$ ) integration from a regional  $H$  model; and (c) the difference (b–a) in biomass due to  $H$  integration for 327 plots.

Continent	Region	$n$ plots	(a) no $H^*$	(b) with $H^*$	(c) $\Delta B$ due to $H$
Africa	C. Africa	16	392.9 (122.3–570.1)	379.4 (124.1–547)	–13.5 (–24.3–1.8)
	E. Africa	20	470.3 (213.5–760.7)	362.4 (163.4–591.8)	–107.9 (–168.9–50.1)
	W. Africa	26	374.4 (229.3–458.3)	330.2 (199.6–405.1)	–44.2 (–54.6–29.7)
S. America	Brazilian Shield	35	250.3 (138.2–377.2)	194.5 (108.2–308.8)	–55.9 (–74.8–30.0)
	E. C. Amazonia	44	410.7 (280.8–604.7)	344.1 (237.3–509.7)	–66.6 (–94.3–43.7)
	Guyana Shield	45	441.1 (293.9–763.4)	434.4 (291.2–728.4)	–6.7 (–35.3–12.6)
	W. Amazonia	101	299.6 (162.4–484.9)	251.7 (141.5–391.9)	–48.0 (–90.8–14.7)
Asia	S. E. Asia	14	434.6 (266.8–669.7)	424.2 (259.2–655.3)	–10.5 (–15.6–5.8)
Australia	N. Australia	26	571.8 (138.9–857.1)	455.3 (116.0–678.0)	–116.5 (–179.0–22.9)
Grand mean			405.1 (205.1–616.2)	352.9 (182.3–535.1)	–52.2 (–82.0–20.3)

\* Biomass estimated from the moist forest pantropical model based on tree diameter and  $\rho_W$  or based on tree diameter,  $\rho_W$  and  $H$ , where  $H$  is estimated from Weibull region-specific tree  $H$  models based on the pantropical tree  $H:D$  database from Feldpausch et al. (2011). Region geographic extent is shown in Fig. 1.

in mass, from 4.6 to 70.2 Mg (mean 15.3 Mg); similarly, a wide range of wood specific gravity, 0.26 to 0.9 g cm<sup>3</sup> (mean 0.56); and vary in  $H$  from 32 to 71 m (mean 46). These differences may represent the substantial variation in life-strategies among “emergent” canopy species, where large diameter low-density light demanding trees coexist with shade tolerant species. Thus, not only larger sample sizes of large size trees are needed, but in the future perhaps two differing equations for differing life history strategies will be required (e.g. see Henry et al. (2010), for some data analysed in this way).

Clearly, greater collaboration is required to sample trees and unify the many destructively sampled tree datasets into one database to improve regional or pantropical biomass equations with inclusion of  $H$ . Our study provides a first step in dissecting one component of this variation (regional  $H:D$  relationships) to revise tropical biomass estimates, e.g. we show that regions differ in their distribution of biomass among  $D$  class (Fig. 3), and that as a result, effects of inclusion of  $H$  estimates on predicted biomass values vary strongly from region to region (Table 5).

#### 4.1.3 Regional and continental differences

While noting the limited sample sizes for some regions, we show that forest biomass, after taking  $H$  into account, was highest in Australian forests. Biomass was as high in the Guyana Shield as in SE Asian forests, which is inconsistent with the view from previous studies that have suggested that aboveground biomass storage is higher in Southeast Asia (e.g. Slik et al., 2010). In addition, regional adjustments in biomass estimates due to elevation and tree  $H$  may be necessary for some areas. For example, tree  $H$  varies with el-

evation in Tanzania, with the tallest trees at mid-elevation (Marshall et al., 2012).

We found substantially different biomass distribution among diameter classes between the forests of South America and Australia, and Africa and SE Asia, which affected error propagation and determined  $H$  model selection. Forests of South America have a greater proportion of the total biomass in the smaller size classes  $\leq 40$  cm  $D$ ; flatter distributions are found in Africa and Asian forests, with East African forests showing the lowest proportion of biomass in small size classes (22 %) (Fig. 3). With the exception of the Guyana Shield, these regional patterns broadly correspond to reported differences in the relationship in  $H:D$  allometry (Feldpausch et al., 2011). Larger sample sizes are needed to assess whether these biomass distribution differences are consistent when expanded beyond the regional clusters. The Weibull- $H$  model was selected because it reduced uncertainty in the smallest diameter size classes, which for most forests hold a large part of the biomass. As a result of the large region-to-region variation in biomass distribution among diameter classes (Fig. 3), future work may indicate that other  $H$  forms are more effective in reducing uncertainty in forests that contain different biomass distribution among diameter classes.

