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Monitoring and estimating tropical forest carbon stocks: making REDD a reality

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Abstract

Reducing carbon emissions from deforestation and degradation in developing countries is of central importance in efforts to combat climate change. Key scientific challenges must be addressed to prevent any policy roadblocks. Foremost among the challenges is quantifying nations' carbon emissions from deforestation and forest degradation, which requires information on forest clearing and carbon storage. Here we review a range of methods available to estimate national-level forest carbon stocks in developing countries. While there are no practical methods to directly measure all forest carbon stocks across a country, both ground-based and remote-sensing measurements of forest attributes can be converted into estimates of national carbon stocks using allometric relationships. Here we synthesize, map and update prominent forest biomass carbon databases to create the first complete set of national-level forest carbon stock estimates. These forest carbon estimates expand on the default values recommended by the Intergovernmental Panel on Climate Change's National Greenhouse Gas Inventory Guidelines and provide a range of globally consistent estimates.

Keywords: deforestation, tropical forests, forest biomass, carbon stocks, emissions, forest inventory, UNFCCC, REDD, LULUCF, avoided deforestation

1. Introduction

Forests sequester and store more carbon than any other terrestrial ecosystem and are an important natural 'brake' on climate change. When forests are cleared or degraded, their stored carbon is released into the atmosphere as carbon dioxide (CO_2). Tropical deforestation is estimated to have released of the order of 1–2 billion tonnes of carbon per year during the 1990s, roughly 15–25% of annual global greenhouse gas emissions (Malhi and Grace 2000, Fearnside and Laurance 2003, 2004, Houghton 2005). The largest source of greenhouse gas emissions in most tropical countries is from deforestation and forest degradation. In Africa, for example, deforestation accounts for nearly 70% of total emissions (FAO 2005). Moreover, clearing tropical forests also destroys globally important carbon sinks that are currently sequestering CO_2 from the atmosphere and are critical to future climate stabilization (Stephens *et al* 2007).

Despite the importance of avoiding deforestation and associated emissions, developing countries have had few economic or policy incentives to reduce emissions from land-use change (Santilli *et al* 2005). 'Avoided deforestation' projects were excluded from the 2008–2012 first commitment period of the Kyoto Protocol because of concerns about diluting fossil fuel reductions, sovereignty and methods to measure emissions reductions (Niles 2002, Gullison *et al* 2007). More recently the importance of including emissions reductions from tropical deforestation in future climate change policy has grown. The United Nations Framework Convention on Climate Change recently agreed to study and consider a new initiative, led by forest-rich developing countries, that calls for economic incentives to help facilitate reductions in emissions from deforestation in developing countries (REDD).

The REDD concept is—at its core—a proposal to provide financial incentives to help developing countries voluntarily reduce national deforestation rates and associated carbon emissions below a baseline (based either on a historical reference case or future projection). Countries that demonstrate emissions reductions may be able to sell those carbon credits on the international carbon market or elsewhere. These emissions reductions could simultaneously combat climate change, conserve biodiversity and protect other ecosystem goods and services.

Political acceptance and implementation of climate policies aimed at reducing carbon emissions from deforestation will require resolution of scientific challenges. Foremost among these challenges is identifying feasible approaches to assess national-level carbon emissions from deforestation and degradation in developing countries. To estimate emissions, we need to know the area of cleared forest and the amount of carbon that was stored in those forests. Methods to assess tropical deforestation are described elsewhere (DeFries *et al* 2005, 2007, Herold and Johns 2007, Olander *et al* 2007, Achard *et al* 2007). The purpose of this paper is to synthesize options to estimate national-level forest biomass carbon stocks in developing countries and propose methods to link forest carbon and deforestation estimates. Here we compile, update and map prominent forest biomass carbon databases to create the first complete set of national-level estimates.

2. Overview of forest carbon stock measurements

The main carbon pools in tropical forest ecosystems are the living biomass of trees and understory vegetation and the dead mass of litter, woody debris and soil organic matter. The carbon stored in the aboveground living biomass of trees is typically the largest pool and the most directly impacted by deforestation and degradation. Thus, estimating aboveground forest biomass carbon is the most critical step in quantifying carbon stocks and fluxes from tropical forests, and the focus of this paper. Measurement protocols for other carbon pools are described elsewhere (e.g. Post *et al* 1999, Brown and Masera 2003, Pearson *et al* 2005a, IPCC 2006).

In many cases widely used values from look-up tables and correlations with aboveground biomass will be adequate to estimate carbon stocks in other pools. For example, root biomass is typically estimated to be 20% of the aboveground forest carbon stocks (e.g. Houghton *et al* 2001, Achard *et al* 2002, Ramankutty *et al* 2007) based on a predictive relationship established from extensive literature reviews (Cairns *et al* 1997, Mokany *et al* 2006). Similarly, dead wood or litter carbon stocks (down trees, standing dead, broken branches, leaves, etc) are generally assumed to be equivalent to ∼10–20% of the aboveground forest carbon estimate in mature forests (Harmon and Sexton 1996, Delaney *et al* 1998, Houghton *et al* 2001, Achard *et al* 2002). Soil carbon stock estimation is not discussed here, but is critical to consider for regions such as Southeast Asia's peat-swamp forests where soils are a massive source of carbon emissions following deforestation (Page *et al* 2002).

The most direct way to quantify the carbon stored in aboveground living forest biomass (hereafter referred to as forest carbon stocks) is to harvest all trees in a known area, dry them and weigh the biomass. The dry biomass can be converted to carbon content by taking half of the biomass weight (carbon content ≈50% of biomass; Westlake 1966). While this method is accurate for a particular location, it is prohibitively time-consuming, expensive, destructive and impractical for country-level analyses.

