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An integrated pan-tropical biomass map using multiple reference datasets

(PAN-TROPICAL FUSED BIOMASS MAP)

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Abstract

We combined two existing vegetation biomass datasets (Saatchi et al., 2011; Baccini et al., 2012) into a pan-tropical aboveground biomass map at 1-km resolution using an independent reference dataset of field observations and locally-calibrated high-resolution biomass maps, harmonized and upscaled to 14,477 1-km biomass estimates. Our data fusion approach uses bias removal and weighted linear averaging that incorporates and spatializes the biomass patterns indicated by the reference data. The method was applied independently in areas (strata) with homogeneous error patterns of the input (Saatchi and Baccini) maps, which were estimated from the reference data and additional covariates. Based on the fused map, we estimated biomass stocks for the tropics (23.4 N – 23.4 S) of 375 Pg dry mass, 9% - 18% lower than the Saatchi and Baccini estimates. The fused map also showed differing spatial patterns of biomass density over large areas, with higher biomass density in the dense forest areas in the Congo basin, Eastern Amazon and South-East Asia, and lower values in Central America and in most dry vegetation areas of Africa than either of the input maps. The validation exercise, based on 2,118 estimates from the reference dataset not used in the fusion process, showed that the fused map had a RMSE 15 – 21% lower than that of the input maps and, most importantly, nearly unbiased estimates (mean bias 5 Mg dry mass ha^{-1} vs. 21 and 28 Mg ha^{-1} for the input maps). The fusion method can be applied at any scale including the policy-relevant national level, where it can provide improved biomass estimates by integrating existing regional biomass maps as input maps and additional, country-specific reference datasets.

Introduction

Recently, considerable efforts have been made to better quantify the amounts and spatial distribution of aboveground biomass, a key parameter for estimating carbon emissions and removals due to land-use change, and related impacts on climate (Saatchi et al., 2011; Baccini et al., 2012; Harris et al., 2012; Houghton et al., 2012; Mitchard et al., 2014; Achard et al., 2014). Particular attention has been given to the tropical regions, where uncertainties are higher (Pan et al., 2011; Ziegler et al., 2012; Grace et al., 2014). In addition to ground observations acquired by research networks or for forest inventory purposes, several biomass maps have been recently produced at different scales, using a variety of empirical modelling approaches based on remote sensing data calibrated by field observations (e.g., Goetz et al., 2011; Birdsey et al., 2013). Biomass maps at moderate resolution have been produced for the entire tropical belt by integrating various satellite observations (Saatchi et al., 2011; Baccini et al., 2012), while higher resolution datasets have been produced at local or national level using medium-high resolution satellite data (e.g., Avitabile et al., 2012; Cartus et al., 2014), sometimes in combination with airborne Light Detection and Ranging (LiDAR) data (Asner et al., 2012a, 2012b, 2013, 2014a). The various datasets often have different purposes: research plots provide a detailed and accurate estimation of biomass (and other ecological parameters or processes) at the local level, forest inventory networks use a sampling approach to obtain statistics of biomass stocks (or growing stock volume) per forest type at the sub-national or national level, while high-resolution biomass maps can provide detailed and spatially explicit estimates of biomass density to assist natural resource management, and large scale datasets depict biomass distribution for global-scale carbon accounting and modelling.

In the context of the United Nations mechanism for Reducing Emissions from Deforestation and forest Degradation (REDD+), emission estimates obtained from spatially explicit biomass datasets may be favoured compared to those based on mean values derived from plot networks. This preference stems from the fact that plot networks are not designed to represent land cover change events, which usually do not occur randomly and may affect forests with biomass density systematically different from the mean value (Baccini and Asner, 2013). With very few tropical countries having national biomass maps or reliable statistics on forest carbon stocks, regional maps may provide advantages compared to the use of default mean values (e.g., IPCC (2006) Tier 1 values) to assess emissions from deforestation, if their accuracy is reasonable and their estimates are not affected by systematic errors (Avitabile et al., 2011). However, these conditions are difficult to assess since proper validation of regional biomass maps remains problematic, given their large area coverage and large mapping unit (Mitchard et al., 2013), while ground observations are only available for a limited number of small sample areas.

The comparison of two recent pan-tropical biomass maps (Saatchi et al., 2011; Baccini et al., 2012) reveals substantial differences between the two products (Mitchard et al., 2013). Further comparison with ground observations and high-resolution maps indicated substantially different biomass patterns at regional scales (Baccini and Asner, 2013; Hills et al., 2013; Mitchard et al., 2014). Such comparisons have stimulated a debate over the use and capabilities of different types of biomass products (Saatchi et al., 2014; Langner et al., 2014) and have highlighted both the importance and sometimes the lack of integration of different datasets. On one hand, the two pan-tropical maps are consistent in terms of methodology because both use the same primary data source (GLAS LiDAR) alongside a similar modelling approach to upscale the LiDAR data to larger scales. Moreover, they have the advantage of being calibrated using hundreds of thousands of biomass estimates derived from height metrics computed by a spaceborne LiDAR sensor distributed over the tropics. However, such maps are based on remotely sensed variables that do not directly measure biomass, but are sensitive to canopy cover and canopy height parameters that do not fully capture the biomass variability of complex tropical forests. Furthermore, both products assume global or continental allometric relationships in which biomass varies only with stand height, and further errors are introduced by upscaling the calibration data to the coarser satellite data. On the other hand, ground plots use allometric equations to estimate biomass at individual tree level using directly measurable parameters such as diameter, height and species identity (hence wood density). However, they have limited coverage, are not error-free, and compiling various datasets over large areas is made more complex due to differing sampling strategies (e.g., stratification (or not) of landscapes, plot size, minimum diameter of trees measured). Considering the rapid increase of biomass observations at different scales and the different capabilities and limitations of the various datasets, it is becoming more and more important to identify strategies that are capable of making best use of existing information and optimally integrate various data sources for improved large area biomass assessment (e.g., see Willcock et al., 2012).