Feldpausch et al. (2011) used a similar regional analysis, and showed a group of tall-stature forests (African, Asia and Guyana Shield) and other lower-statured forests (Amazon and Australia), while Banin et al. (2012) reported significant differences in maximum heights among continents. Intriguingly, the biomass distribution by diameter class appear to follow a continental split, not a forest stature split, with the Guyana Shield forests grouping with the rest of South

**Table 5.** Stocks and change in estimated pantropical C in aboveground live trees (mean and bootstrapped 95 % CI) due to  $H$  integrated into biomass estimates based on region-specific estimates of tree  $H$ , compared to the pantropical forest biomass model that excludes  $H^*$ .

Continent	Region	Area (10 <sup>6</sup> ha)	without height	with height	$\Delta C$ due to height –	
			Total C (Pg)	Total C (Pg)	Total C (Pg)	Relative reduction
Africa	C. Africa	422.6	83.0 (68.4–96.7)	80.2 (66.6–93.2)	–2.9 (–3.7––2.0)	–0.03
	E. Africa	123.1	29.0 (25.0–33.3)	22.3 (19.1–25.6)	–6.6 (–7.5––5.7)	–0.23
	W. Africa	69.8	13.1 (12.1–13.9)	11.5 (10.7–12.3)	–1.5 (–1.6––1.4)	–0.12
	Total	615.6	125.1 (105.5–143.9)	114.0 (96.4–131.1)	–11.0 (–12.8––9.1)	–0.13
South-Central America	Brazilian Shield	220.9	27.7 (25.4–30.0)	21.5 (19.7–23.4)	–6.2 (–6.6––5.7)	–0.22
	E. C. Amazonia	106.2	21.8 (20.4–23.3)	18.3 (17.1–19.4)	–3.5 (–3.8––3.3)	–0.16
	Guyana Shield	148.3	32.7 (30.0–35.6)	32.2 (29.7–34.6)	–0.5 (–0.8––0.2)	–0.02
	W. Amazonia	286.4	42.9 (41–44.9)	36.0 (34.5–37.5)	–6.9 (–7.3––6.4)	–0.16
	Total	761.9	125.1 (116.8–133.8)	108.0 (101.0–114.9)	–17.1 (–18.5––15.6)	–0.14
Asia	S.E. Asia	185.0	40.2 (34.0–46.9)	39.2 (33.7–45.9)	–1.0 (–1.1––0.8)	–0.02
Australia	N. Australia	105.1	30.1 (26.1–34.0)	23.9 (20.7–27.0)	–6.1 (–7.0––5.2)	–0.20
Total		1667.5	320.5 (282.4–358.6)	285.1 (251.8–318.9)	–35.2 (–39.4––30.7)	–0.13

\* Tree height estimated from region-specific Weibull- $H$  models adapted from the pantropical tree  $H:D$  database of Feldpausch et al. (2011). Region geographic extent is shown in Fig. 1. Tropical forest area was estimated for each region based on the broadleaf deciduous open and closed and evergreen tree cover classification from GLC2000 (Global Land Cover Map 2000) (Bartholomé and Belward, 2005).

America and not African forests. The reasons for this are unclear, but may be related to the interaction between stem density and  $H$ . These studies showed that  $H:D$  relationships were related to stem density, with forests with higher stem density having shorter trees for a given diameter. Trees of the Guyana Shield, for example, have the lowest stem density for plots in South America, and also are on average taller and have the highest biomass stocks for the continent (Table 4; Supplement Table S2). Our current results indicate that the inclusion of  $H$  in biomass estimates for the Guyana Shield, Asia and Central Africa forests, with trees on average taller for a given  $D$ , does not substantially modify estimates compared to estimates based on the no- $H$  Eq. (1), but that including  $H$  in biomass estimates for those regions reduces the bias in destructive estimates relative to excluding  $H$  (Table 2). These results showing substantial variation in biomass distribution and forest structure among regions and continents indicate that future biomass models based on continents and regions may prove more robust than pantropical models.

#### 4.1.4 Climate and biogeography

Furthermore, the patterns that emerge in tree  $H$  variation as a function of region, climate, and forest structure suggest alternative structuring is needed for pantropical *Biomass:Diameter* tree allometric models rather than basing them solely on forest moisture class (e.g. dry, moist, wet).