No methodology can yet *directly* measure forest carbon stocks across a landscape. Consequently, much effort has gone into developing tools and models that can 'scale up' or extrapolate destructive harvest data points to larger scales based on proxies measured in the field or from remote-sensing instruments (e.g. Brown *et al*, 1989, 1993, Waring *et al* 1995, Brown 1997, Chave *et al* 2005, Saatchi *et al* 2007). Most previous work has focused on project-level, or single-site approaches (e.g. MacDicken 1997, Brown and Masera 2003, Pearson *et al* 2005a). At the national level, the Intergovernmental Panel on Climate Change (IPCC) has produced a set of guidelines for estimating greenhouse gas inventories at different tiers of quality, ranging from Tier 1 (simplest to use; globally available data) up to Tier 3 (high-resolution methods specific for each country and repeated through time) (Penman *et al* 2003, (chapter 3, 4), IPCC 2006, (chapter 2, 4)).

In this paper, we review and summarize a range of approaches that could be adapted to estimate forest carbon stocks across tropical countries at different tiers of detail and accuracy (table 1). Biome averages and new geographically explicit datasets, for instance, provide rough approximations that can be immediately used to estimate a nation's carbon stocks (Tier 1). Ground-based measurements of tree diameters and height can be combined with predictive relationships to estimate forest carbon stocks (Tiers 2 and 3). Remote-sensing instruments mounted on satellites or airplanes can estimate tree volume and other proxies that can also be converted using statistical relationships with ground-based forest carbon measurements (Tiers 2 and 3). These approaches have varying benefits and limitations.

3. Global estimates of forest carbon stocks: the biome-average approach

Nearly all estimates of emissions from tropical deforestation are based on a handful of biome-average datasets where a single representative value of forest carbon per unit area (e.g. tonnes of C per hectare) is applied to broad forest categories or biomes (e.g. Fearnside 2000, Houghton 1999, Houghton *et al* 2001, DeFries *et al* 2002, Achard *et al* 2002, 2004, Ramankutty *et al* 2007). The earliest compilations of biome averages were made decades ago and have been subsequently updated and modified by the research community (e.g. Whittaker and Likens 1973, Ajtay *et al* 1979, Olson *et al* 1983, Brown and Lugo 1984, 1992). This continuous updating of biome averages makes it difficult to identify original data sources and other key information. Many contemporary estimates of forest carbon stocks are based on multiple versions or iterations

Table 1. Benefits and limitations of available methods to estimate national-level forest carbon stocks.

Method	Description	Benefits	Limitations	Uncertainty
Biome averages	Estimates of average forest carbon stocks for broad forest categories based on a variety of input data sources	• Immediately available at no cost • Data refinements could increase accuracy • Globally consistent	• Fairly generalized • Data sources not properly sampled to describe large areas	High
Forest inventory	Relates ground-based measurements of tree diameters or volume to forest carbon stocks using allometric relationships	• Generic relationships readily available • Low-tech method widely understood • Can be relatively inexpensive as field-labor is largest cost	• Generic relationships not appropriate for all regions • Can be expensive and slow • Challenging to produce globally consistent results	Low
Optical remote sensors	• Uses visible and infrared wavelengths to measure spectral indices and correlate to ground-based forest carbon measurements • Ex: Landsat, MODIS	• Satellite data routinely collected and freely available at global scale • Globally consistent	• Limited ability to develop good models for tropical forests • Spectral indices saturate at relatively low C stocks • Can be technically demanding	High
Very high-res. airborne optical remote sensors	• Uses very high-resolution (∼10–20 cm) images to measure tree height and crown area and allometry to estimate carbon stocks • Ex: Aerial photos, 3D digital aerial imagery	• Reduces time and cost of collecting forest inventory data • Reasonable accuracy • Excellent ground verification for deforestation baseline	• Only covers small areas (10 000s ha) • Can be expensive and technically demanding • No allometric relations based on crown area are available	Low to medium
Radar remote sensors	• Uses microwave or radar signal to measure forest vertical structure • Ex: ALOS PALSAR, ERS-1, JERS-1, Envisat)	• Satellite data are generally free • New systems launched in 2005 expected to provide improved data • Can be accurate for young or sparse forest	• Less accurate in complex canopies of mature forests because signal saturates • Mountainous terrain also increases errors • Can be expensive and technically demanding	Medium
Laser remote sensors	• LiDAR uses laser light to estimates forest height/vertical structure • Ex: Carbon 3-D satellite system combines Vegetation canopy LiDAR (VCL) with horizontal imager	• Accurately estimates full spatial variability of forest carbon stocks • Potential for satellite-based system to estimate global forest carbon stocks	• Airplane-mounted sensors only option • Satellite system not yet funded • Requires extensive field data for calibration • Can be expensive and technically demanding	Low to medium

of analyses. Often, 'best guesses' are employed as multiple biome averages are combined or modified (e.g. Houghton 1999, Houghton *et al* 2001, Fearnside 2000, Watson *et al* 2000, IPCC 2006).

Biome averages are based on two main sources of information: compilations of whole-tree harvest measurement data and analysis of forest inventory data archived by the United Nations Food and Agricultural Organization (FAO) and others.

