The contribution of trees outside forests to national tree biomass and carbon stocks—a comparative study across three continents

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Abstract In contrast to forest trees, trees outside forests (TOF) often are not included in the national monitoring of tree resources. Consequently, data about this particular resource is rare, and available information is typically fragmented across the different institutions and stakeholders that deal with one or more of the various TOF types. Thus, even if information is available, it is difficult to aggregate data into overall national statistics. However, the National Forest Monitoring and Assessment (NFMA) programme of FAO offers a unique possibility to study TOF resources because TOF are integrated by default into the NFMA inventory design. We have analysed NFMA data from 11 countries across three continents. For six countries, we found that more

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Chair of Forest Inventory and Remote Sensing, Georg-August-University Göttingen, Büsgenweg 5, 37077 Göttingen, Germany e-mail: ckleinn@gwdg.de than 10 % of the national above-ground tree biomass was actually accumulated outside forests. The highest value (73 %) was observed for Bangladesh (total forest cover 8.1 %, average biomass per hectare in forest 33.4 t ha^{-1}) and the lowest (3 %) was observed for Zambia (total forest cover 63.9 %, average biomass per hectare in forest 32 t ha⁻¹). Average TOF biomass stocks were estimated to be smaller than 10 t ha^{-1} . However, given the large extent of non-forest areas, these stocks sum up to considerable quantities in many countries. There are good reasons to overcome sectoral boundaries and to extend national forest monitoring programmes on a more systematic basis that includes TOF. Such an approach, for example, would generate a more complete picture of the national tree biomass. In the context of climate change mitigation and adaptation, international climate mitigation programmes (e.g. Clean Development Mechanism and Reduced Emission from Deforestation and Degradation) focus on forest trees without considering the impact of TOF, a consideration this study finds crucial if accurate measurements of national tree biomass and carbon pools are required.

Keywords Trees outside forests \cdot National forest inventory \cdot National forest monitoring and assessment \cdot FAO NFMA

Introduction

While planning the Global Forest Resources Assessment (FRA) 2000, a programme of the Food and

Agriculture Organization (FAO) of the United Nations (UN), the term trees outside forests (TOF) was introduced into global forest monitoring (Pain-Orcet and Bellefontaine 2004; Nyssönnen and Ahti 1996). TOF includes all trees that exist beyond the FRA definitions for forest and other wooded land (FAO 2001), and the inclusion of TOF can be interpreted as an important recognition of the national and global relevance of this resource for human livelihoods, the environment, and biodiversity (Pain-Orcet and Bellefontaine 2004). However, interest in TOF has of course a much longer history. In 1713, Hans Carl von Carlowitz, in addition to introducing the term "sustainability" in the context of forest management, referred to non-forest tree resources several times in his opus Silvicultura Oeconomica (Carlowitz 1713). Further, people for centuries had managed various agroforestry systems-e.g. fruit tree meadows, hedgerows, riparian buffers, or parkland trees (Boffa 2000; Herzog 2000). In addition, there is a long history and wealth of literature from agroforestry and urban planning that emphasise the role of TOF.

TOF and, in particular, agroforestry offers a range of ecological, economic, and social functions (Auclair et al. 2000; Bellefontaine et al. 2002; Idol et al. 2011). These functions include carbon sequestration (Atangana et al. 2014; Nair 2011; Plieninger 2011) and additional environmental services, offering a win-win land-use strategy for climate change mitigation and adaptation (Leakey 2001; Plieninger 2011). As a result, landowners, governmental organisations, and other national stakeholders may have a need for national-level information on TOF. Similarly, the United Nations Framework Convention on Climate Change (UNFCCC), the Convention on Biological Diversity, the United Nations Convention to Combat Desertification, and the FRA require TOF information as it relates to international reporting obligations. In croplands, grasslands, and settlements, for example, the UNFCCC requires information about TOF woody biomass for greenhouse gas reporting (IPCC 2006). In addition, direct payments to farmers in the EU will depend, to some extent, on their ability to use techniques that soften their climate and environmental impact (European Commission 2011). Furthermore, rural development plans under the common agricultural policy of the EU promote the establishment, conservation, and management of woody vegetation structures in the landscape, including farm trees and hedgerows (Schleyer and Plieninger 2011). To assess the effectiveness of these requirements, agencies will need to monitor TOF elements such as trees, bushes, and hedgerows on farmland.

There is, however, little information about TOF across large areas. A few studies have pointed to the potentially substantial contribution of TOF to large-area wood resources (FAO 1998; FSI 2011; Kleinn et al. 2005; Riemann 2003; Smith and Gilbert 2003), although a systematic and comparable assessment is missing in most countries. In India, however, systematic TOF inventories were started in 1991 at the subregional level and for the entire country since 2002 (Tewari et al. 2013). Some other countries—UK (Smith and Gilbert 2003), Switzerland (Brändli 2010), France (Bélouard and Coulon 2002), and Sweden (Axelsson et al. 2010; Ståhl et al. 2011)-have started to integrate TOF into their existing national monitoring systems for tree resources. Here, either the scope of the national forest inventories (NFI) was widened to include TOF or TOF was assessed within coexisting landscape inventories. From the first inventory in 2000, FAO's programme for National Forest Monitoring and Assessment (NFMA) included TOF by default and to date, has assisted 19 countries in implementing their national forest inventories (see de Foresta et al. (2013, p.129) for a more detailed list of countries with some sort TOF assessment at the national level).

Where TOF is already integrated into national inventory programmes, usually not all TOF types are covered. For example, trees on agricultural lands are usually included but urban trees frequently are not. Information from other sources, such as citywide inventories (Nowak 2002) and agricultural production statistics (de Foresta et al. 2013, pp. 94-95) might be used to develop a more complete picture if these data are available at a national level. Although TOF information is often available, it is usually fragmented in terms of space and time and difficult to aggregate into overall national statistics. This fragmentation of information is usually a result of the sectoral jurisdiction where different institutions deal with the varying lands on which TOF grow. Access to the lands for tree mensuration is a major challenge when the aim is to include TOF in national "forest" inventories: the NFI mandate usually ends at the forest edge and inventory teams must seek permission to measure trees in private gardens or agricultural fields. To extend that mandate may require lengthy legislative processes.