For example,  $H:D$  relationships vary not only according to climate (e.g. taller trees in moist climates), but also by forest structure (e.g. taller trees in higher basal area forests), soil quality, and geography (e.g. taller trees for a given diameter in the Guyana Shield, Africa and Asia than in the rest of South America and Australia, Feldpausch et al., 2011). *Biomass:Diameter* allometry for most published large-scale biomass models, however, is fixed by region (e.g. Amazonia, Chambers et al., 2001) or is pantropical (e.g. Chave et al., 2005), or is based on broad classifications of forest moisture (e.g. dry, moist, or wet forest, Chave et al., 2005) or vegetation (e.g. dipterocarp, secondary forest, Basuki et al., 2009; Nelson et al., 1999). These models therefore lack parameters to account for possible climate-driven or biogeographic variation in *Biomass:Diameter* relationships. However, the clear biogeographical differences amongst SE Asian (dominated by the Dipterocarpaceae) and forests on other continents are not shown here, and were not the proximate reason for differences in  $H:D$  allometry in Asia versus elsewhere (Banin et al., 2012). Formation of region-specific  $H$  models provides a first step in parameterising regional biomass estimates based on reported variation in tree  $H$  allometry (Nogueira et al., 2008b; Feldpausch et al., 2011).

Current pantropical biomass models are also unable to account for regional or forest-specific variation in crown diameter, where wider crowns may impart greater biomass for a given diameter. Based on high-resolution remote sensing



data, Barbier et al. (2010) indicated that crown size increases by  $\sim 20\%$  from the wetter to the more-seasonal regions of Amazonia. The regional  $H$  patterns showing shorter trees in Southern Amazonia (Nogueira et al., 2008b; Feldpausch et al., 2011) that would result in reduced biomass stocks, may be partially offset by wider crowns that contain more mass for a given diameter. Such possible effects remain to be tested with field data.

#### 4.1.5 Intra-species, diameter-specific and regional wood density variation

Tree wood specific gravity ( $\rho_W$ ) variation is another parameter that biomass models may inadequately represent. This is because wood specific gravity (1) is highly variable across regions (2) a key determinant of large-scale tree biomass spatial patterns (Baker et al., 2004b; Chave et al., 2006) and (3) is a more important predictor than tree height in biomass models (Chave et al., 2005). Therefore, accounting for it holds a central role in reducing uncertainty in biomass estimates. Current biomass calculations use  $\rho_W$  databases to assign the finest taxonomic value to an individual (e.g. species-specific  $\rho_W$ ) independent of stem diameter, and our bootstrapped estimates account for uncertainty in  $\rho_W$  (in addition to  $H$ ). Data from Barro Colorado Island, Panama, showed significantly lower  $\rho_W$  in large-diameter trees than in smaller trees (Chave et al., 2004), while Patiño et al. (2009) showed, using branch wood density (which may be more plastic than stem wood density), that there is considerable plot-to-plot variation in wood specific gravity. Additionally, mean tree  $\rho_W$  is significantly lower in some regions of Amazonia (Nogueira et al., 2007). In addition, engineering theory suggests that trees with low density wood have an advantage in both  $H$  growth and in mechanical stability as compared to high wood density trees (Anten and Schieving, 2010; Iida et al., 2012); in contrast to vertical growth, high density wood imparts greater efficiency for horizontal expansion. Together, these results suggest that biomass models may benefit from greater parameterisation.

Variation in the wood carbon fraction is another source of uncertainty in estimating regional and pantropical carbon stocks. Many studies, as in the current study, take the wood carbon fraction as 0.5 to convert estimated biomass to carbon (e.g. Lewis et al., 2009; Malhi et al., 2004; Clark et al., 2001). However, carbon content varies regionally (Elias and Potvin, 2003), where, for example, a forest in Panama has mean carbon values of  $0.474 \pm 0.025$ , which would result in an overestimate of  $4.1\text{--}6.8 \text{ Mg C ha}^{-1}$  if the assumed 0.5 carbon content were used (Martin and Thomas, 2011). Accounting for such variation may assist in refining future pantropical carbon estimates.

