CSIRO PUBLISHING

Pacific Conservation Biology, 2015, **21**, 307–314
http://dx.doi.org/10.1071/PC15015

An estimate of above-ground carbon stock in tropical rainforest on Manus Island, Papua New Guinea

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Abstract. Forest carbon emission mitigation schemes seek to protect tropical forest, combat effects of climate change, and offer potential cash and development opportunities. Reducing emissions from deforestation and degradation (REDD+) projects based on a foundation of accurate carbon stock assessment provide such an opportunity for Papua New Guinea. The objective of this study was to quantify the carbon stock of the central forests of Manus Island, Papua New Guinea, and identify factors that underpin any observed variation within it. We employed the Winrock Standard Operating Procedures for Terrestrial Carbon Measurement for plots and associated measurements. In 75 variable-radius nested plots (total area = 14.4 ha), we assessed above-ground and total carbon stock of stems ≥5 cm diameter at breast height via general linear models in a model-selection framework. The top models described variation in average carbon stock at 95% lower and upper confidence interval in above-ground biomass solely in terms of forest type: primary hill forest 165.0 Mg C ha^{-1} (148.3–183.7, n = 48), primary plain forest 100.9 Mg C ha^{-1} (78.0–130.6, n = 10) and secondary hill forests 99.7 Mg C ha^{-1} (80.9–122.9, n = 17). To a lesser extent, above-ground carbon stock increased with slope and varied idiosyncratically by the nearest village. Our estimates are comparable with published studies for Papua New Guinea and the wider tropical region. These data should strengthen pre-existing knowledge and inform policies on carbon accounting for REDD+ projects in the region.

Additional keywords: aboveground carbon, biomass, environmental variables, Papua New Guinea, plain forest, primary hill forest, REDD+, secondary hill forest.

Received 15 June 2015, accepted 10 November 2015, published online 4 December 2015

Introduction

Tropical deforestation is a major contributor to greenhouse gas emissions (Malhi and Grace 2000; Bryan *et al.* 2010*a*; Harris *et al.* 2012), largely resulting from agriculture and forestry activities (Van Laake and Sanchez-Azofeifa 2004; Ferraz *et al.* 2005; Cayuela *et al.* 2006). Recently, tropical countries have been able to take advantage of a developing mitigation system that aims to reduce emissions from deforestation and degradation (REDD+) as a means of protecting forests and combating the effects of climate change. Schemes like REDD+ provide an important opportunity for lowering carbon emissions within tropical countries while generating income from forest retention at the same time (Laurance 2007). The prospect of REDD+ in Papua New Guinea (PNG) offers the ability for many rural communities to access cash and development opportunities without going down the path of resource extraction (GPNG 2007). PNG has a large rural population, and is unusual globally in that most of land remains under community ownership (GPNG 2007). Despite this, PNG has long had difficulty in safeguarding its forest estate (e.g. Saulei 1990; Shearman *et al.* 2008; Laurance *et al.* 2011). Yet, before any emission structures can be developed, quantification of carbon stock content is needed as a prerequisite.

Carbon stocks are quantified through forest inventories, destructive sampling, allometric relationships and remotely sensed data (Malhi and Grace 2000; Chave *et al.* 2003; Bryan *et al.* 2010*b*; Fox *et al.* 2010). Measurements of carbon stock is useful for developing climate change mitigation policies (Chave *et al.* 2003; Fox *et al.* 2010), and at the same time it can be used for monitoring the global carbon cycle (Phillips and Gentry 1994). Some important predictors affecting overall estimates in tropical forest carbon stocks include appropriate classifications of forest type (e.g. dry, moist or wet), specific tree variables (e.g. tree diameter, total tree height and wood specific gravity), slope, drainage class, land-use history, elevation and soil type (Edwards and Grubb 1977; Yamakura *et al.* 1986; Chave *et al.* 2005; Gibbs *et al.* 2007; Lewis *et al.* 2009; Fox *et al.* 2010).

