Forest carbon dynamics in Papua New Guinea; isolating the influence of selective-logging and El Niño

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Authorship

Julian C. Fox performed research, analysed data, and wrote the paper. Ghislain Vieilledent contributed new methods and models, analysed data and contributed to writing of the paper. Rodney J. Keenan conceived of the study and contributed to writing of the paper. Cossey K. Yosi and Joe N. Pokana were responsible for data collection, data analysis, and contributed to writing of the paper.

Abstract

Assessment of forest carbon (C) stock and sequestration and the influence of forest harvesting and climatic variations are important issues in global forest ecology. Quantitative studies of the C balance of tropical forests, such as those in Papua New Guinea (PNG), are also required for climate change mitigation initiatives such as REDD+. We develop a hierarchical Bayesian model (HBM) of aboveground forest C stock and sequestration in primary, selectively-harvested, and El Niño Southern Oscillation (ENSO) effected lowland tropical forest from 15 years of permanent sample plot (PSP) census data for PNG.

HBM parameters indicated; C stock in aboveground live biomass (AGLB) of 137 ± 9 (95% CI) MgC ha^{-1} in primary forest, compared with 62 ± 18 MgC ha^{-1} for selectively-harvested forest (55% difference); C sequestration in primary forest of 0.23 ± 1.70 MgC ha^{-1}yr^{-1} which was lower than in selectively-harvested forest, 1.12 ± 3.41 MgC ha^{-1}yr^{-1}; ENSO induced fire resulted in significant C emissions (-6.87 ± 3.94 MgC ha^{-1}yr^{-1}). High variability between PSPs in C stock and C sequestration rates, and autocorrelation among remeasurements of individual PSPs, necessitated random plot effects for both stock and sequestration. The HBM approach allowed inclusion of hierarchical autocorrelation, providing valid confidence intervals on model parameters and efficient estimation. Model parameters have revealed the C balance of PNG's forests and can be used as quantitative inputs for climate change mitigation initiatives.

Key words: Biomass, Sequestration, Degradation, Selective-harvesting, REDD+, Carbon, Bayesian, Hierarchical.

Introduction

Tropical forests cover 10% of global land area but remain a scientific frontier due to structural and biological complexity and high temporal variability associated with complex successional processes (Chambers et al. 2001). A constraint is the limited number of long-term studies quantifying tropical forest dynamics and the impacts of anthropogenic and natural disturbances, such as harvesting and fire (Clark et al. 2001b; Lewis et al. 2009). Long-term studies, whilst difficult to maintain, especially in developing countries, are essential to the development and testing of hypotheses regarding processes and rates of ecological recovery following disturbance, both anthropogenic and natural (Taylor et al. 2008). In this study we report on a spatially and temporally extensive Permanent Sample Plot (PSP) network in forests in Papua New Guinea (PNG) and examine the impact of selective-harvesting and the El Niño-Southern Oscillation (ENSO) induced fires on forest carbon (C) and C sequestration. To achieve this, we develop a hierarchical Bayesian model (HBM) and derive parameters that can be used to estimate the C and CO_2 balance of selective-harvesting, forest regeneration and degradation after fire which are important inputs for climate change mitigation initiatives.

There is still considerable debate over carbon dynamics in primary tropical forests. Field measurements of C stock change suggest that primary tropical forests are a significant C sink (Phillips et al. 1998; Baker et al. 2004a). For example, Lewis et al. (2009) examined C stock development for PSPs in Africa and reported that primary forest is on average sequestering 0.63 MgC ha^{-1} with 95% confidence interval (CI) 0.22–0.94. The study of Lewis et al. (2009) is consistent with other studies on the C balance of forests, in that they combine PSP measurements across time and space, and report an average and a 95% CI. Other authors suggest that primary forest should be in equilibrium with C sequestration in growth largely balanced by C emissions due mortality and decomposition (Clark 2001b; Wright 2005; Sierra et al. 2007). The role of recovering forest as a C source or a C sink remains poorly understood (Grassi et al. 2008; Olander et al. 2008; Ramankutty et al. 2007), and there is contention over the extent and recovery of forests in PNG after selective-harvesting (Shearman et al. 2009; Filer et al. 2010; Shearman et al. 2010). Studies elsewhere suggest that species differences in wood density are an important consideration in assessing rates of carbon sequestration in tropical regrowth forests (Enquist et al. 1999; Malhi et al. 2004). Other disturbances have also been important in PNG forests. In 1997 and 1998, the 20th century's most intense El Niño Southern Oscillation (ENSO) event provoked severe droughts across equatorial tropical forests which induced forest fires and severely affected C stock (Nepstad et al. 2004). Catastrophic mortality events such as fires drive tropical forest structure and dynamics (Connell 1978; Johns 1986, 1989), and their impact needs further investigation (Phillips et al. 2004).