In the present study, we use data from countries that have completed forest resource or landscape inventories under the NFMA programme (established in 2000) to study the overall quality of the periodic FRA reporting on the worlds' forests. Upon request from governments of developing countries, the NFMA programme helps countries install long-term, methodologically sound, and sustainable forest monitoring systems on a national level. The NFMA approach, relying heavily on direct observations from sample-based field inventories, tries to keep the corresponding costs low by working with modest sample sizes in combination with relatively large observational plots. The NFMA programme has introduced two innovative components on a systematic basis: (1) the default integration of TOF as target objects beyond "forests"-i.e. the sampling frame is the entire country and not only forest lands and (2) the assessment of variables beyond biophysical observationsi.e. interviewing land owners and users of forests and trees. The national forest monitoring projects that are assisted by the NFMA programme are strictly in country ownership and under national funding; they aim to generate relevant national level data and information on forests and non-forest trees, focusing on current state and changes regarding their social, economic, and environmental functions (FAO 2012). The suggested methods, definitions, and classification systems are developed together with an international team of experts and are adapted to the national circumstances. This approach offers a unique possibility for a methodologically sound compilation of the results on TOF across a large number of countries and continents. The results of these monitoring programmes should have a high degree of compatibility and offer excellent grounds for scientific comparisons.

By analysing data from countries that had completed inventories under the NFMA programme, this is the first study ever that compares national level estimates of TOF stocks on common methodological grounds, in the sense that data had been gathered and analysed along a consistent and transparent methodology. This offers for the first time a more holistic view onto the nationallevel tree resource than would have been possible from a forest-focused monitoring alone. With the emphasis on biomass and carbon stock estimates, we provide quantitative evidence that TOF constitute a substantial terrestrial carbon stock in many regions.

Material and methods

Study countries

The selection of the 11 countries included in this study (Fig. 1) was based on the completion of NFMA-assisted inventories by July 2011 and that access to the gathered data was granted by the data owners. The 11 countries are from three continents, and nine out of these 11 countries are located in the tropics.

Definitions

Land use was assessed according to the global categories forest, other wooded land (OWL), other land (OL), and inland water (IW) as defined by FAO's FRA programme (FAO 2010). Forest and OWL are land areas under tree cover with a size of at least 0.5 ha that are not predominantly under agricultural or urban land use and where trees are able to exceed a height of 5 m at maturity in situ. To qualify as forest land, the tree crown cover must be at least 10 % (at maturity). For OWL, tree crown cover must be between 5 and 10 % or the combined tree/shrub cover must be at least 10 %. OL is all land that does not qualify as forest or OWL, including tree-covered lands with predominantly agricultural or urban land use. Finally, IW is composed of major rivers, lakes, ponds, and reservoirs. TOF concerns the tree resources on OL and on IW, although the tree resources in the latter category are typically extremely small. The major part of TOF is associated with agricultural and urban land uses, but TOF may also be found as small wooded areas or tree line formations outside these categories. Scattered tree formations with very low canopy densities, typically growing under difficult environmental conditions, are also considered TOF (de Foresta et al. 2013, p. 31). Some countries reported trees growing on IW, which are related to river banks and lakeshores. As this practice was not done consistently over the study countries and only concerned very few trees, we moved such trees to OL and consequently report biomass only for forest, OWL, and OL; however, area estimates were done including IW.

We use FAO's definition of a tree (FAO 2010): trees are woody perennial plants able to reach a height of at least 5 m in situ. Note that bamboo and palms are included according to this definition. In our analysis, however, we excluded bamboo, as the data were



Fig. 1 Map of countries studied

incomplete for some countries. Furthermore, all dead trees and stumps were excluded from the analysis.

Inventory design and variables used

The inventory approach of the NFMA programme was systematic sampling with cluster-plots. The FAO's template manual for integrated field data collection (FAO 2012) provides a detailed description on the procedures and organisation of the field survey. The final reports and field manuals of each NFMA project can be found at FAO's homepage (FAO 2013). Here, we focus on the features relevant for the estimation of TOF-related variables. Each cluster-plot consisted of four rectangular subplots with a size of 20 m×250 m so that a plot area of 2.0 ha was tallied at each sample location (Fig. 2). The sampling frame was defined in terms of area and corresponded to the entire country's territory so that all cluster-plots were field-visited regardless of the current land use: that is, trees were measured wherever they occurred, and the inventory approach was not restricted to forest land as is common in traditional forest inventories. For each subplot, land use was recorded. Because the clusters as a whole and the individual subplots were relatively large, one cluster-plot often included several land uses. In such cases, subplots were divided into different land-use sections. For each land-use section, the shape and size was recorded, so that the whole cluster and subplots were mapped in the field according to actual land use. Diameter at breast height (dbh) and height were recorded for all trees with a *dbh* of at least 10 cm. Within forests, smaller trees (dbh < 20 cm) were measured on three evenly arranged micro-plots of 200 m² per subplot—i.e. 12 micro-plots per cluster-plot (Fig. 2).

As countries adjusted the basic inventory design when necessary, we compiled an overview of basic design characteristics such as the country's land area, the total sample size, and the number of strata used for



Fig. 2 Basic plot design used in the NFMA programme. Only the elements necessary for the present analysis are illustrated, a detailed description is given in FAO (2012). The application of micro-plots is optional and not applied equally by all countries. For Costa Rica, the subplot length is 150 m

the implementation of the inventory (Table 1). Stratification was used in Cameroon and Guatemala. The land area of Cameroon was divided into two strata to ensure more sampling units in the densely forested southern part of the country. In Guatemala, three strata were distinguished, dividing the country into a northern, central, and southern part, following the natural regions of Guatemala. A higher sampling density was used for the central stratum, accounting for an increased variation in ecosystems, human activity, and land use. The application of micro-plots in forests, an optional strategy, was not used in Bangladesh, Kyrgyzstan, or Lebanon. In these three countries, all trees above the applied *dbh* threshold were measured on the subplots irrespective of the land use. In addition, Kyrgyzstan and Zambia used smaller dbh thresholds (Table 1). In the analyses, we did not correct for this, and results should be interpreted bearing in mind these relatively minor variations among countries. Another deviation from the standard design occurred in Costa Rica, where the very first NFMA inventory was carried out using subplots only 150 m long.