#### 4.1.6 Limited spatial extent

A further concern is the use of spatially limited, destructively sampled biomass data forming the base of biomass models used to estimate biomass for trees in other regions. Until only recently, destructive data were unavailable for Africa, so that large-scale biomass estimates for this continent were based on data from elsewhere. Regional biomass equations may yield site-specific bias. For example, the Chambers et al. (2001) equation, which is based on data from a small area north of Manaus, Brazil, yet by necessity has been used to estimate biomass across the Amazon Basin (Baker et al., 2004a; Malhi et al., 2004, 2006), an area with important variation in tree architecture (Nogueira et al., 2008b; Feldpausch et al., 2011; Barbier et al., 2010), taxonomy (Pitman et al., 1999), and wood density (Baker et al., 2004b). Application of this model to Southern Amazonia requires a height factor to down-scale biomass estimates to account for shorter trees (Nogueira et al., 2008b, 2007). Country-level assessments of biomass model effects on estimates indicate that application of generic pantropical biomass models (e.g. Brown et al., 1989; Chave et al., 2005) should be evaluated prior to application, especially those that lack  $H$  parameterisation (Alvarez et al., 2012; Vieilledent et al., 2012; Marshall et al., 2012). Our current results showed tropics-wide geographical variation in biomass distribution among  $D$  classes in permanent plots, which, together with tropics-wide variation in  $H:D$  relationships (Feldpausch et al., 2011), may not be represented when forming small regional subsets or pooling pantropical destructive data without accounting for  $H$ .

#### 4.2 Consequences for remote sensing

Observed tropical forest  $H:D$  allometry differences in ground-based studies (Feldpausch et al., 2011; Nogueira et al., 2008b; Banin et al., 2012) and their associated regional effects on biomass estimates shown here will be important for improving retrieval of biomass estimates from LiDAR (e.g. Drake et al., 2002; Lefsky et al., 2005; Asner et al., 2010) and radar (Geoscience Laser Altimeter System, GLAS; e.g. Saatchi et al., 2011) techniques that estimate a canopy  $H$ , or are used to estimate forest structure (full waveform LiDAR), either of which is then translated into a biomass estimate. Current pantropical remote sensing biomass estimates (e.g. Saatchi et al., 2011) transform remotely-sensed estimates of canopy height into biomass estimates based on the relationship between basal-area weighted  $H$  (Lorey's  $H$ ) for a ground-based plot and biomass estimates for trees within those plots, or based on the relationship between carbon density estimated from allometric models (e.g. Chave et al., 2005) and remotely-sensed estimates of canopy height (e.g. Baccini et al., 2012). Minimising error in estimating biomass for trees within plots will likewise reduce error when calibrating remotely sensed estimates of biomass via LiDAR or radar. Height inclusion in

the allometry used to estimate biomass for those plots reduces uncertainty, as we have shown here. Future remote sensing biomass estimates that address regional variations in  $H$  and its effect on biomass estimates when calibrating remotely sensed  $H$  to estimate biomass should therefore assist in evaluating potential bias and be able to provide tropical biomass estimates of improved accuracy.

#### 4.3 Implications for carbon sink and estimates of nutrient turnover

Permanent plot data indicate that intact apparently mature tropical forests are not in biomass equilibrium, but have tended to gain biomass per unit area. Tree recruitment has outpaced mortality (Phillips et al., 2004) and total tree aboveground biomass has increased over recent decades (Phillips et al., 1998, 2009; Lewis et al., 2009). It has been estimated that, on average, trees in tropical forests add  $0.49 \text{ Mg C ha}^{-1}$  in aboveground mass each year, implying a carbon sink in aboveground live biomass of  $0.9 \text{ Pg C yr}^{-1}$  (Lewis et al., 2009). This process, however, is susceptible to drought, and for Amazonia the 2005 drought at least temporarily reduced the long-term aboveground carbon sequestration (Phillips et al., 2009).

Our lower mean biomass estimates from forest plots implies that the calculated net carbon sink or the magnitude of any reversal or reduction in the sink due to drought may also be reduced for some regions as a direct result of  $H$  parameterisations using current pantropical biomass models. This assumes that the proportional sink remains unchanged. Furthermore, biomass estimates for individual trees are frequently used to estimate nutrient stocks such as nitrogen and phosphorus in trees and stands (Feldpausch et al., 2004, 2010; Buschbacher et al., 1988) based on component tissue concentrations (Martinelli et al., 2000). Downscaling biomass estimates due to  $H$  will therefore reduce the total estimated aboveground nutrient stocks and flux due to land-use change (e.g. selective logging, deforestation, forest regrowth and fire).