Although precise estimates of forest carbon pools are required for participation in REDD+ schemes, quantification for both above- and below-ground carbon pools in PNG has been scant (Edwards and Grubb 1977; Abe 2007; Bryan *et al.* 2010*a*, 2010*b*; Fox *et al.* 2010; FPCD and IGES 2013; Vincent *et al.* 2015). The central forests of Manus Island in PNG have been identified as a prospective REDD+ site; consequently, the Wildlife Conservation Society (WCSPNG) Program was funded

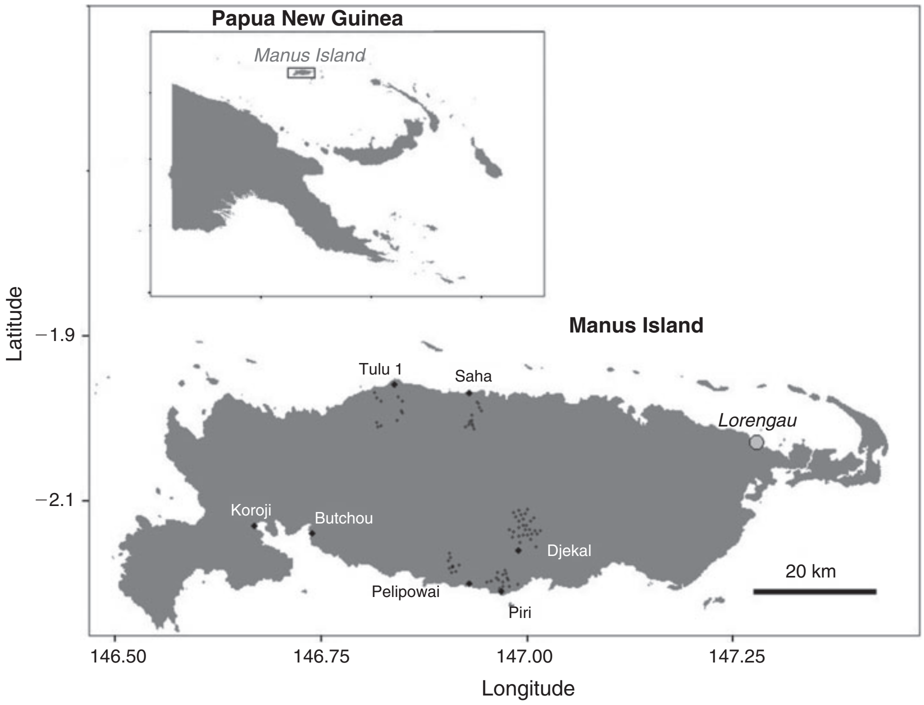

Fig. 1. Map of Papua New Guinea showing Manus Island and location of 75 forest carbon plots (black dots) assessed in five villages of central Manus.

by the Australian Department of Foreign Affairs and Trade to carry out a REDD+ readiness project in this area. As part of this project, we quantified the carbon stock in above-ground biomass of these forests and identified factors that underpinned major patterns of variation.

Methods

Study site

We conducted this study from May 2013 to April 2014 within lowland forests of central Manus Island, PNG (Fig. 1). Manus Island is the major island within the Admiralty Group of islands and covers one of the largest remaining forest areas in the Bismarck Archipelago. The study was undertaken within lands belonging to nine consenting landowner clans at five villages: Tulu 1, Saha, Pelipowai, Piri and Djekal (Fig. 1). The general climate of Manus Province is equatorial with high daily temperatures at 25–32°C. The annual rainfall is between 3000 and 4000 mm, with two noticeable wetter seasons corresponding to the times of the trade winds (Croft 1983): the south-easterly trade winds from the middle half to the end of the year and the north-west trade winds for the remainder of the year (Kisokau 1974). The forest on central Manus Island is a typical lowland tropical forest (*sensu* Paijmans 1976) dominated by *Calophyllum* spp. (Calophyllaceae) and *Dillenia papuana* (Dilleniaceae), and common tree families include Sapindaceae, Lauraceae, Myristicaceae, Myrtaceae, Euphorbiaceae and Apocynaceae. The main vegetation types include: hill forest, plain forests, swamp forests (commonly covered with sago palms), and mangrove forest along estuaries and coastlines. Secondary forests at varying ages in regeneration, from both natural and anthropogenic disturbances (e.g. shifting cultivation, settlement), are common throughout.