- *Compilations of point-based biomass harvest measurement data* provide direct estimates of the actual forest volume or biomass at a particular site (e.g. Whittaker and Likens 1973, Olson *et al* 1983, Reichle 1981, Brown and Lugo 1984). While highly accurate for specific locations, these data were collected to describe only very local conditions and cover a tiny portion of total forest area (Brown 1997). Consequently, these compilations could be highly biased (depending on where the individual point measurements are made), and provide only rough approximations of forest carbon stocks over larger spatial scales.
- *Analysis of forest inventory data* archived by the FAO and others have also been used to develop biome averages. Forest inventory data can provide high quality information for a particular region, but existing

inventories were generally not collected using sampling schemes appropriate for the biome scale. Country-level estimates of forest carbon stocks reported in the FAO Forest Resources Assessments are also based on forest inventory data, but these estimates are highly suspect because of inadequate sampling for the national scale and inconsistent methods (Brown 1997, FAO 2000, 2005). In the latest FAO report, national forest carbon estimates based on inventory data remain very questionable, with more than half of tropical countries relying on 'best guesses' rather than actual measurements (FAO 2005).

Biomes likely represent the most important variation of forest carbon stocks because they account for major bioclimatic gradients such as temperature, precipitation and geologic substrate. However, forest carbon stocks vary further within each biome according to slope, elevation, drainage class, soil type and land-use history. An average value cannot adequately represent the variation for an entire forest category or country. Estimates of emissions from deforestation could be biased if the forests that are cleared have carbon stocks that systematically differ from the biome-average values (Houghton *et al* 2001, Houghton 2005). Further, the compilations of studies used to develop the biome averages generally focused on mature stands and were based on a few plots that may not adequately represent the biome or region. Use of biome averages is further constrained because it is very difficult to assess the uncertainty or accuracy of source data.

Biome averages, however, are freely and immediately available and currently provide the only source of globally consistent forest carbon information. For these reasons, and despite the uncertainties, biome averages continue to be the most routinely used source of forest carbon stock data. Moreover, biome averages provide an important starting point for a country to assess the relative magnitude of their emissions from deforestation and degradation (IPCC Tier 1). Here we have compiled biome-average carbon stock estimates from prominent data sources (table 2). We attempted to trace the original source data and explain all modifications made by the biomass dataset producers, but that was not possible in every instance. We also standardized assumptions about carbon storage in different pools to allow true comparison.

We calculated a range of forest carbon stock estimates for each tropical country by applying the standardized biome averages to the widely accepted forest classification scheme of the Global Land Cover 2000 (GLC 2000) vegetation map (stratified by FAO ecological zone map) and then overlaying country boundaries in a geographical information system (table 3).

Our analysis does not account for different forest conditions that could lead to lower carbon stocks, such as logged, burnt or secondary forest. The same biome-average carbon value was applied to all forests within each broad class regardless of their condition. Olson *et al* (1983) provided a single value for all tropical forests, which likely overestimates carbon storage in the dry tropics and open forests and underestimates carbon storage in humid and dense forests. Most sources provided a breakdown by forest type and continents (Houghton 1999, Achard *et al* 2002, 2004, IPCC 2006). Only the Gibbs and Brown (2007a, 2007b) estimates account for variations within forest classes from human disturbance and ecological conditions (described in section 4.3). Accuracy assessment is not possible until additional field data are collected across the tropics, so we cannot determine which dataset provides the most certain estimate.

These are the only estimates of country-level forest carbon stocks to date, and provide an important reference point for policy discussions. The estimates based on the IPCC (2006) default values provide Tier 1 estimates of national carbon stocks that can be used immediately. The other estimates are based on prominent estimates of carbon emissions from deforestation at the global scale (Houghton *et al* 2001, DeFries *et al* 2002, Achard *et al* 2002, 2004). The ground-based and remote-sensing approaches described next could help refine forest carbon stocks estimates for REDD and other incentive mechanisms to reduce emissions from deforestation.

4. Ground-based forest inventory data

Field campaigns focused on forest inventory measurements and direct estimation of aboveground biomass through destructive harvesting could greatly improve our quantification of forest carbon stocks. Measurements of diameter at breast height (DBH) alone or in combination with tree height can be converted to estimates of forest carbon stocks using allometric relationships. Allometric equations statistically relate these measured forest attributes to destructive harvest measurements, and exist for most forests (e.g. Brown 1997, Chave *et al* 2005, Keller *et al* 2001).

Developing allometric relationships is time-consuming and expensive because it requires destructive harvesting of a large number of trees. Tropical forests often contain 300 or more species, but research has shown that species-specific allometric relationships are not needed to generate reliable estimates of forest carbon stocks. Grouping all species together and using generalized allometric relationships, stratified by broad forest types or ecological zones, is highly effective for the tropics because DBH alone explains more than 95% of the variation in aboveground tropical forest carbon stocks, even in highly diverse regions (Brown 2002).

Generalized allometric equations also have the major advantage of being based on larger numbers of trees that span a wider range of diameters (Brown 1997, Chave *et al* 2005). An extensive review of allometric equations concluded that the pan-tropic models were 'the best available' way to estimate forest biomass and recommended them over local allometric models that may be based on less than 100 destructively sampled trees (Chave *et al* 2004). Chave *et al* (2005) developed generalized allometric equations for the pan-tropics based on an exceptionally large dataset of 2410 trees that can be used to accurately estimate forest carbon stocks across a wide range of forest types.

The effort required to develop species- or location-specific relationships will not typically improve accuracy (Chambers *et al* 2001, Keller *et al* 2001, Chave *et al* 2005) but occasionally a localized relationship is warranted, as generalized equations

Table 2. Biome-average tropical forest biomass carbon stock estimates (t C/ha)[a].