In the present study, we compiled existing ground observations and locally-calibrated high-resolution biomass maps to obtain a high-quality reference dataset of aboveground biomass for the tropical region (objective 1). This reference dataset was used to assess two existing pan-tropical biomass maps (objective 2) and to combine them in a fused map that optimally integrates the two maps, based on the method presented by Ge et al. (2014) (objective 3). Lastly, the fused map was assessed and compared to known biomass patterns and stocks across the tropics (objective 4).

Overall, the approach consisted of pre-processing, screening and harmonizing the pan-tropical biomass maps (called ‘input maps’), the high-resolution biomass maps (called ‘reference maps’) and the field plots (called ‘reference plots’; ‘reference dataset’ refers to the maps and plots combined) to a common spatial resolution and geospatial reference system (Figure 1). The input maps were combined using bias removal and weighted linear averaging (‘fusion’). The fusion model was applied independently in areas representing different error patterns of the input maps (called ‘error strata’), which were estimated from the reference data and additional covariates (called ‘covariate maps’). The reference dataset included only a subset of the reference maps (i.e., the cells with highest confidence) and if a stratum was lacking reference data (‘reference data gaps’), additional data were extracted from the reference maps (‘consolidation’). The fused map was validated using independent data and its uncertainty quantified using model parameters. In this study, the term biomass refers to aboveground live woody biomass and is reported in units of Mg dry mass ha^{-1}. The fused map and the corresponding reference dataset ~~will be publicly available~~can be freely downloaded from http://www.wageningenur.nl/forestbiomass.

Materials and methods

Input maps

The input maps used for this study were the two pan-tropical datasets published by Saatchi et al. (2011) and Baccini et al. (2012), hereafter referred to as the Saatchi and Baccini maps individually, or collectively as input maps. The Baccini map was provided in MODIS sinusoidal projection with a spatial resolution of 463 m while the Saatchi map is in a geographic projection (WGS-84) at 0.00833 degrees (c. 1 km) pixel size. The two datasets were harmonized by first projecting the Baccini map to the coordinate system of the Saatchi map using the Geospatial Data Abstraction Library (www.gdal.org) and then aggregating it to match the spatial resolution and grid of the Saatchi map. Spatial aggregation was performed by computing the mean value of the pixels whose centre was located within each 1-km cell of the Saatchi map. Resampling was then undertaken using the nearest neighbor method.

Reference dataset

The reference dataset comprised individual tree-based field data and high-resolution biomass maps independent from the input maps. The field data included biomass estimates derived from field measurement of tree parameters and allometric equations. The biomass maps included high-resolution (≤ 100 m) datasets derived from satellite data using empirical models calibrated and validated using local ground observations and, in some cases, airborne LiDAR measurements. Given the variability of procedures used to acquire and produce the various datasets, they were first screened according to a set of quality criteria to select only the most reliable biomass estimates, and then pre-processed to be harmonized with the pan-tropical biomass maps in terms of spatial resolution and variable observed. Field and map datasets providing aboveground carbon density were converted to biomass units using the same coefficients used for their original conversion from biomass to carbon. The sources and characteristics of the reference data are listed in the Supplementary Information (Tables S8 - S11).

Data screening and pre-processing

Reference field data

The reference field data included ground observations in forest inventory plots, for which accurate geolocation and biomass estimates were available. The pre-processing of the data consisted of a 2-step screening and a harmonization procedure. A preliminary screening selected only the ground data that estimated aboveground biomass of all living trees with diameter at breast height ≥ 5-10 cm, acquired on or after the year 2000, not used to calibrate the LiDAR-biomass relationships of the input maps, and where plot coordinates were measured using a GPS. Since the taxonomic identities of trees strongly indicate wood density and hence stand-level biomass (e.g., Baker et al., 2004; Mitchard et al. 2014), plots were only selected if tree biomass was estimated using at least tree diameter and wood density as input parameters. All datasets not conforming to these requirements or not providing clear information on the biomass pool measured, the tree parameters measured in the field, the allometric model applied, the year of measurement and the plot geolocation and extent were excluded. Next, the plot data were projected to the geographic reference system WGS-84 and harmonized with the input maps by averaging the biomass values located within the same 1-km pixel if there was more than one plot per pixel, or by directly attributing the plot biomass to the respective pixel if there was only one plot per pixel. The field plots not fully located within one pixel were attributed to the map cell where the majority of the plot area (i.e., the plot centroid) was located.