Forest stratification

We collected data from three main forest types: primary hill forest (intact forest on well-raised slopes with good drainage), primary plain forest (intact forest on flat lands and at low elevation, and may be subject to periodic inundation during the wet season), and secondary hill forest (original forest structure and species composition are altered, and occur on well-raised slopes with good drainage). As stratification increases survey efficiency and captures major variations among forest types (Gibbs *et al.* 2007), our forest classifications were consistent with the forest classes produced by the Japanese International Cooperation Agency and the government of the PNG Forest Authority: hill forest, plain forest and non-forest. We differentiated the hill forest into primary and secondary forests; however, we did not observe any secondary forests within the plain forest. Secondary forests elsewhere resulted mostly from anthropogenic activities. Secondary forests may also be classified into different ages (e.g. young, medium and old) after disturbance for effective sampling. Here we sampled only old secondary hill forest estimated at ≥40 years old on the basis of local knowledge and our field observations of forest structure and species composition present at that time. This limit was set to avoid sampling in young forest areas, which are routinely disturbed by shifting cultivations and subsistence use.

Determination of plots

On a digitised 1980 Australian Survey Corps topographic map, random plot locations were mapped within the sampling area

Table 1. Size classes of trees for both live and dead-standing trees measured within the circular nested plot design adapted from Walker *et al.* (2012)
Total area sampled was 14.4 ha

Subplot size	Radius (m)	Area (m^2)	DBH size class (cm)	Total area (ha)
Small	4	50.3	5–19.9	0.4
Medium	14	615.7	20–49.9	4.6
Large	20	1256.6	≥50	9.4
Total				14.4

using ArcGIS software with a minimum of 500 m distance between each plot. The points were projected within ArcGIS Editor, using a random sample point generator tool via a stratified random sampling technique. Buffer zones were created – 30 m from rivers, 30 m from a clan boundary, and 500 m away from any settlement – to eliminate chances that a plot was located outside of the three forest types. Sampling points were then created on clan boundary maps and printed for use before undertaking field work.

Plot design and tree data measurement

The protocol for setting up plots and taking measurements followed Walker *et al.* (2012). Seventy-five plots (primary hill = 48, secondary hill = 17 and primary plain = 10) were sampled within ≈71 737 ha of forested landscape identified as a possible REDD+ project. We were limited to sampling only on the land of consenting clans. The number of plots targeted for each forest type was deemed sufficient by the Winrock Carbon Stock Calculation Tool (WCSCT) algorithm to achieve a 95% confidence level within 5% of the true mean of the above-ground carbon (AGC) (Walker *et al.* 2012), and it was sufficient to account for the variability in each forest type. Plot locations were identified in the field (from preselected points) with handheld GPS units. A plot was relocated using a random compass bearing (0–360°) and distance (determined by dividing the bearing by 4) if the plot centre lay on a steep slope, cliff or within a non-forested area. Non-forested areas, defined as >90% canopy opening or >10% of the plot covered by grassland, bamboo or scrambling fern (*Dicranopteris linearis*) were not sampled. A variable-radius nested plot (each consisting of three concentric circular plots) design was employed to take measurements (diameter at breast height (DBH) and height) for both live and dead standing trees, as in Table 1. Within each plot, we recorded DBH at 1.3 m above ground for all stems ≥5 cm, the location (distance and bearing) of each tree from the plot centre, slope and elevation. Each dead standing tree in the plot was classified as either Condition '1' or '2' (1: with branches and twigs and resembles a live tree except for leaves; 2: those containing small and large branches or only the bole remaining) (*sensu* Walker *et al.* 2012). Height for dead standing trees was measured using a clinometer. DBH and length of coarse woody debris (CWD) lying on the ground was measured along two transects crossing perpendicularly to each other at the centre of the circular plot, giving a total transect length of 80 m. Density class was estimated (i.e. sound, intermediate, rotten) for each piece of CWD on the transect.

We used two groups of locally trained field assistants who assisted with undertaking measurements in the field (*sensu* Butt *et al.* 2015): WCS community facilitators (CFs), and interested members of the community from each village. CFs were community members trained in community conservation and supervised by a WCS staff member throughout. Six CFs were trained in forest inventory along with more than 40 local community members for this project. In this inventory, above-ground carbon stocks (both dead and live) for stems ≥5 cm DBH were quantified, and below-ground carbon was calculated *post hoc* using the WCSCT (Walker *et al.* 2012). Time and cost prohibited measuring of carbon in other carbon pools: soil, litter and above-ground non-trees (e.g. trees <5 cm DBH, herbs, epiphytes, palms, pandanus and lianas), and consequently these carbon stock were not quantified. However, established above-ground biomass (AGB) ratios of trees are readily available and often used to estimate other above-ground carbon pools and below-ground carbon (e.g. Mokany *et al.* 2006; Fox *et al.* 2010).