Forest type or region[b]	Houghton (1999)/ DeFries *et al* (2002)[c]	Brown (1997)/ Achard *et al* (2004)[d]	Gibbs and Brown (2007a, 2007b)[e]	IPCC (2006)[f]
Central America	—	—	—	—
Pan-Amazon	—	129	—	—
Brazilian Amazon	—	186	—	—
Latin America				
Tropical equatorial forest	200	—	—	193
Tropical seasonal forest	140	—	—	128
Tropical dry forest	55	47	—	126
Warm coniferous forest	168	—	—	—
Temp. broadleaved forest	100	—	—	—
Sub-Saharan Africa				
All forests	—	143	—	—
Tropical equatorial forest	—	—	99	200
Tropical seasonal forest	—	—	38	152
Tropical dry forest	—	—	17	72
Closed forest	136	—	—	—
Open forest	30	36	—	—
Tropical Asia				
All forests	—	151	—	—
Tropical equatorial forest	250	—	164	180 / 225[g]
Tropical seasonal forest	150	—	142	105 / 169
Tropical dry forest	—	—	120	78 / 96

[a] Table modified from Ramankutty *et al* (2007). Estimates of forest carbon stocks (t C/ha) are based on different biome-average datasets and most have slight modifications. All values are for above- and belowground forest biomass carbon. Olson *et al* (1983) was excluded from this table because he provides only a single value for all tropical forests (120 t C/ha) and for dry forest/woodland (60 t C/ha).
[b] Houghton (1999)/DeFries *et al* (2002) and IPCC (2006) distinguished forest types within each region, whereas Brown (1997)/Achard *et al* (2004) distinguished only by region and not by forest type.
[c] Used values from Houghton and Hackler (2001), which was based on a compilation of harvest measurements from ecological studies and originally published in Houghton (1999); 'The values were obtained from summaries of global vegetation Whittaker and Likens (1973), Ajtay *et al* (1979), Olson *et al* (1983) as well as from regional studies (for additional sources see Melillo *et al* 1988, Houghton *et al* 1991, Houghton and Hackler 1995)' (Houghton 1999: p 302). Values include aboveground, belowground and groundcover carbon stocks.
[d] Estimated values based on Brown (1997), which was based on forest inventory data and converted to carbon stocks using allometric relationships. Achard *et al* (2002, 2004) increased values by 20% for root carbon stocks. Here, we report mean values; Achard *et al* (2004) added a range by adding ±20%.
[e] Estimated values were calculated by taking the average forest carbon stock estimate for each biome from Gibbs and Brown (2007a, 2007b) maps for Southeast Asia and Africa that represent actual forest carbon in the year 2000. FAO ecofloristic zones were used to identify biomes. Note that this estimate accounts for anthropogenic disturbances including land use and degradation while the other biome averages presented here represent carbon stocks of undisturbed forests. Gibbs and Brown (2007a, 2007b) are based on methods pioneered by Brown and colleagues using a rule-base GIS analysis to spatially extrapolated forest inventory data archived by the FAO based on climate, soils, topographic, population and land-use information and produce maps of forest carbon stocks in the 1980s (Brown *et al* 1993, Iverson *et al* 1994, Brown and Gaston 1995, Gaston *et al* 1998). Central and South America have not yet been mapped using this method. Belowground carbon stocks included by Brown and colleagues were based on root:shoot ratios calculated from previously published data and stratified by dry, seasonal and moist climate zones. Biomass values converted to carbon stocks using 0.5 carbon fraction.
[f] IPCC (2006) default values for forest biomass; based mostly on Penman *et al* (2003), which is in turn based on interpretation of compilations of published studies. We converted the biomass values presented in table 4.7 of IPCC (2006) to carbon stocks using the IPCC default 0.47 carbon fraction (McGroddy *et al* 2004). We added in the belowground carbon stocks using the ratio of belowground biomass to aboveground biomass in table 4.4 of IPCC (2006); Average values were used in all cases.
[g] Values here are for continental and insular Southeast Asia, respectively.

may not adequately represent all forest types in all areas. Destructive sampling of 2–3 large trees should be used to check the validity of an allometric equation for specific locations (Brown 2002). This type of validation will be particularly important for Africa where there are very few ground-based datasets to develop or validate allometric equations. For example, none of the trees Chave *et al* (2005) used to develop the generic allometric equations were from an African forest.

4.1. Sampling approaches for collecting ground-based data

Before an allometric relationship can be used, ground-based forest inventory data must be collected using standardized sampling schemes appropriate for a country or forest type. Sampling data from targeted locations saves time by creating a means to infer carbon stocks for an entire forest or forest class while measuring only a fraction of it. It is best to use a sampling design developed specifically for each country

Table 3. National-level forest biomass carbon stocks estimates (M t C)[a].