Tropical forests play a crucial role in the global C cycle through the storage and sequestration of C in living forest biomass. This has been recognised in international climate change negotiations with the initiative to include reduced CO_2 emissions from deforestation and forest degradation (REDD+) coupled with the enhancement of forest C stocks through forest restoration, sustainable forest management and forest conservation in developing tropical countries (UNFCCC 2009). REDD+ can potentially offer economic, environmental and social benefits with the intersection of carbon markets, climate and environmental protection and, if implemented appropriately, could provide wider social and economic opportunities for indigenous people.

PNG has over 28 M ha of tropical forests which have been subject to a high rate of conversion due to timber harvesting and agriculture (Shearman et al. 2008, Filer et al. 2009), and has therefore become a focus of REDD+ initiatives. However, significant policy, institutional and technical challenges need to be overcome before REDD+ becomes operational. Technical challenges include: estimation of forest C stock in different forest stratum (Gibbs et al. 2007; Fox et al. 2010); change in these stocks due to forest harvesting (Kauffman et al. 2009) and forest fires (Phillips et al. 2004); and estimating rates of C sequestration in primary and regenerating forests across the forest estate (Olander et al. 2008). Purchasers of reduced emission credits (whether they be international organisations, other countries or corporate entities) will require assurance that estimates of C stock, C sequestration, and reductions in net CO_2 emissions are accurate and precise. All these challenges have high scientific currency given the urgency of climate change mitigation coupled with the loss of biodiversity associated with deforestation and degradation in the tropics (Venter et al. 2009).

Given the importance of discussions on the global carbon balance and the climate mitigation potential of tropical forests, there is a need to identify improved statistical approaches that go beyond simply averaging across datasets and constructing 95% CIs. One of the challenges with statistical analysis of PSP data is autocorrelation between measurements. Autocorrelation eventuates when spatial, temporal, or hierarchical variation cannot be captured by deterministic model structures (such as a simple mean) reducing estimation efficiency and biasing hypothesis tests on estimated parameters or inferences on the average such as a 95% CI (Fox et al. 2001). It is likely that autocorrelation is pervasive in models of forest C stock and sequestration, as they are parameterised using data that has an implicit hierarchical structure; trees are nested within plots which are repeatedly measured through time and/or space. Furthermore, studies have observed strong spatial and temporal variation in C stocks (Rolin 2005; Malhi and Wright 2004); however, examination of the literature reveals that these variations are rarely accounted for. This is significant given that these models are being used to estimate the C balance of forests and more recently, as quantitative input to forest-based climate change mitigation initiatives.

Hierarchical Bayesian models (HBMs) can facilitate the explicit modeling of autocorrelation (Clark 2005; Clark and Gelfand 2006; Cressie et al. 2009). The objective of this study is to test the HBM approach for modelling forest C stock and sequestration in PNG's forests.

Materials and Methods

PNGFRI Permanent Sample Plots

The PNG Forest Research Institute (PNGFRI) established a system of PSPs in the early 1990s, some in forest immediately after selective-harvesting, and others in primary forest across PNG (Figure 1). Plot measurements spanned the ENSO event which induced fires in many lowland tropical forests in PNG in 1997 and 1998 (Barr 1999). The same ENSO event was observed to cause drought and increased tree mortality in Sarawak (Nakagawa et al. 2000), and in the Amazon (Cochrane et al. 1999; Laurance et al. 2004). These PSPs are described in detail elsewhere (Fox et al. 2010). In summary, the PSPs consist of 133, 1 ha (100 m x 100 m) plots, a majority of which (121) were established in selectively-harvested forests, while 12 plots were established in primary forests. To supplement our limited sample in primary forest we included an additional 22 measurements of aboveground C as collated by Bryan et al. (2010). In total, we used 411 measurements of aboveground C in selectively-harvested forests and 44 measurements in primary forest.