Quantifying carbon stock

Allometric models are commonly used in biomass studies to estimate forest carbon stock if a biomass expansion factor method is not used (Pedroni 2007). We used the allometric equation of Chave *et al.* (2005) for estimating above-ground biomass for tropical moist forests that receive rainfall of 1500–3500 mm annually. Their analysis (based on series of allometric equations) relied upon compilation of tree harvested studies from 27 datasets across a broad range of tropical forests. We have been consistent with other studies (e.g. Bryan *et al.* 2010*b*; Fox *et al.* 2010) in using the allometric equation of Chave *et al.* (2005) to estimate carbon stock in tropical forests of PNG. With an average error in the allometric models on the estimation of a tree's biomass to be ±5%, Chave *et al.* (2005) have assured that these regression models can reliably be used to predict carbon across forest types in tropical forests.

We used the average wood density estimate of 0.477 g cm^{-3} for PNG lowland forests (Fox *et al.* 2010) to calculate the AGC of all trees in the stand. Complete identifications of all trees recorded within our sampling plots were not available at the time of publication, but preliminary analysis carried out revealed that the average wood density of 0.476 g cm^{-3} across the known species was comparable to the estimate of Fox *et al.* (2010). Average wood density estimates have been used in other studies either at species, genus or stand level when such data were unavailable (Chave *et al.* 2003; Fox *et al.* 2010; Butt *et al.* 2015). AGB (in kilograms), based on Chave *et al.* (2005), was calculated as:

$$\begin{aligned}\mathrm{AGB} = \text{wood density} * \exp(&-1.499 + 2.148\ln(\mathrm{DBH}) \\ &+ 0.207(\ln(\mathrm{DBH}))^2 - 0.0281(\ln(\mathrm{DBH}))^3)\end{aligned}$$

where wood density is in grams per cubic centimetre (g cm^{-3}) and DBH is in centimetres (cm).

Estimations of AGB (kg ha^{-1}) were converted to megagrams of AGC per hectare (Mg C ha^{-1}) using a carbon fraction of 47% (Walker *et al.* 2012). Following Walker *et al.* (2012), below-ground carbon was calculated using a

Table 2. Twelve candidate models selected for determining appropriate AGC stock level for trees ≥5 cm DBH in primary hill, secondary hill and primary plain forests ranked by AICc

Key: K, number of parameters; AICc, Akaike's information criterion with a small sample correction; ΔAICc, difference between candidate model and top model in terms of AICc; LL, maximised value of the log-likelihood function (LL)

Rank	Candidate model	K	AICc	ΔAICc	Model weight	LL
1	AGC ~forest type	4	−52.55	0	0.64	30.56
2	AGC ~forest type + slope	5	−50.51	2.05	0.23	30.69
3	AGC ~forest type + location	12	−49.34	3.21	0.13	39.19
4	AGC ~forest class	3	−34.57	17.98	0	20.45
5	AGC ~forest class + location	11	−34.46	18.10	0	30.32
6	AGC ~slope	3	−33.60	18.96	0	19.97
7	AGC ~forest class + slope	4	−33.56	18.99	0	21.07
8	AGC ~simple intercept	2	−30.75	21.80	0	17.46
9	AGC ~elevation	3	−30.33	22.22	0	18.33
10	AGC ~slope + elevation	5	−29.94	22.61	0	20.41
11	AGC ~location	10	−28.04	24.51	0	25.74
12	AGC ~slope + location	19	−23.64	28.91	0	37.73

root : shoot AGB ratio for tropical moist forest as in Mokany *et al.* (2006):

$$BGC = 0.235 * AGC \text{ if above-ground biomass carbon } > 62.5\ \mathrm{Mg\,C\,ha^{-1}}$$

and

$$BGC = 0.205 * AGC \text{ if above-ground biomass carbon } \leq 62.5\ \mathrm{Mg\,C\,ha^{-1}}$$

where BGC = below-ground carbon, and AGC = above-ground carbon.