Sample sizes (Table 1)-i.e. the number of clusterplots distributed over the countries-varied from 40 to 765, largely as a result of differences in country size and available resources. For some of the clusters, access to the field was impossible due to topography, vegetation, owner denial, and restricted areas so that information was either totally missing or only available for some parts of a cluster. For some of the inaccessible land, land use could be observed from a distance; for the rest, it was completely unknown. The latter case is reported as a separate category of nonresponse. Thus, some tree populations and land-use categories, e.g. trees on steep slopes or remote forest areas, are underrepresented as a consequence of this nonresponse. However, as we applied broad land-use categories, the effect should be minor. In a strict sense, the presence of nonresponse means that our results are only representative for land areas to which access was possible during the inventories.

Estimation framework

The estimation of attributes, such as area proportions or total biomass, from a mapped plot design, as in our case, is discussed in detail in Zarnoch and Bechtold (2000). Briefly, the ratio of means estimator (Cochran 1977, chapter 6) relates the total biomass observed on a

cluster-plot to the area of that cluster to obtain an average biomass. For variance estimation, we applied the respective simple random sampling estimator framework, despite the fact that the sample design is systematic. In such cases, random sampling estimators deliver conservative estimates, so the true error is likely to be overestimated although the magnitude of overestimation is unknown (Ene et al. 2012; Gregoire and Valentine 2008, p. 55).

Because we applied a nested plot design to forest land in some of the countries, an additional step was required to estimate the forest-related results, used as a baseline for comparisons with TOF estimates. Instead of one ratio estimator, two were required—one for the small trees on the microplots and one for the large trees on the subplots. The two ratios were then simply added, and the variance of the sum calculated.

Totals (e.g., total forest biomass) were estimated by multiplying the per hectare estimates with estimates of the total area covered by the respective land uses. Area estimates were in turn derived by multiplying estimated area proportions with the known total land area (Table 1). We do not report the totals but rather the share each land-use category contributes to the overall total in a country.

Tree level biomass

Because allometric models specifically derived for TOF are extremely limited (e.g. McHale et al. 2009), we needed to resort to models that were derived from forest trees. To demonstrate the differences caused by uncertainties in existing biomass models, we used three approaches for biomass estimation (van Breugel et al. 2011).

Approach 1 makes use of the mixed species tree biomass regression models developed by Chave et al. (2005) on the basis of a large dataset comprising 2410 trees from 27 study sites across the tropics. The models were specific to four broad forest types: wet, moist, moist mangrove, and dry forests. We used the global ecological zones as defined by FAO (2001) to select the appropriate set of functions in each case. The independent variables in the models were diameter at breast height, wood specific gravity, and tree height. In our case, tree height information was available for all recorded trees, either measured

Country	Area km ²	Sample size no.	Strata no.	<i>dbh</i> limit cm	Micro-plot bin	Year
Bangladesh	147,570	298	1	10 (10)	no	2005–2007
Cameroon	475,440	207 (205)	2	20 (10)	yes	2003-2004
Costa Rica	51,000	40 (39)	1	30 (10)	yes	2001
The Gambia	11,000	144 (129)	1	20 (10)	yes	2008-2010
Guatemala	108,899	114	3	20 (10)	yes	2002-2003
Honduras	112,492	181	1	20 (10)	yes	2005-2006
Kyrgyzstan	199,940	765 (733)	1	8 (8)	no	2008-2010
Lebanon	10,452	222 (220)	1	10 (10)	no	2003-2005
Nicaragua	130,000	371 (368)	1	20 (10)	yes	2007-2008
Philippines	300,000	351 (349)	1	20 (10)	yes	2003-2005
Zambia	752,614	238 (232)	1	20 (7)	yes	2005-2008

Table 1 Basic characteristics of the sample and plot design used in the single countries

Sample size gives the number of clusters used, in case of inaccessibility, the reduced number of clusters is given in parentheses; *dbh* limit is the threshold for measuring trees on forest subplots, with thresholds for trees on rectangular micro-plots and outside forests in parentheses; the binary variable micro-plot indicates whether micro-plots were used (yes) or not (no)

with hypsometers or estimated visually. This approach is denoted here as *Chave H*.

Approach 2 is equal to approach 1 in all aspects except that height was not used as an independent variable. Thus, in this case, we used those models from Chave et al. (2005) that do not require tree height as an independent variable. Consequently, approach 2 is denoted here as *Chave D*.

For approach 3, we adopted the methodology used by the individual countries for their reporting. Many used the mixed species regression models described in Brown (1997), which only use diameter at breast height as an independent variable and which were developed from rather small datasets. Other countries used the inventoried tree volume together with wood specific gravity and biomass expansion factors to estimate biomass. A more detailed description of the applied models, wood specific gravities, and expansion factors is provided in the Appendix. In the following, we denote this approach *NFMA*.

Tropical conifers, as found in Guatemala, Honduras, and Nicaragua, were treated equally across all three approaches. We used either the preliminary model from Brown (1997) or, if available, country-specific functions for forest trees (see Appendix). For the two nontropical countries, Kyrgyzstan and Lebanon, biomass was estimated using biomass expansion factors as described in the NFMA reports (FAO 2013; IPCC 2006). Specific allometric functions were not available for these regions.

Because wood density is a fundamental part of the applied equations, the *World Wood Density Database* (Chave et al. 2009; Zanne et al. 2009) was used to obtain values for the observed species. Following the approach that Chave et al. (2006) used, we first tried to find values on the species level. If no value could be found, genus averages were applied and subsequently, family averages if the genus was missing as well. For cases where the species was completely unknown or neither species nor genus nor family could be found in the wood density database, the median of the ten most abundant species per land-use type was applied as a proxy (Fischer et al. 2011).

The biomass of palms was estimated with the same models as those used for trees despite the fundamentally different allometry and highly variable wood density within single palm stems (Rich 1987). This approach was done because of the lack of allometric equations for biomass estimation of palm trees based on input variables (diameter and height) available from our forest inventory data. Models based on trunk height exist for some Mesoamerican species. However, these palm species differ substantially in average size and height from Asian species. The lack of allometric biomass models for palms appears to be a major methodological gap for biomass estimation in tropical regions.