Lastly, the representativeness of the plot over the 1-km pixels was considered, and the ground data were further screened to discard plots not representative of the map cells in terms of biomass density. More specifically, since the two input maps in their native reference systems are not aligned and therefore their pixels do not correspond to the same geographic area, the plot representativeness was assessed on the area of both pixels (identified before the map resampling). The representativeness was evaluated on the basis of the homogeneity of the tree cover and crown size within the pixel, and it was assessed using visual interpretation of high-resolution images provided on the Google Earth platform. If the tree cover and tree crowns were not homogeneous over at least 90% of the pixel area, the plots located within the pixel were discarded (Fig. S1). In addition, if subsequent Google Earth images indicated that forest change processes (e.g., deforestation or regrowth) occurred in the period between the field measurement and the reference years of the input maps, the corresponding plots were also discarded.~~More details on the selection procedure are provided in the Supplementary Information.~~

Reference biomass maps

The reference biomass maps consisted of high-resolution~~quality~~ local or national maps published in the scientific literature. Maps providing biomass estimates grouped in classes (e.g., Willcock et al., 2012) were not used since the class values represent the mean biomass over large areas, usually spanning multiple strata used in the present study (see ‘Stratification approach’). The reference biomass maps were first pre-processed to match the input maps through re-projection, aggregation and resampling using the same procedures described for the pre-processing of the Baccini map. Then, only the cells with largest confidence (i.e., lowest uncertainty) were selected from the maps. Since uncertainty maps were usually not available, and considering that the reference maps were based on empirical models, the map cells with greatest confidence were assumed to be those in correspondence of the training data (field plots and/or LiDAR data). When the locations of the training data were not available, random pixels were extracted from the maps. For maps based only on radar or optical data, whose signals saturate above a certain biomass density value, only pixels below such a threshold were considered. In order to compile a reference database that was representative of the area of interest and well-balanced among the various input datasets (as defined in 'Consolidation of the reference dataset'), the amount of reference data extracted from the biomass maps was proportional to their area and not greater than the amount of samples provided by the field datasets representing a similar area. In the case where maps with extensive training areas provided a disproportionate number of reference pixels, a further screening selected only the areas underpinned by the largest amount of training data.

Consolidation of the reference dataset

Considering that the modelling approach used in this study is applied independently by stratum (which represent areas with homogeneous error structure in both input maps, see 'Stratification approach') and is sensitive to the characteristics of the reference data (see 'Modelling approach'), each stratum requires that calibration data are relatively well-balanced between the various reference datasets. Specifically, if a stratum contains few calibration data, the model becomes more sensitive to outliers, while if a reference dataset is much larger than the others, the model is more strongly determined by the dominant dataset. For these reasons, for the strata where the reference dataset was under-represented or un-balanced, it was consolidated by additional reference data taken from the reference biomass maps, if available. The reference data were considered insufficient if a stratum had less than half of the average reference data per stratum, and were considered un-balanced if a single dataset provided more than 75% of the reference data of the whole stratum and it was not representative of more than

75% of its area. In such cases, additional reference data were randomly extracted from the reference biomass maps that did not provide more than 75% of the reference data. The amount of data to be extracted from each map was computed in a way to obtain a reference dataset with an average number of reference data per stratum and not dominated by a single dataset. If necessary, additional training data representing areas with no biomass (e.g., bare soil) were included, using visual analysis of Google Earth images to identify locations without vegetation.

Selected reference data

The biomass reference dataset compiled for this study consists of 14,477 1-km reference pixels, distributed as follows: 953 in Africa, 449 in South America, 7,675 in Central America, 400 in Asia and 5,000 in Australia (Fig. 2, Table 1). The reference data were relatively uniformly distributed among the strata (Table S6) but their amount varied considerably by continent. The average amount of reference data per stratum ranged from 50 (Asia) to 958 (Central America) 1-km reference pixels and their variability (computed as standard deviation relative to the mean) ranged from 25% (South America) to 52% (Central America). The uneven distribution of reference data across the continents is mostly caused by the availability of ground observations: as indicated above, in order to have a balanced reference dataset for each stratum the reference data extracted from biomass maps were limited to the (smaller) amount of direct field observations. When biomass maps were the only source of data this constrain was not occurring and larger datasets could be derived from the maps (i.e., Central America, Australia).

The reference data were selected from 18 ground datasets and from 9 high-resolution biomass maps calibrated by field observations and, in 4 cases, airborne LiDAR data (Table 1). The field plots used for the calibration of the maps are not included in this section because they were only used to select the reference pixels from the maps. The visual screening of the field plots removed 35% of the input data (from 6,627 to 4,283) and their aggregation to 1-km resolution further removed 70% of the reference units derived from field plots (from 4,283 to 1,274), while 10,741 reference pixels were extracted from the high-resolution biomass maps. The criteria used to select the reference pixels for each map are reported in Table S2. The consolidation procedure was necessary only for Central America where it added 2,415 reference data, while 47 pixels representing areas with no biomass were identified in Asia (Table S1). In general, ground observations were mostly discarded in areas characterized by fragmented or heterogeneous vegetation cover and high biomass spatial variability. In such contexts, reference data were often acquired from the biomass maps.