Statistical analysis

Five explanatory variables were modelled to determine local spatial effects on the most likely factors affecting variation in AGC stock: forest class, forest type, slope, elevation and location. AGC was calculated from AGB estimation; 'forest class' was hill or plain forest; 'forest type' was primary, secondary or plain forests; 'slope' was the average inclination of plot; 'elevation' was height above sea level (m); and 'location' was the name of the clan (or village) that owned a specific forest area. 'Location' allows interpretations of differences in carbon stock due to village management and related local attributes. A simple intercept model was also run within the models to reveal a baseline for poor performance. We used an information theoretic approach to assess 12 linear models in terms of parsimony (*sensu* Burnham and Anderson 2002). The candidate models reflected our *a priori* hypotheses about how differing factors could influence AGC and combined carbon (CC) stocks (total carbon of above-ground, below-ground, dead standing and CWD).

All analysis was carried out using R ver. 3.0 (R Development Core Team 2013). As the residuals of our carbon stock measurements did not meet the requirement of normality, AGC and CC were log-transformed before analysis. We report means with 95% (lower and upper) confidence intervals (CI) derived from our top-ranked models.

Results

The only independent variable for the most parsimonious model for AGC stocks was forest type (model weight 64%: Table 2). There was also some lower support for models with forest type and slope (model weight 23%) and forest type and location (model weight 13%) as explanatory variables (Table 2). Mean carbon stocks in AGB were: primary hill forest 165.0 Mg C ha^{-1} (95% CI: 148.3–183.7, n = 48), primary plain 100.9 Mg C ha^{-1} (78.0–130.6, n = 10) and secondary hill forests 99.7 Mg C ha^{-1} (80.9–122.9, n = 17) (Fig. 2). AGC increased with increasing slope while location indicated correlations with population pressure on forests and carbon stock levels. Summary coefficients for the top-ranked AGC model are presented in Table 3.

The same top three models (forest type, forest type and slope, and forest type and location) were the top-ranked candidate models and had similar support in terms of model weight for CC (Table 4) compared with AGC (Table 2). Mean CC stocks were: primary hill 215.4 Mg C ha^{-1} (95% CI: 194.8–238.2, n = 48), primary plain 128.8 Mg C ha^{-1} (100.5–165.1, n = 10) and secondary hill forests 130.4 Mg C ha^{-1} (106.6–159.5, n = 17) (Fig. 2). Summary coefficients for the top-ranked CC model are presented in Table 5.

Discussion

Factors affecting carbon stock variation

The top model describing AGC as being best explained in terms of different forest types suggests the presence of three forest strata: primary hill, primary plain and secondary hill forests (Table 2). The mean carbon stock in AGB for primary hill forest (165.0 Mg C ha^{-1}) estimated in this study was within a similar range (105–180 Mg C ha^{-1}) reported from other primary forests in PNG (Edwards and Grubb 1977; Bryan *et al.* 2010*a*; Fox *et al.* 2010; FPCD and IGES 2013; Vincent *et al.* 2015) and the tropical forests (Aiba and Kitayama 1999; Chave *et al.* 2003; IPCC 2006; Butt *et al.* 2015) (Table 6). However, one study in primary lowland forest of PNG has reported a higher above-ground carbon stock range of 207.5–296 Mg C ha^{-1} using