#### 4.4 Comparison with global emissions

The biomass and carbon downscaling due to  $H$  also affects estimates of carbon emissions. The recent Intergovernmental Panel on Climate Change (IPCC) estimate of global emissions contribution of tropical deforestation estimates a net annual emission from this source of  $1.6 \text{ Pg C}$  (range  $1.0\text{--}2.2 \text{ Pg C}$ ) (Denman et al., 2007) based on the mean of estimates by DeFries et al. (2002) and Houghton (2003) from the 1980s and 1990s. The recent “unofficial” estimate with the same methodology is  $1.47 \text{ Pg C yr}^{-1}$  for the 2000–2005 period (Houghton, 2008). Our new results incorporating  $H$  into these estimates imply that this is an overestimate of  $\sim 0.1 \text{ Pg C yr}^{-1}$ , this being based on the more recent number for the values used in the estimate for emissions from below-

ground biomass and uptake of secondary forest regeneration, the contribution of live aboveground biomass cut in tropical deforestation of  $0.85 \text{ Pg C yr}^{-1}$ , and a 0.13 downward adjustment for tree  $H$  (Table 5). For comparison, the last national inventory of the UK under Climate Convention indicates a total emission in 2007 of  $0.17 \text{ Pg yr}^{-1}$  of  $\text{CO}_2$ -equivalent carbon (UK Department of Energy and Climate Change, 2009).

#### 4.5 Repercussions for carbon estimation and REDD+

Integration of  $H$  into biomass estimates reduces estimates of tropical carbon storage by 13 %. This estimated decrease has potential economic implications based on the calculated high carbon storage of pantropical forests under Reducing Emissions from Deforestation and Degradation (REDD+) carbon-payment schemes (Miles and Kapos, 2008). In monetary terms, our calculated decrease in carbon storage represents a reduction in value, in some regions, per unit area of tropical forests based on current carbon market prices (e.g. Chicago Climate Exchange, European Climate Exchange) if previous estimates utilised published pantropical allometry and excluded  $H$  measurements. However, we stress (1) the actual carbon storage of these forests has not changed, only the estimated amount; (2) the large-scale RAINFOR South American estimates of biomass and change (e.g. Malhi et al., 2006; Phillips et al., 2009) used the Baker et al. (2004b) regional biomass model; for Africa, Weibull asymptotic continental-scale  $H$  equations were used to estimate height in the Chave et al. (2005) pantropical allometric equations (Lewis et al., 2009); hence, the effect of accounting for  $H$  in their estimates remains unexplored; (3) that our adjustments in plot-based estimates are sensitive to the current pantropical biomass equations as discussed above; future improvement and inclusion of additional data (e.g. from Africa) and harvested trees of larger diameter will further reduce uncertainty in estimates over a heterogeneous landscape and at a variety of scales; new models may eventually show that such downscaling is unnecessary; (4) tree  $H$  integration can reduce uncertainty in biomass estimates (Figs. 2b and 4), which should benefit REDD+ carbon accounting; (5) our extrapolations to regions and the tropics are based on necessarily limited sample sizes. Furthermore, the tier-I estimation method of forest carbon density issued in support of REDD+ by IPCC is based on average carbon values for biomes (IPCC, 2006), not plot-based estimates. The approach outlined in the present study, coupled with better measurement of  $H$  (e.g. using LiDAR), can help generate accurate, verifiable biomass estimates which will ultimately increase confidence in large-scale carbon estimates, potentially increasing the area receiving carbon credits, and greater investment per unit of carbon (Asner et al., 2010).

## 5 Conclusions and future considerations

Based on these results, it is possible to make a number of recommendations:

1. A major initiative is needed to improve the pantropical destructive tree data to support global carbon modelling and policy; additional sampling is needed from under-represented regions, forest types, growth forms (e.g. palms), and tree diameter classes to represent the full diversity of tropical forests. We showed distinct differences in the biomass distribution among diameter classes of tropical forests in different regions across the tropics, and such apparently important differences will only be fully accounted for in biomass estimates when we have improved understanding through destructive sampling.
2. Pantropical permanent forest plots, some monitored since the 1970s, are now a baseline standard by which scientists and policymakers understand forest dynamics and potential changes in net carbon gain, with implications for carbon valuation under REDD+. There is known large variation in  $H$  among these plots. To account for this variation and make full use of permanent-plot data, we recommend a stratified random sample of  $H$  measurements. If possible,  $H$  measurements of every tree are desirable. Where local  $H$ -diameter relationships are not known, using those described in this paper is recommended.

Biomass estimates of tropical forests are prone to error because of the very small destructive dataset, biomass models,  $H$  models and also because of uncertainty in unambiguously defining an area of tropical forest. Our study has explored the uncertainty associated with current biomass estimates and has shown the importance of accounting for tree-level variation in  $H:D$  relationships for scaling to more precise regional and global biomass estimates. By reducing uncertainty in pantropical estimates, we make a step forward in providing realistic, verifiable carbon estimates for models and policy instruments such as REDD+.

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