Stratification approach

Preliminary comparison of the reference data with the input maps showed that the error variances and biases of the input maps were not spatially homogeneous but varied considerably in different regions. Since the fusion model used in this study (see 'Modelling approach') is based on bias removal and weighted combination of the input maps, the more homogeneous the error characteristics in the input maps are, the better they can be reduced by the model. For this reason, the stratification approach aimed at identifying areas with homogeneous error structure (hereafter named 'error strata') in both input maps. A first stratification was done by geographic location (namely Central America, South America, Africa, Asia and Australia) to reflect the regional allometric relationships between biomass and tree diameter and height (Feldpausch et al., 2011, 2012). Then, the error strata were identified for each continent, using a two-step process. Firstly, the error maps of the Saatchi and Baccini maps were predicted separately. Since the biomass estimates of the input maps were mostly based on optical and LiDAR data that are sensitive to tree cover and tree height, it was assumed that their uncertainties were related to the spatial variability of these parameters. In addition, the errors of the input maps resulted to be linearly correlated with the respective biomass estimates. For these reasons, the biomass maps themselves as well as global datasets of ~~on the basis of their biomass estimates and~~ land cover (ESA, 2014a), tree cover (Di Miceli et al., 2014) and tree height (Simard et al., 2011) ~~parameters by~~ were used to predict the map errors using a Random Forest model (Breiman, 2001), calibrated on the basis of the reference dataset. Secondly, the error maps of the Saatchi and Baccini datasets were clustered using the K-Means approach. Eight clusters (hence, eight error strata) was considered as a sensible trade-off between homogeneity of the errors of the input maps and number of reference observations available per stratum, with a larger number of clusters providing only a marginal increase in homogeneity but leading to a small number of reference data in some strata (Fig. S2). In areas where the predictors presented no data (i.e., outside the coverage of the Baccini map) or for classes of the categorical predictor without reference data (i.e., land cover) the error strata (instead of the error maps) were predicted using an additional Random Forest model based on the predictors without missing values (i.e., Saatchi map, tree cover and tree height) and 10,000 training data randomly extracted from the stratification map.

This method produced a stratification map that identifies eight strata for each continent with homogeneous error patterns in the input maps (Fig. S3). The root mean square error (RMSE) computed on the Out-Of-Bag data (i.e., data not used for training) of the Random Forest models that predicted the errors of the input maps ranged between 22.8 ± 0.3 Mg ha^{-1} (Central America) to 83.7 ± 2.5 Mg ha^{-1} (Africa), with the two models (one for each input map) achieving similar accuracies in each continent (Table S4, Fig. S4). In most cases the main predictors of the errors of the input maps were the biomass values of the maps themselves, followed by tree cover and tree height, while land cover was always the least important predictor (Table S5). Further details on ~~error modelling and~~the processing of the input data are provided in the Supplementary Information.

The use of a stratification based on the errors of the input maps was compared with a stratification based on an alternative variable, ~~such as~~namely land cover (used by Ge et al., 2014), tree cover ~~or~~ and tree height. A separate stratification map was obtained for each of these alternative variables by aggregating them ~~Each of these variables was aggregated~~ into eight ~~classes~~ strata (to maintain comparability with the number of clusters used in the error strata), and each stratification map was used to develop a specific fused map. The performance of alternative stratification approaches was assessed by validating the respective fused maps (see Supplementary Information – Alternative stratification approaches). The results demonstrated that the stratification based on error modelling and clustering (i.e., the error strata) produced a fused map with higher accuracy than that of the maps based on other stratification approaches, and therefore was used in this study (Fig. S5).

Modelling approach

The fusion model

The integration of the two input maps was performed with a fusion model based on the concept presented by Ge et al. (2014) and further developed for this study. The fusion model consists of bias removal and weighted linear averaging of the input maps to produce an output with greater accuracy than each of the input maps. The reference biomass dataset described above was used to calibrate the model and to assess the accuracy of the input and fused maps. A specific model was developed for each stratum.

Following Ge et al. (2014), the p input maps for locations $s \in D$, where D is the geographical domain of interest common to the input maps, were combined using a weighted linear average:

$$(1) \quad f(s) = \sum_{i=1}^{p} w_i(s) \cdot (z_i(s) - v_i(s))$$

where f is the fused map, the $w_i(s)$ are weights, z_i the estimate of the i-th input map and $v_i(s)$ is the bias estimate. The bias term was computed as the average difference between the input map and the reference data for each stratum. The weights were obtained from a statistical model that assumes the map estimates z_i to be the sum of the true biomass b_i with a bias term v_i and a random noise term ε_i with zero mean for each location $s \in D$. We further assumed that the ε_i of the input maps are jointly normally distributed with variance-covariance matrix $\mathbf{C}(s)$. Differently from Ge et al. (2014), $\mathbf{C}(s)$ was estimated using a robust covariance estimator as implemented by the 'robust' package in R (Wang et al., 2014), which uses the Stahel-Donoho estimator for strata with fewer than 5,000 observations and the Fast Minimum Covariance Determinant estimator for larger strata. Under these assumptions, the variance of the estimation error of the fused map f(s) is minimized by calculating the weights w(s) as Searle (1971, p. 89):

$$(2) \quad w(s)^T = \left(\mathbf{1}^T \mathbf{C}(s)^{-1} \mathbf{1}\right)^{-1} \mathbf{1}^T \mathbf{C}(s)^{-1}$$

where $\mathbf{1}=[1, ..., 1]^T$ is the p-dimensional unit vector and where T means transpose. The sum of the weights computed for each stratum is equal to 1 and their value is inversely proportional to the error variance of the map. Larger weights were assigned to the map with lower error variance, i.e. to the map able to provide more accurate estimates after its bias has been removed. The fusion model assured that the variance of the error in the fused map was smaller than that of the input maps (Bates and Granger, 1969), especially if the errors associated with these maps were not strongly positively correlated and their error variances were close to the smallest error variance. The fusion model can be applied to any number of input maps. Where there is only one input map, the model estimates and removes its bias and the weights are set equal to 1.