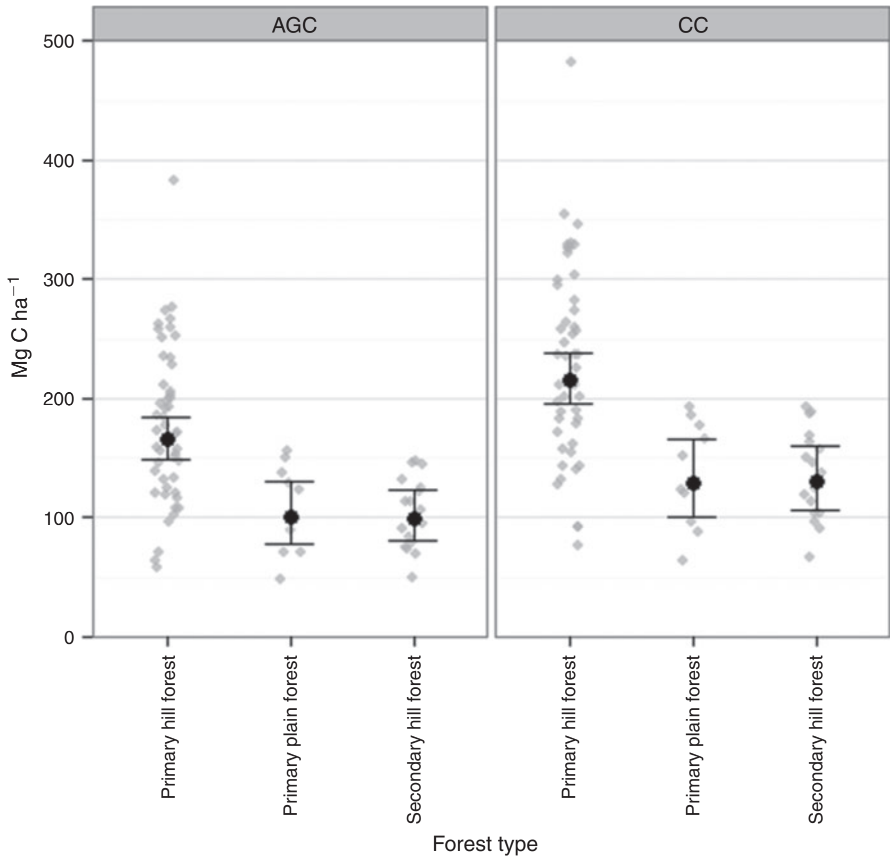

Fig. 2. Estimates of above-ground carbon (AGC) and combined carbon (CC) stocks across three different forest types on Manus Island drawn from the top-ranked candidate models. Black dots represent average values, error bars represent 95% confidence intervals, and grey dots represent range.

Table 3. Summary coefficients for the top-ranked AGC model

Forest type	Log_{10}(estimate)	Log(s.e.)	Mean carbon (Mg C ha^{-1}) (95% CI)
Primary hill forest (intercept)	2.22	0.02	165.0 (148.3–183.7)
Primary plain forest	−0.21	0.06	100.9 (100.5–165.1)
Secondary hill forest	−0.22	0.05	99.7 (106.6–159.5)

destructive sampling; however, the data are based on sampling only 37 trees of variable size from five dominant species (Abe 2007). Several other tropical studies have also reported higher carbon estimates (210–324 Mg C ha^{-1}) from destructive sampling (e.g. Rai and Proctor 1986). Differences in setting minimum limits in measuring DBH of trees could affect variation in carbon estimates among studies. For example, the minimum limit of ≥5 cm DBH of trees in our study could have produced higher carbon estimates compared with most other studies in PNG with minimum limits of ≥10 cm DBH (Table 6). The mean AGC estimated in secondary hill forests in our study was higher (99.7 Mg C ha^{-1}) than that of Fox *et al.* (2010) and Bryan *et al.* (2010*a*) determined from logged over secondary forests (66.3 Mg C ha^{-1} and 82.0 Mg C ha^{-1} respectively) in PNG (Table 6). Successional stages of forest or severity of forest fragmentation will affect carbon stock levels; thus sampling only older anthropogenic secondary forests (≥40 years old), as done in this study, could have resulted in higher carbon stock estimates compared with other logged over secondary forests. Our mean estimates for AGC for primary plain forests (100.9 Mg C ha^{-1}) and secondary hill forest (99.7 Mg C ha^{-1}) were practically indistinguishable; from this, we infer that there are only two categories of forest type on Manus: primary hill forest and other forests.

A potential secondary factor identified from our modelling process was forest type and slope (23% model support), which

Table 4. Twelve candidate models selected for determining CC stock level for trees ≥5 cm DBH in primary hill, secondary hill and primary plain forests ranked by AICc

Key: K, number of parameters; AICc, Akaike's information criterion with a small sample correction; ΔAICc, difference between candidate model and top model in terms of AICc; LL, maximised value of the log-likelihood function (LL)