Carbon estimation

For a validation of the biomass estimates, results were compared to national forest carbon stock estimates published in Gibbs et al. (2007). For that purpose, biomass estimates, as calculated from our data, were converted to carbon applying the Intergovernmental Panel on Climate Change (IPCC) default carbon fraction of 0.47 (McGroddy et al. 2004) for above-ground forest biomass. As the reported figures refer to above-ground and belowground forest biomass carbon stocks, results were additionally expanded with a conversion factor of 1.2 to account for roots (Gibbs et al. 2007).

Results

Estimated areas by land-use classes

As may be expected from the diversity of countries involved, cover estimates for the four major land-use classes vary considerably (Table 2). The three countries with the lowest forest cover are Kyrgyzstan, Bangladesh, and Lebanon. These low values represent the fact that these countries are mainly covered by OL, the landuse category where TOF grow. Forest cover of more than 40 % was estimated for Zambia, Costa Rica, Honduras, and Cameroon. The other countries lie in the range from 20 to 40 %. OWL is highest in Cameroon, and most of the other countries have between 10 and 20 % of that land-use category. Except for the countries with low forest cover, the share of other land ranges between 35 and 60 %, whereas Cameron and Zambia only have about 20 % of that land-use type. Bangladesh, Gambia, and Nicaragua have relatively high proportions of IW. Furthermore, the proportion of land, where land use is unknown due to inaccessible sample units may represent up to 8 % of a country's area. In Table 2, we provide estimates of forest cover as given in the Global Forest Resources Assessment 2010 (FAO 2010). Numbers differ slightly from our own estimates but are generally on the same order of magnitude.

Estimated biomass and carbon stocks

The results of living above-ground tree biomass according to *Chave H* are summarised in Table 3, where we present the average biomass per hectare, its relative standard error, and the share of the country's total biomass. The largest average biomass stocks for TOF were observed in Cameroon (16.4 t ha^{-1}) and the Philippines (12.3 t ha^{-1}). The other countries had stocks of less than 10 t ha^{-1} and were generally in a comparable range to the ones found on OWL. Average biomass stocks in forests were naturally higher and ranged from 21.8 to 159.9 t ha^{-1} .

Forests typically held the major part of the tree biomass of the inventoried countries. For six of the 11 countries, however, more than 10 % of the total tree biomass was found outside of forests and OWL. An exceptional case is Bangladesh, where as much as 75 % of the national tree biomass stocks were estimated to be TOF. This is mainly because OL is by far the largest land-use class in this country and stocks on forest land are relatively low (33.4 t ha⁻¹) compared to the ones on OL (9.6 t ha^{-1}). Relating TOF biomass shares to forest cover, we observed a relative strong linear correlation of -0.68: a lower forest cover implies a relatively large amount of the national biomass in TOF. Comparing the biomass stocks of TOF to the ones on OWL, we found that in almost all cases, more biomass is accumulated in total on OL than on OWL. The main reason for this is the comparably small area of OWL.

Table 4 provides a comparison of total above-ground tree biomass estimates applying all three estimation approaches to the same data for the three land-use types-F, OWL, and OL. We also report published figures on forest carbon stocks to check our results. Compared to the models used in the NFMA reports, in most cases, Chave et al.'s (2005) models produced lower estimates of total biomass. With the exception of Gambia, the differences were more pronounced for the African and Asian countries than for the Central American countries. We further observed a strong effect of including tree height in the pantropic models, which resulted in considerably lower estimates. For a more detailed comparison of biomass estimates, we refer to Appendix A.1 and Fig. 3, where confidence intervals are provided.

The last two columns of Table 4 contain estimated totals of carbon stock. The given numbers refer to above-ground and belowground tree carbon stocks. The first of the two columns gives the range of our estimates from the three approaches of biomass estimation, and the second contains published figures from the literature (Gibbs et al. 2007). In contrast to our estimates, the literature values are based on land-use

Country	Forest	FRA 2010 ^a	OWL	OL	IW	Unknown
Bangladesh	8.1 (18.1)	11	0.7 (62.6)	76.8 (2.9)	13.7 (12.4)	0.7 (70.6)
Cameroon	44.2 (2.6)	42	31.1 (4.2)	23.5 (3.9)	0.6 (0.3)	0.6 (0.8)
Costa Rica	46.7 (10.9)	51	1.8 (73.3)	43.1 (13.2)	4.0 (65.9)	4.4 (53.7)
Gambia	26.6 (11.4)	48	10.9 (18.2)	52.1 (6.5)	10.5 (22.7)	n/a
Guatemala	37.3 (4)	34	16.3 (2.4)	42.6 (3.7)	1.8 (1.5)	2.0 (9.5)
Honduras	42.7 (6.9)	46	11.7 (12.1)	34.7 (7.7)	2.9 (34.7)	8.0 (25)
Kyrgyzstan	3.4 (14.2)	5	3.1 (14.3)	88.8 (1.1)	4.7 (15.5)	n/a
Lebanon	12.6 (12.9)	13	10.4 (13)	71.7 (3.4)	0.0 (76.7)	5.3 (27.9)
Nicaragua	25 (7.1)	26	17 (7.6)	48.8 (4.1)	9.2 (15.3)	n/a
Philippines	23.8 (7.9)	26	12.2 (10.1)	61.3 (3.4)	2.7 (20.6)	n/a
Zambia	63.9 (4.2)	67	7.4 (18.9)	19.7 (10.5)	4.2 (29.3)	4.8 (28.9)

Table 2 Area estimates for the major land-use classes forest, other wooded land (OWL), other land (OL), and inland water (IW) given in percent of total land area

The corresponding standard errors are given in parentheses as a percentage of the estimated total. In the column "FRA 2010", estimates for forest area as reported by FAO in the Global Forest Resources Assessment 2010 (FAO 2010) are given in percent of the total area

^a Estimates of forest area in the FRA 2010 report are related to the total land area excluding IW, whereas we relate to total land area including IW. Differences are partly explained not only by that but also by slightly differing inventory dates and methodologies. The large deviation for Gambia might be a consequence of differing land-use definitions and points to the eternal challenge of compatibility of definitions in global forest monitoring

classification and biome averages and are only available for forests and tropical countries. The differences are considerable. In particular, the application of the equations from Chave et al. (2005) provided much lower estimates than the ones published in Gibbs et al. (2007).