The model parameters

The fusion model computed a set of bias and weight parameters for each stratum and continent on the basis of the respective reference data, and used these for the linear weighted combination of the input maps (Table S6). Since the stratification approach grouped together data with similar error patterns, the biases varied considerably among the strata and could reach values up to ±200 Mg ha^{-1}. However, considering the area of the strata, the biases of both input maps were smaller than ± 45 Mg ha^{-1} for at least 50% of the area of all continents and smaller than ±100 Mg ha^{-1} for 81% - 98% of the area of all continents.

Post-processing

Predictions outside the coverage of the Baccini map

The Baccini map covers the tropical belt between 23.4 degree north latitude and 23.4 degree south latitude while the Saatchi map presents a larger latitudinal coverage (Fig. 2). The fusion model was firstly applied to the area common to both input maps (Baccini extent) and then extended to the area where only the Saatchi map is available. In the latter area, the model focused only on removing the bias of the Saatchi map using the values estimated for the Baccini extent. The model predictions for the Saatchi extent were mosaicked to those for the Baccini extent using a smoothing function (inverse distance weight) on an overlapping area of 1 degree within the Baccini extent between the two maps. Water bodies were masked over the whole study area using the ESA CCI Water Bodies map (ESA, 2014b). The resulting fused map was projected to an equal area reference system (MODIS Sinusoidal) before computing the total biomass stocks for each continent, which were obtained by summing the products of the biomass density of each pixel with their area.

Assessing biomass in intact and non-intact forest

The biomass estimates of the fused and input maps in forest areas were further investigated regarding their distribution in ecozones and between intact and non-intact landscapes. Forest areas were defined as areas dominated by tree cover according to the GLC2000 map (~~Mayaux~~ Bartholomé and Belward, 2005~~et al., 2004~~). Ecozones were defined according to the Global Ecological Zone (GEZ) map for the year 2000 (FAO, 2000). The intact landscapes were defined according to the Intact Forest Landscape (IFL) map for the year 2000 (Potapov et al., 2008). On the basis of these datasets the mean forest biomass density of the fused and input maps were computed for intact and non-intact landscapes for each continent and major ecozone. To allow direct comparison of the results among the maps, the analysis was performed only for the area common to all maps (Baccini extent). In addition, to reduce the impact of spatial inaccuracies in the maps, only ecozones with IFL intact forest areas larger than 1,000 km^2 were considered. The mean biomass density of intact and non-intact forests per continent was computed as the area-weighted mean of the contributing ecozones.

Validation and uncertainty

Validation of the fused and input maps was performed by randomly splitting the reference data into a calibration set (70% of the data) and a validation set (remaining 30%). The 'final' fused map presented in Fig. 3 used 100% of the reference data ~~and~~ while for validation purposes a 'test' fused map was produced using only the calibration data and its estimates, as well as those of the input maps, were compared with the validation data. Thus, the validation results refer to the 'test' fused map based only on the calibration set and are expected to be representative (if not conservative) of the accuracy of the 'final' fused map based on all the reference data. To maintain full independence, validation data were not used for any step related to the development of the 'test' fused map, including production of the stratification map. To account for any potential impacts of the random selection of validation data, the procedure was repeated 100 times, computing each time a new random selection of the calibration and validation datasets. This procedure allowed computing the mean RMSE and assessing its standard deviation for ~~each~~ the fused and input maps.

The uncertainty of the fused map was computed with respect to model uncertainty, not including the error sources in the input data (see 'Discussion'). The model uncertainty consisted of the expected variance of the error of the fused map (which is assumed bias-free) and was derived for each stratum from **C**(s), hence the uncertainty was estimated by strata and not at pixel level. The error variance was converted to an uncertainty map by reclassifying the stratification map, where the stratum value was converted to the respective error variance computed for each stratum and continent.

Results

Biomass map

The fusion model produced a biomass map at 1-km resolution for the tropical region, with an extent equal to that of the Saatchi map (Fig. 3). In terms of aboveground stocks, the fused map gave biomass estimates lower than both input maps at continental level. The total stock for the tropical belt covered by the Baccini map (23.4 N – 23.4 S, see Fig. 2) was 375 Pg dry mass, 9% and 18% lower than the Saatchi (413 Pg) and Baccini (457 Pg) estimates, respectively. Considering the larger extent of the Saatchi map, the fused map estimate was 462 Pg, 15% lower than the estimate of the Saatchi map (545 Pg) (Table S7).

Moreover, the fused map presented spatial patterns substantially different from both input maps (Fig. 4): the biomass estimates were higher than the Saatchi and Baccini maps in the dense forest areas in the Congo basin, in West Africa, in the north-eastern part of the Amazon basin (Guyana shield) and in South-East Asia, and lower in Central America and in most dry vegetation areas of Africa. In the central part of the Amazon basin the fused map showed lower estimates than the Baccini map and higher estimates than the Saatchi map, while in the southern part of the Amazon basin these differences were inversed. Similar trends emerged when comparing the maps separately for intact and non-intact forest ecozones (Supporting Information). In addition, the average difference between intact and non-intact forests was larger than that derived from the input maps in Africa and Asia, similar or slightly larger in South America, and smaller in Central America (Fig. S6).