Rank	Model selection	K	AICc	ΔAICc	Model weight	LL
1	CC ~forest type	4	−58.18	0	0.69	33.37
2	CC ~forest type + slope	5	−56.17	2.01	0.25	33.52
3	CC ~forest type + location	12	−53.18	5.00	0.06	41.10
4	CC ~forest class	3	−38.97	19.21	0	22.65
5	CC ~forest class + slope	4	−38.06	20.12	0	23.31
6	CC ~forest class + location	11	−37.66	20.52	0	31.92
7	CC ~slope	3	−37.54	20.64	0	21.94
8	CC ~elevation	3	−34.18	24.00	0	20.26
9	CC ~slope + elevation	5	−34.15	24.03	0	22.51
10	CC ~simple intercept	2	−34.00	24.18	0	19.08
11	CC ~location	10	−30.45	27.73	0	26.94
12	CC ~slope + location	19	−27.13	31.05	0	39.47

Table 5. Summary coefficients for the top-ranked CC model

Forest type	Log_{10}(estimate)	Log(s.e.)	Mean carbon (Mg C ha^{-1}) (95% CI)
Primary hill forest (intercept)	2.33	0.02	215.4 (194.8–238.2)
Primary plain forest	−0.22	0.06	128.8 (194.8–238.2)
Secondary hill forest	−0.22	0.04	130.4 (106.6–159.5)

Table 6. Average above-ground carbon stock (Mg C ha^{-1}) estimated for PNG forest trees compared with some regional (Asia) and biome averages for tropical rainforests

Dead wood consists of standing dead and fallen trees. Estimations of AGB (in kg or t ha^{-1}) have been converted to AGC (Mg C ha^{-1}) using a conversion factor of 0.5. Logged forests are all selectively logged

Forest type	Location	AGC (Mg C ha^{-1})	Dead wood (Mg C ha^{-1})	BGC (Mg C ha^{-1})	Tree definition	Citation
Lowland primary hill forest	PNG	165.0	14.5	47.5	≥5 cm DBH	This study
Lowland secondary hill forest	PNG	99.7	6.1	30.4	≥5 cm DBH	This study
Lowland primary plain forest	PNG	100.9	10.8	1.3	≥5 cm DBH	This study
Lowland primary forest	PNG	120.1	7.6	n.a.	≥5 cm DBH	FPCD and IGES (2013)
Lowland primary forest	PNG	106.3	10.3	n.a.	≥10 cm DBH	Fox *et al.* (2010)
Primary lower montane forest	PNG	141.1	14.1	n.a.	≥10 cm DBH	Fox *et al.* (2010)
Lowland selectively logged forest	PNG	66.3	16.6	n.a.	≥10 cm DBH	Fox *et al.* (2010)
Lower montane selectively logged	PNG	58.8	14.7	n.a.	≥10 cm DBH	Fox *et al.* (2010)
Lowland primary forest	PNG	111.4	n.a.	n.a.	Extrapolated	Bryan *et al.* (2010*a*)
Lowland selectively logged forest	PNG	82.0	n.a.	n.a.	Extrapolated	Bryan *et al.* (2010*a*)
Lowland primary forest	PNG	207.5–296	n.a.	n.a.	≥5 cm DBH	Abe (2007)
Primary mid-montane forest	PNG	147.5	n.a.	20	≥10 cm DBH	Edwards and Grubb (1977)
Lowland primary forest	PNG	105.4	n.a.	n.a.	>1 cm DBH	Vincent *et al.* (2015)
Dipterocarp forest	SE Asia	243	n.a.	n.a.	≥10 cm DBH	Yamakura *et al.* (1986)
Dipterocarp forest	SE Asia	256	n.a.	n.a.	≥10 cm DBH	Aiba and Kitayama (1999)
Wet tropical forest	Africa	202	n.a.	n.a.	≥10 cm DBH	Lewis *et al.* (2009)
Moist tropical forest	Guyana	153	n.a.	n.a.	≥10 cm DBH	Butt *et al.* (2015)
Neotropical forest	Panama	140	n.a.	n.a.	≥1 cm DBH	Chave *et al.* (2003)
Lowland primary forest	India	210–324	n.a.	n.a.	≥5 cm DBH	Rai and Proctor (1986)
Lowland forest	Tropical	180	n.a.	n.a.	Default value	IPCC (2006)