	Based on compilations of harvest data			Based on forest inventory		Total range
Country	Olson *et al* (1983)/ Gibbs (2006)[b]	Houghton (1999)/ DeFries *et al* (2002)	IPCC (2006)[c]	Brown (1997)/ Achard *et al* (2002, 2004)	Gibbs and Brown (2007a, 2007b)	Based on all estimates
Angola	7811	6702	11 767	7215	3557	3557–11 767
Bangladesh	65	137	93	92	158	65–158
Belize	198	318	261	218	—	198–318
Benin	410	260	792	292	262	260–792
Bhutan	13	29	121	22	2	1–121
Bolivia	6542	9541	9189	2469	—	2469–9189
Brazil	54 697	81 087	82 510	82 699	—	54697–82 699
Brunei	58	112	115	72	40	40–115
Burundi	69	51	43	55	9	9–69
Cambodia	1008	1800	1222	1334	1914	957–1914
Cameroon	3721	3454	6138	3695	3622	3454–6138
CAR	4059	3176	7405	3524	4096	3176–7405
Colombia	6737	10 085	11 467	2529	—	2529–11 467
Congo	3458	3549	5472	3740	4739	3458–5472
Costa Rica	471	704	593	493	—	471–704
D.R. Congo	22 986	22 657	36 672	24 020	20 416	20 416–36 672
Ecuador	941	1379	2071	351	—	351–2071
El Salvador	105	153	108	117	—	105–153
Eq. Guinea	304	313	474	330	268	268–474
Ethiopia	183	153	553	168	867	153–867
Fr. Guiana	1097	1683	1588	403	—	403–1683
Gabon	3063	3150	4742	3315	4114	3063–4742
Gambia, The	7	7	11	7	6	6–11
Ghana	880	612	2172	678	609	609–2172
Guatemala	787	1147	923	823	—	787–1147
Guinea	854	598	2051	664	973	598–2051
Guin.-Bissau	204	145	381	161	78	78–381
Guyana	2494	3742	3354	923	—	923–3354
Honduras	852	1268	1123	901	—	852–1268
India	5420	8997	5085	7333	8560	5085–8997
Indonesia	13 143	25 547	25 397	16 448	20 504	10 252–25 547
Ivory Coast	1047	750	3355	830	1238	750–3355
Kenya	314	320	618	339	163	163–618
Laos	718	1523	1388	1163	1870	718–1870
Liberia	506	515	1302	543	707	506–1302
Madagascar	1043	1055	2114	1116	1796	1043–2114
Malawi	290	246	391	267	152	152–391
Malaysia	2405	4625	4821	2984	3994	2405–4821
Mexico	4361	5924	5790	4646	—	4361–5924
Mozambique	4567	3749	5148	4068	1894	1894–5148

or group of countries as land-use history and environmental conditions likely vary across political boundaries.

Systematic and random sampling designs are the two broad types of schemes used to estimate forest carbon stocks at the country level (Paciomik and Rypdal 2003). Systematic sampling uses a regularly spaced grid to identify plot locations across an entire region, while random sampling chooses plot locations by chance. Without stratification, both schemes may over- or under-sample because patterns in nature are inherently clumpy and not likely to be randomly distributed.

Stratification of systematic and random sampling schemes by broad forest types greatly increases survey efficiency by reducing unnecessary sampling and ensuring that major variation has been captured. It is important to assess how forest carbon stocks vary across a country before designing a stratified sampling scheme (Brown 2002). This information is used to define *sampling strata* or broad forest categories with similar forest carbon stocks. Information on soil types, drainage class, elevation, topography and land-use history are likely universally important to understanding the spatial distribution of carbon stocks. We recommend developing a 'stratification matrix' for each country or region using broad forest types (e.g. evergreen broadleaf, palm forests, semi-deciduous dry forests) and forest conditions such as drainage (e.g. flooded or dry), slope (e.g. steep or flat), level of degradation (e.g. logged, fragmented, pristine) and age (e.g. young fallow, secondary forest, mature) (figure 1).

Once a country's forest strata have been identified, the layout and number of plots needed to achieve a desired level of precision can be determined based on standards of acceptable sampling error. There are established methods and guidelines for determining the number, size, and distribution of sample

Table 3. (Continued.)

	Based on compilations of harvest data			Based on forest inventory		Total range
Country	Olson *et al* (1983)/ Gibbs (2006)[b]	Houghton (1999)/ DeFries *et al* (2002)	IPCC (2006)[c]	Brown (1997)/ Achard *et al* (2002, 2004)	Gibbs and Brown (2007a, 2007b)	Based on all estimates
Myanmar	2843	5182	4867	4024	4754	2377–5182
Nepal	246	393	369	337	334	246–393
Nicaragua	930	1395	1275	972	—	930–1395
Nigeria	1805	1377	3952	1510	1278	1278–3952
Panama	509	763	685	549	—	509–763
PNG	4154	8037	7075	5160	—	4154–8037
Paraguay	2831	3659	3063	1087	—	1087–3659
Peru	7694	11 521	13 241	2782	—	2782–13 241
Philippines	869	1765	2503	1213	1530	765–2503
Rwanda	45	45	36	48	6	6–48
Senegal	171	141	228	153	86	86–228
Sierra Leone	136	114	683	123	240	114–683
Sri Lanka	302	509	296	400	138	138–509
Surinam	1793	2753	2330	663	—	663–2753
Tanzania	2716	2221	3400	2409	1281	1281–3400
Thailand	1346	2489	2215	1923	2104	1346–2489
Togo	252	172	510	192	145	145–510
Uganda	536	434	1237	479	429	429–1237
Venezuela	6141	9202	7886	2326	—	2326–9202
Vietnam	774	1632	1546	1169	1642	774–1642
Zambia	4295	3423	6378	3725	1455	1455–6378

[a] **Overview of methods used to develop table 3:** In most cases, total forest carbon stocks per country were calculated by applying biome-average forest carbon values to a satellite-based global land cover map for the year 2000 (GLC 2000) stratified by the FAO forest ecological zone map (FAO 2001). Gibbs and Brown (2007a, 2007b) applied a rule-based model to the GLC 2000 map. Additional description of data sources can be found in table 2 footnotes. All values are for above- and belowground forest biomass carbon stocks (trunk, branches, roots). Units expressed as million tonnes of carbon (M t C). (1) We attempted to trace each biome average to the original source of data and explain all modifications made by the biomass dataset producers, but this was not always possible. (2) Forest classes from the global classification scheme of GLC 2000 include the following: broadleaved evergreen, broadleaved deciduous open, broadleaved deciduous closed, needleleaved evergreen, needleleaved deciduous, mixed leaf, mosaic, and burnt. All non-forest land cover categories were excluded. (3) Each data set provided different values for different biome types. If only a single forest class was provided it was applied universally to all of the above classes (open and closed). When more than one forest category was provided it was translated and applied accordingly. (4) Note that only Gibbs and Brown (2007a, 2007b) account for the impact of human disturbance on forest carbon stocks. All other estimates use the same biome-average carbon value for all forests within each broad class regardless of their condition—however, we divided the average forest carbon stocks values in half for the mosaic and burnt classes in GLC 2000.