The fused map records the highest biomass density (> 400 Mg ha^{-1}) in the Guyana shield, in the Central and Western part of the Congo basin and in the intact forest areas of Borneo and Papua New Guinea. The analysis of the distribution of forest biomass in intact and non-intact ecozones showed that, according to the fused map, the mean biomass density was greatest in intact African (360 Mg ha^{-1}) and Asian (335 Mg ha^{-1}) forests, followed by intact forests in South America (266 Mg ha^{-1}) and Central America (146 Mg ha^{-1}) (Fig. S6). Biomass in non-intact forests was much lower in all regions (Africa, 78 Mg ha^{-1}; Asia, 211 Mg ha^{-1}; South America, 149 Mg ha^{-1}; and Central America, 57 Mg ha^{-1}) (Fig. S6).

Validation

The validation exercise showed that the fused map achieved a lower RMSE (a decrease of 5 – 74%) and bias (a decrease of 90 – 153%) than the input maps for all continents (Fig. 5). While the RMSE of the fused map was consistently lower than that of the input maps but still substantial (87 – 98 Mg ha^{-1}) in the largest continents (Africa, South America and Asia), the mean error (bias) of the fused map was almost null in most cases. Moreover, in the three main continents the bias of the input maps tended to vary with biomass, with overestimation at low values and underestimation at high values, while the errors of the fused map were more consistently distributed (Fig. 6). When computing the error statistics for the pan-tropics (Baccini extent) as average of the regional validation results weighted by the respective area coverage, the mean bias (in absolute terms) for the fused, Saatchi and Baccini maps was 5, 21 and 28 Mg ha^{-1} and the mean RMSE was 89, 104 and 112 Mg ha^{-1}, respectively (Fig. 5). The accuracy of the input maps reported above was computed using the validation dataset (30% of the reference dataset) to be consistent with the accuracy of the fused map. The accuracy of the input maps was also computed using all reference data and the results (Table S3) were similar to those based on the validation dataset.

Uncertainty map

The uncertainty of the model predictions ~~at 1 km resolution~~ indicated that the standard deviation of the error of the fused map for each stratum was in the range 11 - 108 Mg ha^{-1}, with largest uncertainties in areas with largest biomass estimates (Congo basin, Eastern Amazon basin and Borneo). When computed in relative terms (as percentage of the biomass estimate) the model uncertainties presented opposite patterns, with uncertainties larger than the estimates (> 100%) in low biomass areas (< 20 Mg ha^{-1} on average) of Africa, South America and Central America, while high biomass forests (> 210 Mg ha^{-1} on average) had uncertainties lower than 25% (Fig. 7). The uncertainty measure derived from **C**(s) is computed only when two or more input maps are available. Hence it could not be calculated for Australia because the model for this continent was based on only one input map (Saatchi map).

Discussion

Biomass patterns and stocks emerging from the reference data

The biomass map produced with the fusion approach is largely driven by the reference dataset and essentially the method is aimed at spatializing the biomass patterns indicated by the reference data using the support of the input maps. For this reason, great care was taken in the pre-processing of the reference data, which included a two-step quality screening based on metadata analysis and visual interpretation, and their consolidation after stratification. As a result, the reference dataset provides an unprecedented compilation of biomass estimates at 1-km resolution for the tropical region, covering a wide range of vegetation types, biomass ranges and ecological regions across the tropics. It includes the most comprehensive and accurate tropical field plot networks and high-quality maps calibrated with airborne LiDAR, which provide more accurate estimates compared to those obtained from other sensors (Zolkos et al., 2013). The main trends present in the fused map emerged from the combination of different and independent reference datasets and are in agreement with the estimates derived from long-term research plot networks (Malhi et al., 2006; Phillips et al., 2009; Lewis et al., 2009; Slik et al., 2010, 2013; Lewis et al., 2013) and high-resolution maps (Asner et al., 2012a, 2012b, 2013, 2014a). Specifically, the biomass patterns in South America represent spatial trends described by research plot networks in the dense intact and non-intact forests in the Amazon basin, forest inventory plots collected in the dense forests of Guyana and samples extracted from biomass maps for Colombia and Peru representing a wide range of vegetation types, from arid grasslands to humid forests. Similarly, biomass patterns depicted in Africa were derived from a combination of various research plots in dense undisturbed forest (Gabon, Cameroon, Democratic Republic of Congo, Ghana, Liberia), inventory plots in forest concessions (Democratic Republic of Congo), biomass maps in woodland and savannah ecosystems (Uganda, Mozambique) and research plots and maps in montane forests (Ethiopia, Madagascar). Most vegetation types in Central America, Asia and Australia were also well-represented by the extensive forest inventory plots (Indonesia, Vietnam and Laos) and high-resolution maps (Mexico, Panama, Australia).

In spite of the extensive coverage, the current database is far from being representative of the biomass variability across the tropics. As a consequence, the model estimates are expected to be less accurate in contexts not adequately represented. In the case of the fusion approach, this corresponds to the areas where the input maps present error patterns different than those identified in areas with reference data: in such areas the model parameters used to correct the input maps (bias and weight) may not adequately reflect the errors of the input maps and hence cannot optimally correct them. In particular, deciduous vegetation and heavily disturbed forest of Africa and South America, and large parts of Asia were lacking quality reference data. Moreover, even though plot data were spatially distributed over the central Amazon and the Congo basin, large extents of these two main blocks of tropical forest have never been measured (cf. maps in Lewis et al., 2013; Mitchard et al., 2014). Considering the evidence of significant local differences in forest structure and biomass density within the same forest ecosystems (Kearsley et al., 2013), additional data are needed to strengthen the confidence of the fused map as well as that of any other biomass map covering the tropical region. Moreover, a dedicated gap analysis to assess the main regions lacking biomass reference data and identify priority areas for new field sampling and LiDAR campaigns would be very valuable for future improved biomass mapping.