showed that AGC and combined carbon values increased with increasing slope. This relationship most likely results from forests on steeper slopes being less accessible to humans than those on lower slopes, and they are thereby less disturbed by anthropogenic activities (Gibbs *et al.* 2007). Trees in the uphill primary forests were generally taller and denser than the primary plain forests on the flatlands (*sensu* Butt *et al.* 2015). Additionally, diverse environmental factors (e.g. water stress and the effect of sunlight on aspect) could also affect carbon stock levels, making trees on well raised slopes with good drainage accumulate more biomass than trees on lower slopes or from the plains (Aiba and Kitayama 1999). Another potential model for consideration was forest type and location (13% model support). We suspect that location in this study is associated with human accessibility to forests and the land-use history (Gibbs *et al.* 2007), as secondary forests were located closer to existing villages and deserted settlements. Indeed, we know that one of our sampling sites near Pelipowai village (Karowan forest) (Fig. 1) had lower carbon stock levels compared with other sites as a result of the area being a colonial–post settlement in the 1940–50s, which resulted in much of the forests being cleared during that period.

Use of established AGB ratios in estimating other carbon pools

Established AGB ratios for trees are often used to estimate other above-ground carbon pools (e.g. non-trees including herbs, climber and epiphytes, and litter and dead wood including fallen flowers, fruits, leaves and small branches) and below-ground carbon. For example, Fox *et al.* (2010) estimated from the literature in an undisturbed lowland forest in PNG that unmeasured components of non-trees $<$10 cm DBH, litter and dead wood (both standing and fallen) accounted for 5%, 2.5% and 10% of AGB of trees $\geq$10 cm DBH respectively. Similarly, below-ground biomass is determined through the application of a regression model following Walker *et al.* (2012). Thus, BGC of root biomass in this study was estimated from established root to shoot ratios as either 23% or 20% of AGC if AGB carbon was $>$62.5 Mg C ha^{-1} or $\leq$62.5 Mg C ha^{-1} respectively (Mokany *et al.* 2006).

Implications for community participation in estimating carbon stocks

The last remaining forests of central Manus Island are under threat from logging activities in a manner similar to other lowland areas of PNG (Shearman *et al.* 2009; Bryan *et al.* 2010*b*). It is necessary to develop and test standardised methodologies for quantifying carbon stocks to inform management decisions and policies on REDD+ and other forest carbon mitigation schemes in PNG (Shearman *et al.* 2009). Yet the systematic sampling of the proposed Manus REDD+ project area ($\approx$71 737 ha) in this study would have been impractical due to issues related to: remoteness of the inland parts of the area, identification of landowners for consent and clan land disputes. This study was carried out on traditional lands, and sampling was carried out only in consented areas. With this situation, we added value to the project by engaging local landowners as locally trained field assistants and community facilitators in our forest inventory and set the stage for future REDD+ work, which could be of a more extensive nature. Participation of trained local assistants in estimations of AGC in biomass can be efficient compared with other methods of quantifying forest carbon stocks (e.g. remotely sensed data: Butt *et al.* 2015). On this basis, we advocate such community participatory approaches to others working in PNG on traditional lands not only as a means for social inclusion and capacity building but to foster trust within the community. Our findings regarding the forests of Manus Island are consistent with pre-existing studies, which demonstrate that PNG forests hold ~100–200 Mg C ha^{-1} of above-ground tree carbon stock (Table 6). With a better understanding of carbon assessments based on accurate estimates, carbon accounting for REDD+ projects would be feasible.

Acknowledgements

This study was funded by the Australian Department of Foreign Affairs and Trade as part of an activity under the climate change mitigation project grant agreement no. 63060. We thank the WCSPNG Program for making this study possible. We are grateful to Nathan Whitmore for help with data analysis, and Nathan together with Richard Cuthbert for reviewing manuscript drafts and for critical comments. We appreciate the efforts of WCSPNG Manus staff Daniel Charles, June Polomon and Julian Benjamin for logistical support and the community facilitators Matawai Pondrilei, Benson Lian, Misu Nick, Bryan Ausung, Pondrilei Sori and the late David Posa who assisted in carrying out the field work. We are grateful to the Manus Provincial Government and POBUMA and PNKA Local Level Governments in supporting this project. Finally we thank the community leaders, ward councillors and the people of Tulu 1, Saha, Djekal, Piri and Pelipowai villages of Manus Province for allowing us to work in their forests.

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