[b] Based on Gibbs (2006), which translated and applied the original Olson *et al* (1983) data to the GLC 2000 land cover map. Olson *et al* (1983) is based on a large compilation of literature studies; please see on-line documentation for full list. The Olson 'medium' biomass estimates were used here. Note that Olson *et al* (1983) provides only a single value for all tropical forests (120 Mg C/ha) and for dry forest/woodland (60 Mg C/ha).

[c] Note that mountain systems were included in these national-level estimates but excluded from table 2 because they cover a relatively small portion of the tropics and are not distinguished by other databases. Default IPCC Tier 1 values for above and belowground forest biomass carbon stocks for mountain systems are 69, 87, 81, and 122 t C/ha for Africa, Latin America, continental Southeast Asia, and insular Southeast Asia, respectively.

plots (Brown *et al* 2000, Hamburg 2000, Nascimento and Laurance 2002, Paciomik and Rypdal 2003, Pearson *et al* 2005a).

Country-level forest carbon stocks can then be estimated using the statistically sampled ground-based data. Allometric relationships are first applied to the ground-based forest measurements to estimate the average carbon stocks in each forest strata (Forest C/ha).

A country's forest carbon stocks can then be estimated by applying the average carbon density values across a national land-cover map or to a forest statistics table with the same forest strata (see section 6 for more on linking forest carbon and deforestation measurements). This approach could improve upon the Tier 1 results reported in table 3 and provide estimates at the Tier 2 or 3 level.

4.2. Existing forest inventory data

Many tropical countries have already conducted at least one inventory of all or part of their forest area that could supplement new analyses or serve as a 'stopgap' while additional data are collected. However, very few developing countries have comprehensive national inventories, and any existing sub-national inventories must be evaluated before further use (Brown 1997, FAO 2005).

Forest Condition →

Forest Type ↓

	Mature	Logged	Secondary (young)	Secondary (med. aged)	Burnt
Moist					
Dry					
Seasonal					

Figure 1. Generalized stratification matrix that uses forest type and condition to capture the major variation in forest carbon stocks. Specific matrices should be developed for each country or region. Emissions from forest degradation could be quantified by comparing estimates of carbon storage under different forest conditions.

4.3. Mapping forest carbon stocks using existing inventory data

Existing inventory data can be extrapolated across a country using empirical–statistical methods to compensate for imperfect sampling designs. Brown and colleagues (hereafter referred to as Brown) have advanced methods to use other spatially explicit data in a GIS analysis to compensate for missing or dubious inventory data and produce reliable maps of forest carbon stocks. Brown developed rule-based models based on climate, soils, topographic, population and land-use information to spatially extrapolate forest inventory data archived by the FAO and produce maps of forest carbon stocks in the 1980s (Brown *et al* 1993, Iverson *et al* 1994, Brown and Gaston 1995, Gaston *et al* 1998).

Here, we updated the Brown forest carbon maps for Africa and Southeast Asia to account for major changes in forest cover 1980–2000 (Gibbs and Brown 2007a, 2007b). These maps provide the only forest carbon stock information for Southeast Asia and Africa that accounts for spatial variation in response to human and biophysical factors (figure 2).

The spatial distribution of forest carbon in the Amazon remains uncertain (Houghton *et al* 2001) but recent efforts have had more success extending a few reliable ground-based estimates of carbon density to larger scales. For example, Saatchi *et al* (2007) developed a map for the Amazon Basin using a method related to Brown's but based more heavily on remotely sensed indices. Sales *et al* (2007) were also successful in using geostatistics to extrapolate the RADAMBRASIL forest inventory data across Rondonia, Brazil.

5. Remote-sensing options

Forest carbon stocks can also be evaluated using remote-sensing instruments mounted on satellites or airborne platforms, but substantial refinements are needed before routine assessments can be made at national or regional scales (Baccini *et al* 2004, DeFries *et al* 2007). No remote-sensing instrument can measure forest carbon stocks directly, and thus require additional ground-based data collection (Rosenqvist *et al* 2003a, Drake *et al* 2003). A major benefit of a satellite-based approach is the potential to provide 'wall-to-wall' observation of carbon stock proxies. Airplane-based sensors cover relatively small areas so the cost would likely be prohibitive for wall-to-wall coverage for larger countries, but a sampling approach could be used to estimate forest carbon stocks across a country (e.g. Drake *et al* 2003).

Remote-sensing methodologies have been more successful at measuring carbon stocks in boreal and temperate forests and in young stands with lower forest carbon densities (Rosenqvist *et al* 2003b). Tropical forests are among the most carbon-rich and structurally complex ecosystems in the world and signals from remote-sensing instruments tend to saturate quickly. This has inhibited reliable forest carbon stock estimates in these ecosystems. Remote-sensing systems relying on optical data (visible and infrared light) are further limited in the tropics by cloud cover, but newer technologies, such as radar systems, can penetrate clouds and provide data day and night (Asner 2001).