Regarding the biomass stocks, a previous study showed that despite their often very strong local differences the two input maps tended to provide similar estimates of total stocks at national and biome scales and presented an overall net difference of 10% for the pan-tropics (Mitchard et al., 2013). However, such convergence is mostly due to compensation of contrasting estimates when averaging over large areas. The larger differences with the estimates of the present study (9% and 18%) suggest an overestimation of the total stocks by the input maps. This is in agreement with the results of two previous studies that, on the basis of reference maps obtained by field-calibrated airborne LiDAR data, identified an overestimation of 23% - 42% of total stocks in the Saatchi and Baccini maps in the Colombian Amazon (Mitchard et al., 2013) and a mean overestimation of about 100 Mg ha^{-1} for the Baccini map in the Colombian and Peruvian Amazon (Baccini and Asner, 2013).

In general, the biomass density values of the fused map were calibrated and therefore in agreement with the existing estimates obtained from plot networks and high-resolution maps. The comparison of mean biomass values in intact and non-intact forests stratified by ecozone provided further information on the differences among the maps. The mean biomass values of the fused map in non-intact forests were mostly lower than those of the input maps, suggesting that in disturbed forests the biomass estimates derived from stand height parameters retrieved by spaceborne LiDAR (as in the input maps) tend to be higher compared to those based on tree parameters or very high-resolution airborne LiDAR measurements (as in the fused map and reference data). This difference occurred especially in Africa, Asia and Central America while it was less evident in South America and Australia. By contrast, the differences among the maps for intact forests varied by continent, with the fused map having, on average, higher mean biomass values in Africa, Asia and Australia, lower values in Central

America, and variable trends within South America, reflecting the different allometric relationships used by the various datasets in different continents.

As mentioned above, a larger amount of reference data, ideally acquired based on a clear statistical sampling design, instead of an opportunistic one, will be required to confirm such conclusions. While dense sampling of tropical forests using field observations is often impractical, new approaches combining sufficient ground observations of individual trees at calibration plots with airborne LiDAR measurements for larger sampling transects would allow a major increase in the quantity of calibration data. In combination with wall-to-wall medium resolution satellite data (e.g., Landsat) these may be capable of achieving high accuracy over large areas (10% - 20% uncertainty at 1-ha scale) while being cost-effective (e.g., Asner et al., 2013, 2014b). In addition, new technologies, such as terrestrial LiDAR scanning, allows for better estimates at ground level (Calders et al., 2015; Gonzalez de Tanago et al., 2015), reducing considerably the uncertainties of field estimates based on generalized allometric equations without employing destructive sampling. Nevertheless, since floristic composition influences biomass at multiple scales (e.g., the strong pan-Amazon gradient in wood density shown by ter Steege et al., 2006) such techniques benefit from extensive and precise measurements of tree identity in order to determine wood density patterns and to account for variations in hollow stems and rottenness (Nogueira et al., 2006). Moreover, we note that the reference data do not include lianas, which may constitute a substantial amount of woody stems, and their inclusion would allow to obtain more correct estimates of total aboveground biomass of vegetation (Phillips et al., 2002; Schnitzer & Bongers, 2011; Durán & Gianoli, 2013).

Additional error sources

Apart from the uncertainty of the fusion model described above (see 'Uncertainty'), three other sources of error were identified and assessed in the present approach: i) errors in the reference dataset; ii) errors due to temporal mismatch between the reference data and the input maps; iii) errors in the stratification map.

Errors in the reference dataset

The reference dataset is not error-free but it inherits the errors present in the field data and local maps. In addition, additional uncertainties are introduced during the pre-processing of the data by resampling the maps and by upscaling the plot data to 1-km resolution. In particular, while the geolocation error of the original datasets was considered relatively small (< 50 m) since plot coordinates were collected using GPS measurements and the biomass maps were based on satellite data with accurate geolocation (i.e., Landsat, ALOS, MODIS), larger errors (up to 500 m, half a pixel) could have been introduced with the resampling of the 1-km input maps. All these error sources were minimized by selecting only the datasets that fulfilled certain quality criteria and by further screening them by visual analysis of high-resolution images available on the Google Earth platform, discarding the data not representative of the respective map pixels. In case of reference data that clearly did not match with the high-resolution images and/or with the input maps (e.g., reporting no biomass in dense forest areas or high biomass on bare land), the data were considered as an error in the reference dataset, a geolocation error in the plots or maps, or it was assumed that a land change process occurred between the plot measurement and the image acquisition time (see next paragraph).