Discussion

Relevance of TOF

In many of our study countries, relatively large parts of the national-level above-ground woody biomass stocks

 Table 3
 Estimated above-ground live tree biomass density with the corresponding estimated relative standard error in parentheses and the share of the country total for the three major land-use classes

Country	Forest		OWL		OL	
	t ha ⁻¹ (%)	Percentage	t ha ⁻¹ (%)	Percentage	t ha ⁻¹ (%)	Percentage
Bangladesh	33.4 (21.5)	26.7	7.7 (79.5)	0.5	9.6 (8.6)	72.8
Cameroon	159.9 (2.9)	89.4	14.6 (9.9)	5.8	16.4 (15.4)	4.9
Costa Rica	104.0 (15.4)	93.0	0.0 (n/a)	0.0	8.5 (28.7)	7.0
Gambia	21.8 (10.9)	57.6	8.0 (15)	8.7	6.5 (13.5)	33.7
Guatemala	80.6 (14)	86.0	9.3 (15.6)	4.3	7.9 (16.9)	9.6
Honduras	79.2 (9.3)	91.0	9.3 (16.1)	2.9	6.5 (14.5)	6.0
Kyrgyzstan	30.2 (21.8)	84.2	1.0 (29.8)	2.6	0.2 (22.1)	13.2
Lebanon	24.6 (28.5)	51.6	4.6 (26.5)	7.9	3.4 (26.9)	40.5
Nicaragua	74.1 (6.3)	74.4	12.6 (10.9)	8.6	8.6 (9)	17.0
Philippines	82.6 (8.2)	69.0	10.5 (12.1)	4.5	12.3 (9.2)	26.5
Zambia	32.0 (5.3)	95.1	4.9 (21.2)	1.7	3.6 (16.5)	3.3

The estimated contribution of TOF to the total above-ground tree biomass is very different among the countries and goes from 3.3 % (Zambia) to 72.8 % (Bangladesh), owing mainly to differences in overall forest cover

were found in non-forest trees. Similar results have been obtained in other countries as well. In India, for example, 25.6 % of the national growing stock was found outside of forests (FSI 2011), and in some Indian states, even the majority of wood supplies come from nonforest trees (Ahmed 2008; Pandey 2008). For developed countries, figures on total tree resources that also include TOF are rare and, if available, usually do not cover all TOF types. Furthermore, when TOF is assessed, related figures are either often difficult to extract from the reports or are not reported at all. However, for Switzerland, an estimated 4.1 % of the non-forest area was covered by trees or shrubs (Brändli 2010), and in Sweden, trees growing on farmland and grassland accounted for an estimated 0.7 % of the country's growing stock in terms of stem volume. The latter example shows that TOF only plays a relatively minor role on the national scale when forest cover is high, as is the case in Sweden. Locally, for example in human settlements, TOF might, however, very well be of high relevance for providing ecosystem services (Rydberg and Falck 2000). In the USA, pilot studies indicated that TOF can contribute considerably to overall tree stocks. For a study region in Maryland, Riemann (2003) estimated that TOF contributed 30.2 % to total tree basal area. For Great Britain, it was estimated that about 123 million trees exist outside woodlands, which corresponds to a density of 5.4 trees per hectare. A more comprehensive overview of countries that have some sort of TOF assessment can be found in part 2 of de Foresta et al. (2013). Reported numbers should, however, be interpreted with care as TOF monitoring is not as harmonised as forest monitoring is. Currently, the European Cooperation in Science and Technology (COST) action USEWOOD is dealing with this issue on EU level (COST 2014).

TOF might be seen as an indicator for the state of the forests in a country, where a high quantity of TOF would imply that this resource may be particularly relevant as compared to forest trees. Countries may have low forest cover because of climatic and topographic conditions that do not support a high forest cover as for example in Kyrgyzstan, or forest cover is low because of human pressure. According to Gibbs et al. (2010), the expansion of agricultural land to feed an increasing world population has occurred mainly at the expense of intact and degraded forests, woodlands, and savannahs.

Our results confirm that TOF constitutes a relevant tree resource in many developing countries. While we have not looked into uses and management of TOF, the variability of TOF stocks suggests that there is room to increase this resource in all countries. This conclusion is supported by studies on additional tree plantings in agricultural and urban landscapes (Reisner et al. 2007) and by studies that focus on tree planting programmes or payment schemes for ecosystem services (McPherson et al. 2011; Schleyer and Plieninger 2011). Systematic management and fostering of non-forest trees could considerably contribute to increasing tree carbon stocks and landscape diversity. A political goal could be to increase the TOF resources and implement actions that integrate non-forest trees into international carbon markets (Atangana et al. 2014; Plieninger 2011).

In comparison to OWL, we showed that the shares of national biomass stocks are higher on OL in all our study countries. When it comes to national programmes to monitor forest and tree resources, however, OWL is typically included, while only the NFMA programme and the Indian NFI (Tewari et al. 2013) appear to include TOF in a more comprehensive manner. Given the quantitative relevance of TOF as illustrated in this comparative study, there seems to be good reasons to continue fully integrating TOF in national monitoring programmes.