Attempts to use remote-sensing data to estimate carbon stocks have evolved along four major fronts:

5.1. Optical remote sensing data

The present suite of optical satellite sensors, such as Landsat, AVHRR and MODIS, cannot yet be used to estimate carbon stocks of tropical forests with certainty (Thenkabail *et al* 2004). Attempts have been made to estimate forest carbon stocks indirectly by developing statistical relationships between ground-based measurements and satellite-observed vegetation indices (e.g. Foody *et al* 2003, Lu 2005). But this method tends to underestimate carbon stocks in tropical forests where optical satellites are less effective due to dense canopy closure, and has been unsuccessful in generating broad or transferable relationships (Waring *et al* 1995). Nonetheless, optical remote-sensing systems are operational at the global scale and some satellite systems (Landsat and AVHRR) provide a globally consistent record for the last 30 years.

5.2. Very high-resolution aerial imagery

The spatial detail of optical images collected from airborne sensors (as fine as ∼10 cm pixels) can be used to directly collect measurements of tree height and crown area or diameter. Allometric relationships between ground-based measurements of tree carbon stocks and its crown area with or without tree height can be applied to estimate forest carbon

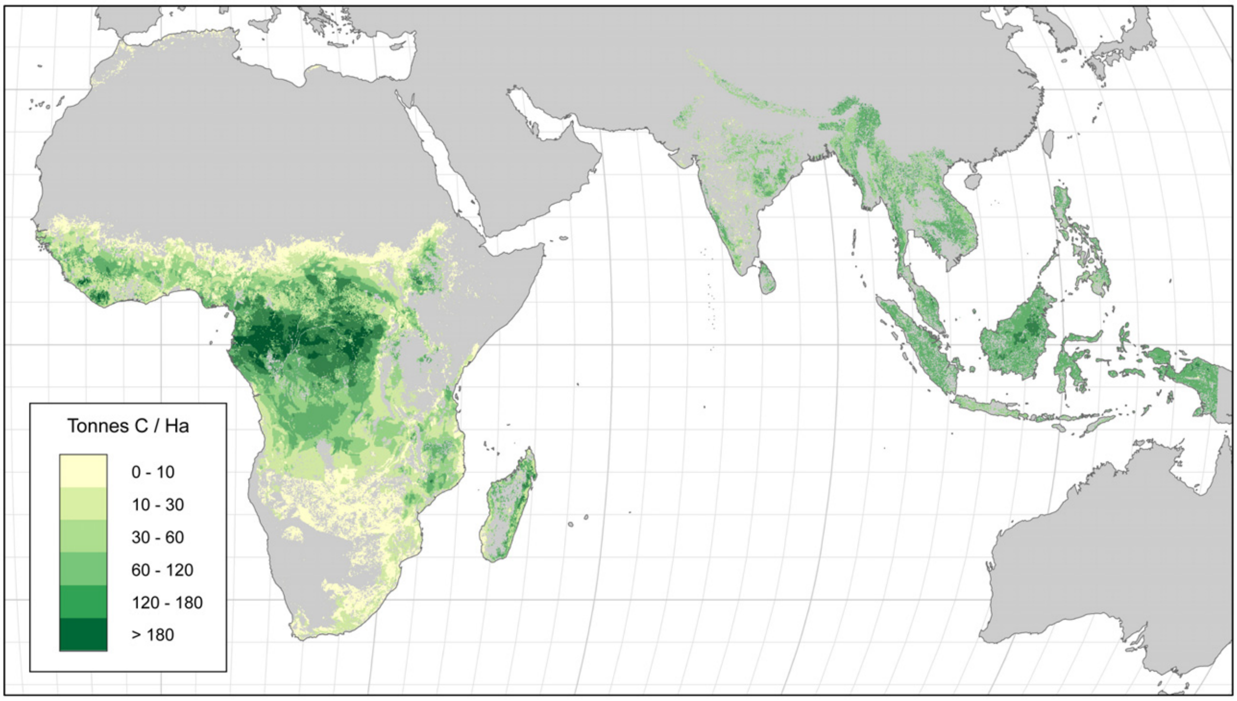

Figure 2. Forest biomass carbon maps for Africa and Southeast Asia produced by using regression-based models to extrapolate forest inventory measurements (Gibbs and Brown 2007a, 2007b).

stocks with high certainty. These data are collected over relatively small areas (several thousands of ha), but could be used for inaccessible areas or in a sampling scheme. An airplane-mounted system, using dual cameras and collecting imagery that can be viewed in 3D, has been demonstrated to reduce costs of conducting forest inventories, particularly for highly variable, widely spaced or inaccessible sites (Brown *et al* 2005, Brown and Pearson 2005) and for dense forests (Pearson *et al* 2005b).

5.3. Microwave or radar data

Radar sensors send out signals that penetrate ground cover and clouds and 'see' the underlying terrain as well as the top of the canopy. The radar signals returned from the ground and tops of trees are used to estimate tree height, which are then converted to forest carbon stock estimates using allometry. Different bands (e.g. C, L, P-bands) provide different information about forest canopies and are sometimes combined. Images collected at slightly different angles can be combined to create a 3D picture of forests using polarimetric interferometry (Mette *et al* 2003, Kellndorfer *et al* 2004, Shimada *et al* 2005). Synthetic aperture radar (SAR) sensors on board several satellites (ERS-1, JERS-1, Envisat) can be used to quantify forest carbon stocks in relatively homogeneous or young forests, but the signal tends to saturate at fairly low biomass levels (~50–100 t C/ha; Patenaude *et al* 2004, Le Toan *et al* 2004). Mountainous or hilly conditions also increase errors. The phased array type L-band SAR (PALSAR) on board the Japanese Advanced Land Observing Satellite (ALOS) launched in 2005 has the potential to improve estimates of carbon stocks across the tropics for degraded or young forests but will be less useful for mature, higher biomass forests (Rosenqvist *et al* 2003b, Shimada *et al* 2005).