Errors due to temporal mismatch

The temporal difference of input and reference data introduced some uncertainty in the fusion model. The input maps refer to the years 2000 – 2001 (Saatchi) and 2007 – 2008 (Baccini) while the reference data mostly spanned the period 2000 – 2013. Therefore, the differences between the input maps and the reference data may also be due to a temporal mismatch of the datasets. However, changes due to deforestation were most likely excluded during the visual selection of the reference data, when high-resolution images showed clear land changes (e.g., bare land or agriculture) in areas where the input maps provided biomass estimates relative to forest areas (or vice-versa, depending on the timing of acquisition of the datasets). However, changes due to forest regrowth and forest degradation events that did not affect the forest canopy could not be considered with the visual analysis and may have affected the mismatch observed between the reference data and the input maps (< 58 – 80 Mg ha^{-1} for 50% of the cases of the Saatchi and Baccini maps, respectively). Part of the mismatch was in the range of biomass changes due to regrowth (1 – 13 Mg ha^{-1} year^{-1}) (IPCC, 2003) or low-intensity degradation (14 – 100 Mg ha^{-1}, or 3 – 15% of total stock) (Asner et al., 2010; Pearson et al., 2014). On the other hand, considering the limited area affected by degradation (about 20% in the humid tropics) (Asner et al., 2009), the temporal mismatch could be responsible only for a correspondent part of the differences observed between the reference data and the input maps. Small additional offsets may also be caused by the documented secular changes in biomass density within intact tropical forests, which has been increasing by 0.2 – 0.5% per year (Phillips et al., 1998, Chave et al., 2008, Phillips and Lewis, 2014). It should also be noted that the reference data were used to optimally integrate the input maps, and in the case of a temporal difference the fused map was 'actualized' to the state of the vegetation when the reference data were acquired. The reference data were acquired between 2000 and 2013, and their mean acquisition year weighted by their contribution to the fusion model (by continent) corresponds to the period 2007 – 2010 (2007 in Africa, 2008 in Central America, 2009 in

South America and 2010 in Asia). Therefore the complete fused map cannot be attributed to a specific year and more generally it represents the first decade of the 2000's.

Errors in the stratification map

The errors in the stratification map (i.e., related to the prediction of the errors of the input maps) were still substantial in some areas and affected the fused map in two ways. First, the reference data that were erroneously attributed to a certain stratum introduced 'noise' in the estimation of the model parameters (bias and weight), but the impact of these 'outliers' was largely reduced by the use of a robust covariance estimator. Second, erroneous predictions of the strata caused the use of incorrect model parameters in the combination of the input maps. The latter is considered to be the main source of error of the fused map and indicates that the method can achieve improved results if the errors of the input maps can be predicted more accurately. However, additional analysis showed that, on average, fused maps based on alternative stratification approaches achieved lower accuracy than the map based on an error stratification approach (Fig. S5). Therefore, this approach was preferred over a stratification based on an individual biophysical variable (e.g., tree cover, tree height, land cover or ecozone).

Application of the method at national scale

The fusion method presented in this study allows for the optimal integration of any number of input maps to match the patterns indicated by the reference data. However, the accuracy of the fused map depends on the availability of reference data representative of the error patterns of the input maps. While the current reference database does not represent adequately all error strata for the tropical region, and the model estimates are expected to have lower confidence in under-represented areas, the proposed method may be applied locally and provide improved biomass estimates where additional reference data are available. For example, the fusion method may be applied at national level using existing forest inventory data, research plots and local maps that cover only part of the country to calibrate global or regional maps, which provide national coverage but may not be tailored to the country context. Such country-calibrated biomass maps may be used to support natural resource management and national reporting under the REDD+ mechanism, especially for countries that have limited capacities to map biomass from remote sensing data (Romijn et al., 2012). Considering the increasing number of global or regional biomass datasets based on different data and methodologies expected in the coming years, and that likely there will not be a single ‘best map’ but rather the accuracy of each will vary spatially, the fusion approach may allow to optimally combine and adjust available datasets to local biomass patterns identified by reference data.

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Supporting Information

Appendix S1. Supplementary methods and results

Tables

Table 1: Number of reference data (plots and 1-km pixels) selected after the screening, upscaling and consolidating procedures, per continent. The reference data selected for each individual dataset are reported in Table S1. The field plots underpinning the reference biomass maps are not included.

Continent	Available	Selected		Consolidated
	Plots	*Plots*	*Pixels*	*Pixels*
Africa	2,281	1,976	953	953
S. America	648	474	449	449
C. America	-	-	5,260	7,675
Asia	3,698	1,833	353	400
Australia	-	-	5,000	5,000
Total	**6,627**	**4,283**	**12,015**	**14,477**

Figure captions

Figure 1: methodology flowchart

Figure 2: Biomass reference dataset for the tropics and spatial coverage of the two input maps

Figure 3: Fused map, representing the distribution of live woody aboveground biomass (AGB) for all land cover types at 1-km resolution for the tropical region.

Figure 4: Difference maps obtained by subtracting the fused map from the Saatchi map (top) and the Baccini map (bottom).

Figure 5: RMSE (left) and bias (right) of the fused and input maps per continent obtained using independent reference data not used for model development. The error bars indicate one standard deviation of the 100 simulations. Numbers reported in brackets indicate the number of reference observations used for each continent. The results for the pan-tropics exclude Asutralia, which is not covered by the Baccini map.

Figure 6: scatterplots of the validation reference data (x-axis) and predictions (y-axis) of the input maps (left plots) and fused map (right plots) by continent.

Figure 7: Uncertainty of the fused map, in absolute values (top) and relative to the biomass estimates (bottom), representing one standard deviation of the error of the fused map.