Biomass estimation

Influence of applied biomass estimation method

For the estimation of TOF biomass, the same challenges hold as in general for the estimation of tree and forest biomass, however, aggravated by the fact that there are hardly any biomass models that were specifically developed for the particular growth conditions of TOF. Examples of studies, where TOFspecific models were developed are given in "TOFspecific issues" section below. Table 4 illustrates that the three-variable pantropical biomass models (diameter, height, and wood specific gravity) generally led to the lowest estimates, followed by the two-variable pantropical models (diameter and wood specific gravity) and the country-specific models. The highest estimates within country and land-use category are 1.5 to 6.6 times larger than the lowest estimates, showing that the method used to estimate biomass significantly affects the results. The largest differences were found for countries (Bangladesh, the Philippines, and Zambia) in which inventoried tree volume was converted to biomass applying wood specific gravity and biomass expansion factors. Furthermore, differences are often larger for OWL and OL than for F. As there are no clear guidelines for the selection of allometric biomass models, van Breugel et al. (2011) suggest the application of models from different sources as a means to conduct sensitivity analyses. In our study, results indicated that a major part of the uncertainty could be addressed by the choice of model for biomass estimation, a finding that has been confirmed by several studies on error propagation (Chave et al. 2004; Molto et al. 2013; van Breugel et al. 2011). In general, four sources of uncertainty for above-ground biomass estimation exist (van Breugel et al. 2011): (1) the sample size used for building the allometric model, (2) the application of multispecies models, (3) the selection of models built from data outside the study area, and (4) the sampling error due to only observing a part of the population. The first two sources can be addressed by selecting pantropical, multispecies models that incorporate wood specific gravity in their equations. Such models were built from large datasets covering a wide range of diameters and tree allometries that may not be present in local models (Chave et al. 2005; van Breugel et al. 2011). Furthermore, including wood specific gravity accounts for much of the species' variability in above-ground biomass estimates (Chave et al. 2005, 2004; van Breugel et al. 2011). The inclusion of wood specific gravity is important for large-area tropical biomass estimates from national inventory data (as in our case), where species-specific models are often not available or valid only for local conditions (Fayolle et al. 2013). Because of these reasons, we selected the models from Chave et al. (2005) as these models include wood specific gravity and are based on one of the largest datasets of individual tree biomasses determined from felling of trees. Recent efforts to expand the dataset even further, in particular, by accounting for the gap in African data, confirmed that Chave's pantropic models provided accurate results (Djomo et al. 2010; Fayolle et al. 2013; Vieilledent et al. 2012).

The application of pantropical models including tree height as a predictor variable consistently delivered the lowest estimates (Table 4); except for Costa Rica, where the country-specific model gave lower estimates of forest above-ground biomass (AGB). Feldpausch et al. (2012) made a similar observation after quantifying the effect of excluding height from biomass estimation based on data from pantropical permanent plots and destructive sampling. They concluded that the exclusion of tree height frequently leads to an overestimation of tropical forest AGB, a finding also reported earlier by Chave et al. (2005). In light of these results, height should be included as a predictor variable in biomass estimation models (Chave et al. 2005; Fayolle et al. 2013; Feldpausch et al. 2012). Consequently, our confidence is highest for the estimates provided by the models of Chave et al. (2005) that include height. If height measurements are unavailable, pantropical models from Feldpausch et al. (2011) can be used to predict height.

The example of the NFIs in Bangladesh, the Philippines, and Zambia showed that the application of biomass expansion factors and average wood specific gravities could lead to highly variable results. One source of uncertainty is the volume models: for all three countries, simple form factor models of the form $v_i = \frac{\pi}{4} d_i^2 \times h_i \times f$ were applied. Here, v_i denotes stem volume of tree *i* in cubic metres; d_i , the diameter at breast height in metres; h_i , total tree height in metres; and f, a dimensionless form factor to reduce cylinder to stem volume. In the NFIs in Bangladesh and Zambia, a common form factor was used across all species, whereas in the Philippines, the form factors were climate and species specific. Additional uncertainty comes from regional averages for wood specific gravity and biomass expansion factors taken from IPCC tables. The latter was done in the studies in Bangladesh and Zambia, while in the Philippines, a function based on the biomass of the inventoried volume from Brown (1997) was applied. This function is a negative exponential and prone to errors when used outside of the data range, which was the case for stands of low density, with the likely result of applying expansion factors that were too high. The application of expansion factors from the IPCC tables is also somewhat arbitrary as only little guidance is given on what factor to pick from a range of values.

There are high uncertainties related to model choice with respect to biomass estimation. However, for reporting carbon emissions within the landuse, land-use change and forestry sector, the Reduced Emission from Deforestation and Degradation programme and the Clean Development Mechanism, estimates of change rather than of state are required. Recent studies for permanent monitoring systems of temperate and boreal forests, for example, have shown that in such cases, the uncertainty related to single-tree biomass models was reduced drastically (Breidenbach et al. 2014; Ståhl et al. 2014). These studies, however, are related to the precision of estimates and not to accuracy. In contrast, we saw that an application of different models to the same data might give very different results. This inconsistency indicates systematic errors, which are hard to quantify without additional biomass measurements (destructive sampling) to verify the suitability of a certain model. When applying the same model and the same inventory methodology, these sorts of errors may not influence estimates if the same objects are observed and the direction of the error does not change. In contrast, other approaches to quantify carbon emissions (e.g. by combining carbon densities with changes in land cover) might be more prone to errors in state estimates and thus model choice (Pelletier et al. 2011).

Comparison to other published results

The range of carbon stocks related to the total above-ground and belowground forest tree biomass from our estimates differed considerably from the results published, for example in Gibbs et al. (2007), yielding much lower estimates. The figures in Gibbs et al. (2007) are all based on land cover classifications and biome averages following tier 1 of IPCC (IPCC 2006), whereas our results are more specifically based on field-based inventories and thus correspond to tier 2. Sources for the differences include (1) non-representativeness of the biome averages, (2) type of method used for predicting AGB, (3) errors in the land cover maps, and (4) errors related to sampling. Biome averages are either based on compilations of plot measurements from ecological studies or on forest inventory data (Gibbs et al. 2007). Here, systematic deviations may arise from a poor coverage of the original data from which the biome averages were calculated, from research plots that often focus on intact mature forests (Chave et al. 2004) or from inventories that do not cover all possible biomes (Gibbs et al. 2007). The second source of differences, model selection, has already been addressed above. It is likely that the AGB estimation method used to calculate biome averages differs from the ones we used in our study. Related to land cover maps, it is likely that estimates of forest area from our study differ from the ones from the maps. This difference is due to differences in the inventory period and the data sources used. In our case, land-use classes were assessed in the field through direct observations and not through interpretation of remotely sensed imagery. The last source for differences is the error introduced due to sampling. The estimators we applied will on average provide approximately unbiased results, but the individual results will differ from the true values; when probability sampling is applied, this variability can be quantified as the standard error of the estimate. However, sampling errors in our case were probably overestimated due to the application of simple random sampling estimators to a systematic design (Ene et al. 2012).