5.4. LiDAR (light detection and ranging)

LiDAR systems send out pulses of laser light and measure the signal return time to directly estimate the height and vertical structure of forests (Dubayah and Drake 2000, Patenaude *et al* 2004). The light hits the forest canopy and ground surfaces and is then reflected back to the instrument. Forest carbon stocks are estimated by applying allometric height–carbon relationships (Hese *et al* 2005), which can introduce some challenges in tropical forests that reach their maximum height relatively quickly but continue to accumulate carbon for many decades. However, large-footprint LiDAR remote sensing far exceeds the capabilities of radar and optical sensors to estimate carbon stocks for all forest types (Means *et al* 1998, Lefsky *et al* 1999, Drake *et al* 2003). Currently, airplane-mounted LiDAR instruments are too costly to be used for more than a small area. A satellite-based LiDAR system could provide global coverage but is not yet an option. However, future satellite missions including LiDAR instruments such as NASA's DESDynI (planned launch in 2014) and the proposed but not yet funded 'Carbon 3D' could greatly improve our capacity to measure carbon stocks from space (Hese *et al* 2005).

6. Linking measurements of carbon stocks and deforestation

To estimate carbon emissions it is necessary to know the area deforested and the amount of carbon these forests stored. Deforestation will likely be assessed using remote sensing and ideally the same observations will be used both to estimate deforestation and to design the forest carbon sampling matrix and scheme. If forest carbon stocks are collected according to a stratified sampling design it is important that deforestation is estimated for those same strata either through 'wall-to-wall' mapping or by 'targeting sampling' using the same stratified sampling scheme (DeFries *et al* 2005, 2007, Olander *et al* 2007). The average carbon stock value for each forest strata can be applied to the satellite-based forest map to estimate national-level forest carbon stocks or to a map of deforestation to estimate national-level forest emissions. Changes in carbon stocks and emissions could be monitored from satellite-based observations of deforestation once the broad spatial distribution of carbon stocks is well established (assuming deforestation and carbon assessments are compatible).

A major advantage of the forest strata approach is that carbon stock estimates could be applied to estimate emissions in the past, present and future, which is important for reference scenarios. Forest conditions will change over time, but the carbon estimates can still be applied as long as the forest classification reflects these changing conditions. A limitation of this approach is that forest carbon stocks for a particular area may be overestimated or underestimated if the forests in question differ from the average forest strata values (Houghton *et al* 2001, Houghton 2005).

7. Accounting for forest degradation and condition

Accounting for differences in the forest carbon stocks as a result of degradation (and recovery from clearing) is important for estimating carbon emissions, particularly considering that degraded and regrowing forests are projected to comprise increasingly large portions of the tropics (FAO 2005). In the Brazilian Amazon, the re-clearance rate of secondary forest may rival the clearance rate of primary forest (Hirsch *et al* 2004) and the area of selectively logged forest is approximately equal to the area deforested (Asner *et al* 2005). Accurate estimates of carbon stored in secondary, logged or other non-primary forests are needed to estimate emissions from degradation and deforestation as the amount of carbon stored and subsequently emitted to the atmosphere varies greatly depending on forest condition.

One approach to account for carbon emissions from degradation is to measure forest carbon under different forest conditions as depicted in the stratification matrix (figure 1). To account for various levels of degradation, sampling schemes could measure carbon across broad forest type (e.g. evergreen broadleaf, seasonally flooded) and condition (e.g. young, logged, fragmented) in each forest stratum. Note that this stratification method is needed to accurately estimate emissions from deforestation even if degradation is excluded from the final climate policy framework.

A significant constraint in identifying forests with different conditions is the capacity to map them from space (Achard *et al* 2006). The ability to identify individual types of non-intact forests has been demonstrated for some regions (e.g. Achard *et al* 2002, FAO 2000, Asner *et al* 2005), but it will be very challenging to map all types over an entire country. Optical satellite data (e.g., MODIS, Landsat, SPOT) most often used to detect deforestation can identify changes in forest area more accurately than the more subtle changes in forest condition due to degradation or recovery. Thus, it is unlikely that the current suite of optical sensors can fully identify all types of degradation (Thenkabail *et al* 2004, Fuller 2006) without innovative methods coupling satellite imagery with ground-based observations (Foody and Cutler 2003, Fuller *et al* 2004).

8. Conclusions

The future of REDD and related climate policies need not be constrained by the technical challenges of estimating tropical forest carbon stocks. A range of options exists to estimate forest carbon stocks in developing countries and will continue to improve in response to the policy needs and signals.

Here we have provided IPCC Tier 1 estimates of national-level forest carbon stocks that can be used immediately by countries and policy-makers. Each country will need to use expert judgment based on financial, time and capacity constraints in deciding whether to use higher Tier methods. In many countries it may be more feasible to rely on ground-based inventories rather than remotely sensed data to estimate forest carbon stocks, as labor costs are often low compared to installing and managing high-tech remote-sensing equipment and expertise. However, satellite-based estimates of forest carbon stocks will likely be more accessible over the next decade as new technologies emerge and technical capacities are strengthened. Collecting additional ground-based data using an appropriate sampling design that accounts for both forest type and condition will be necessary regardless of method and a critical next step for improving the understanding of carbon stocks and fluxes in tropical forests.

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