TOF-specific issues

As the models we applied were all built from data that were collected in mature forests, the magnitude of uncertainty when applying these models to nonforest trees is unknown (Nair 2011). Only a few studies exist that developed TOF-specific allometric biomass equations (e.g. Kumar et al. 1998; Kuyah et al. 2012; McHale et al. 2009; Zhou et al. 2007). For agroforestry systems, which can be considered a major part of the TOF areas, three options for aboveground biomass estimation exist (Nair 2011): (1) application of multispecies models developed for forest trees, (2) estimation of stem volume and conversion to biomass by wood density and an expansion factor of 1.6, and (3) development of site- and species-specific models. We applied option 1 (multispecies models developed for forest trees) and argue that using wood specific gravity, diameter, and tree height accounts for most of the variation in tree allometry, an assumption that a recent study on estimating biomass in agricultural landscapes partly confirmed (Kuyah et al. 2012). Apart from this, little is known about TOF-specific tree allometry, so additional destructive sampling of non-forest trees is urgently required. The second option (stem volume and conversion to biomass by wood density and an expansion factor of 1.6) shifts the problem to the volume model, and further, the application of a common expansion factor might lead to highly biased results. The third option (site- and species-specific models) is probably the best for local studies, but it is hardly feasible on a default basis because of financial restrictions. For large areas (e.g. the country level), substantial destructive sampling would be required and the question is whether TOF versions of pantropic, multispecies biomass models can realistically be developed. A considerable variation of stand densities, planting arrangements, and species composition exists (Nair 2011). In addition, management practices, such as pruning, alter tree allometry. Generally, non-forest trees grow in a variety of conditions from single isolated trees over linear formations to dense forest-like woodlots of small areal extent. Such trees are often exposed to significant edge effects and have relatively simple understory species composition. In the course of increased radiation, wind speed, and agricultural residuals, differences in wood specific gravity and architecture compared to forest trees may be observed (Zhou et al. 2007). The high variation of possible TOF-formations could make it necessary to develop specific allometric models for specific types of TOF (e.g. trees growing in alleys vs. trees growing in small woodlots). In addition, the considerable more variable overall growth conditions of TOF may suggest including additional input variables into such specific allometric models such as crown characteristics (e.g. crown length and crown width) or an upper diameter to better capture variation in stem shape.

In urban environments, Nowak (1994) found that forest-based equations overestimate the biomass of open-grown trees (which may directly be expected from significantly different height-diameter relationships), and thus, he applied a reduction factor of 0.8; for trees growing under denser conditions, no corrections were applied. For species growing in shelterbelts in the Great Plains of the USA, Zhou et al. (2007) found that trunk wood specific gravity for open-grown trees is higher than that of forest trees, leading to an underestimation of trunk biomass when applying forest equations. By including branches, they concluded that it is unlikely to overestimate biomass on a whole tree basis. The possible differences in wood specific gravity found by Zhou et al. (2007) are a further possible source of error as we used wood specific gravities from the Global Wood Density Database (Zanne et al. 2009) that are actually compiled from forest measurements. At another study site in western Kenya, Kuyah et al. (2012) developed biomass models specific to agricultural trees. They found that the best local model showed good agreement with the dry forest model from Chave et al. (2005). This result, however, is also difficult to generalise to larger areas without additional studies. The application of forest-based equations was further investigated by McHale et al. (2009) for an inventory of park and street trees; they identified considerable discrepancies between forest models and models specifically developed for nonforest trees. On the other hand, the study also revealed that averaging existing models and including a diversity of species reduced the variability of estimates.

Conclusions

This study provides quantitative evidence that TOF are an important tree resource on the national level. In many countries, TOF are a substantial part of national woody biomass and may even be an important regional wood resource. Because national forest monitoring does not account for TOF, such monitoring often misses the possibly large carbon pools associated with TOF.

This study supports the notion that forest inventory-related programmes at FAO and forest research institutions in the implementing partner countries should cooperatively engage more intensively into the scientific use and analyses of the data generated under the guidance of the NFMA programme. Such a cooperative engagement will strengthen research institutions, improve inventory methodology, and generate better support for informed policy decisions.

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Appendix

A.1

As a complement to Table 4, we provide confidence intervals for the total biomass estimates in Fig. 3. The purpose was to provide evidence that it matters which biomass estimation approach was used. Intervals were constructed as $\left(\widehat{t}-1.96\sqrt{\widehat{V}\left(\widehat{t}
ight)},\widehat{t}+1.96\sqrt{\widehat{V}\left(\widehat{t}
ight)}\right)$,

where \hat{t} is the estimated total and $\sqrt{\hat{V}(\hat{t})}$ the estimated standard error. The values -1.96 and 1.96 are the 0.0 25 and 0.975 quantiles of the normal probability distribution, yielding a 95 % confidence interval under the assumption of a normal distribution of \hat{t} . Note that

Table 4 National level aboveground tree biomass and carbon stock estimates

Country	Land use	Biomass in N	Biomass in M t			Carbon stock in M t	
		Chave H	Chave D	NFMA	This study	Gibbs et al. (2007)	
Bangladesh Bangladesh	Forest OWL	40.0 0.8	66.0 1.7	208.5 3.9	24–125.1 0.5–2.4	65–158	
Bangladesh	OL	108.9	275.6	545.7	65.4-327.4		
Cameroon Cameroon	Forest OWL	3358.4 216.1	4259.7 509.0	5712.0 367.1	2015–3427.2 129.7–305.4	3454–6138	
Cameroon	OL	183.2	298.0	330.3	109.9-198.2		
Costa Rica Costa Rica	Forest OL	247.7 18.8	337.6 36.6	211.9 27.6	127.2–202.6 11.3–22	471–704	
Gambia Gambia	Forest OWL	6.4 1.0	12.7 2.4	11.1 2.4	3.8–7.6 0.6–1.5	6–11	
Gambia	OL	3.7	9.4	10.0	2.2-6		
Guatemala Guatemala	Forest OWL	327.0 16.5	460.1 29.2	505.2 36.2	196.2–303.1 9.9–21.7	787–1147	
Guatemala	OL	36.5	69.0	92.9	21.9-55.7		
Honduras Honduras	Forest OWL	347.7 11.2	473.6 19.9	524.1 30.0	208.6–314.5 6.7–18	852-1268	
Honduras	OL	23.1	44.2	53.7	13.9-32.2		
Kyrgyzstan	Forest	n/a	n/a	20.4	12.2		
Kyrgyzstan	OWL	n/a	n/a	0.6	0.4		
Kyrgyzstan	OL	n/a	n/a	3.2	1.9		
Lebanon	Forest	n/a	n/a	3.2	1.9		
Lebanon	OWL	n/a	n/a	0.5	0.3		
Lebanon	OL	n/a	n/a	2.6	1.5		
Nicaragua Nicaragua	Forest OWL	240.3 27.9	332.6 47.6	433.2 70.1	144.2–259.9 16.7–42	930–1395	
Nicaragua	OL	54.8	119.1	153.5	32.9-92.1		
Philippines Philippines	Forest OWL	588.7 38.7	897.9 65.4	1728.4 229.0	353.2–1037 23.2–137.4	765–2503	
Philippines	OL	225.8	380.8	928.1	135.5-556.9		
Zambia Zambia	Forest OWL	1540.9 27.1	2796.9 65.3	4185.0 180.0	924.6–2511 16.3–108	1455–6378	
Zambia	OL	52.8	108.9	292.8	31.7–175.7		

Biomass estimates refer to living above-ground biomass (trunk and branches). Carbon stocks are calculated by multiplying the biomass with a conversion factor of 0.47 and expanding the result with 1.2 to get above-ground and belowground stocks for comparison to published estimates from Gibbs et al. (2007)

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the coverage of the intervals is probably slightly larger than 95 % due to the overestimation of the sampling error that follows from using a simple random sampling estimation framework in combination with systematic sampling (see "Estimation framework" section).

In Fig. 3, all estimated totals and their corresponding confidence intervals were related to the corresponding



Biomass estimation method

Fig. 3 Total biomass estimates with 95 % confidence intervals. The estimates for the three different biomass estimation approaches described in "Tree level biomass" section are provided. Pantropic multispecies models from Chave et al. (2005) are indicated by *Chave H* and *Chave D*, where *H* means that height was used as a predictor variable and *D*, that height was not used. *NFMA*

indicates biomass models as used in the original reporting from FAO. The methods applied vary from country to country; details are given in Appendix A.1. The *Chave H* biomass model is the reference to which all other models are compared. Thus, in the figure, these estimates are given the relative value 1.0 and, e.g. a value of 2.0 implies a result twice as large as *Chave H*

 Table 5
 Allometric models that were originally applied by countries for biomass reporting

ID	Species	Forest type	Equation	Source
1	Broadleaves	Dry	$b=0.136 \times d^{2.32}$	(Brown 1997)
2	Broadleaves	Dry	$b=0.17 \times d^{2.25}$	(Kairé 1999)
3	Broadleaves	Moist	b=42.69-12.8d+ 1.242 d^2	(Brown 1997)
4	Broadleaves	Moist	$b=0.118 \times d^{2.53}$	(Brown 1997)
5	Broadleaves	Wet	b=21.297- 6.953 $d+0.74d^2$	(Brown 1997)
6	Broadleaves	Costa Rica	$b = -136.8 + 0.61446d^2$	Unpublished
7	Pinus oocarpa		$b=0.11 \times (d^2h)^{0.85}$	(Alberto and Elvir 2005)
8	Conifers		$b=0.31 \times d^{2.119}$	(Brown 1997)

Table 7 Country-specific approaches to biomass estimation							
Country	Allometry (Table 5)	Biomass expansion (Table 6)					
Bangladesh	_	1					
Cameroon	1, 3	-					
Costa Rica	6	-					
Gambia	2, 3	-					
Guatemala	3, 8	-					
Honduras	4,7	-					
Kyrgyzstan	-	2					
Lebanon	-	2					
Nicaragua	1, 4, 5, 8	-					
Philippines	-	3					
Zambia	_	4					

b above-ground biomass in kilogrammes, d diameter at breast height in centimetres, h total tree height in metres

estimates using *Chave H*. This approach for estimating the biomass of single trees was thus used as a reference level to which all other biomass estimation approaches were compared. This standardisation was done to obtain a better comparability across land uses and countries.

A.2

Here, a summary of the methodology that was originally applied by each country for its biomass reporting is given. The background reports can be found at FAO (2013). In Table 5, the different allometric above-ground tree biomass models as applied by six countries are listed by species and forest type. The models provide direct estimates of above-ground tree biomass in kilogrammes. The remaining five countries estimated biomass based on tree volume and an application of wood specific gravities, *wd*, and biomass expansion factors, *bef*. In the NFI in Zambia, wood specific gravities and biomass expansion factors were combined into biomass conversion and expansion factors, *bcef*. The values applied for *wd*, *bef*, and *bcef* are provided in Table 6. In addition, the table provides information about volume estimation. In Table 7, it is shown what methods were applied by the different countries.

 Table 6
 Factors used when estimating above-ground tree biomass based on expanding inventoried volume

wd wood specific gravity in total per cubic metre, *bef* biomass expansion factor, *bcef* biomass conversion and expansion factor in tonnes per cubic metre (*no wood density is given if values refer to bcef*), b_v biomass of inventoried volume

ID	Wd	bef/bcef	Volume	Source
1	0.57	6	Common form factor	Brown (1997)
2	Conifers 0.4 Broadleaves 0.5 (partly species-specific)	Conifers 1.3 Broadleaves 1.4	Form factor by species group	IPCC (2006)
3	0.57	24.854× $b_{\nu}^{-0.506}$ if $b_{\nu} < 190 t/ha$ 1.74 if $b_{\nu} \ge 190 t/ha$	Form factor by species group and climate	Brown (1997)
4	-	Humid tropical 4–0.7 Dry tropical 2–0.4	Common form factor	IPCC (2006)

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