Figure 1 near here

Aboveground live biomass (AGLB) was estimated using the method of Fox et al. (2010) and the wet forest allometry of Chave et al. (2005). For tree i, we denoted D_i the diameter in centimeters (cm), H_i the total height in meters (m), and q_i the wood specific gravity in grams per cubic centimeter (g cm^{-3}) derived from Eddowes (1977). For plot j at date d, we denoted I_{jd} the total number of trees with DBH ≥ 10 cm and we computed AGLB_{jd}, the aboveground living biomass (Eqn. 1). Consistent with previous studies, AGLB will be reported in megagrams per hectare (Mg ha^{-1}). For further details of the error correction methodology and biometric modelling used to estimate AGLB, refer to Fox et al. (2010).

$$AGLB_{jd} = \sum_{i=1}^{I_{jd}} \left[0.0776 \times \left(q_i D_i^2 H_i \right)^{0.94} \right] \qquad (1)$$

The C content of biomass is reported assuming that dry biomass is 50% C (Clark et al. 2001a, Houghton et al. 2001, Malhi et al. 2004). We then computed C_{jd}, the carbon stock of plot j at date d and applied a multiplier (1.1) to estimate the contribution of stems with DBH < 10 cm (Fox et al. 2010) (2).

$$C_{jd} = \frac{1}{2}\left(AGLB_{jd} \right) \times 1.1 \qquad (2)$$

Details of allometry and AGLB calculations for supplementary primary forest data can be found in Bryan et al. (2010). Note that Bryan et al. (2010) also used the allometry of Chave et al. (2005) to estimate aboveground biomass. To make measurements from Bryan et al. compatible with the PSPs, the AGLB component of C stock is identified using the multiplier 0.88 for lowland and 0.78 for montane forest (Bryan et al. 2010).

Hierarchical Bayesian model for C dynamics

We modelled C stock and sequestration using a hierarchical state-space Bayesian model (Cressie et al. 2009). We benchmark all sequential measurements using a starting date t_0 which corresponds to either the first measurement for primary (undisturbed) plots or the date of disturbance (selective-harvesting or 1998 for fire affected plots) for disturbed plots. Benchmarking plots in this way we can test for differences in the C stock and C sequestration rates for the three types of plots. We use random plot effects to account for the hierarchical structure of the data, and to incorporate year of measurement as a random effect to account for temporal autocorrelation.

We use the notation $N(\mu, V)$ to define the Normal distribution with mean μ and variance V and the notation $IG(s, r)$ to defined the Inverse-Gamma distribution with shape s and rate r. We assumed that C_{jd} was normally distributed, with variance σ^2 and with mean equal to a linear function of t with intercept a and slope b. The intercept a indicated the initial C stock, while the slope b indicated the sequestration rate reported in megagrams C per hectare per year (MgC $ha^{-1}yr^{-1}$) (3).

$$C_{jd} \sim N\left(a_j + b_j t, \sigma^2\right) \quad (3)$$

The full model (Model 1)

We fitted a full model (denoted Model 1) inclusive of (i) fixed effect $\alpha_{\{a,b\},S}$ for plot status S ($S = P$ for primary forest, H for selectively-harvested and B for burnt plots) on both the slope b and the intercept a, (ii) fixed effect $\gamma_{\{a,b\},\{A,T,R\}}$ for altitude A, mean annual temperature T and annual rainfall R on both the slope and the intercept, (iii) plot random effects $\beta_{\{a,b\}}$ on both the slope and the intercept, and (iv) annual random effects δ_a on the year of measurement for temporal autocorrelation. Elevation, temperature and precipitation were derived from the global high resolution climate surfaces of Hijmans et al. (2005) and were normalized using the function $f(x) = [x - \mathrm{E}(x)]/[SD(x)]$ in order to facilitate Markov Chain Monte Carlo (MCMC) convergence.

The intercept a and slope b for Model 1 can be defined as follows;

$$a_j = \alpha_{a,S} + \beta_{a,j} + \gamma_{a,A} f(A) + \gamma_{a,T} f(T) + \gamma_{a,R} f(R) + \delta_{a,d} \tag{4}$$

$$b_j = \alpha_{b,S} + \beta_{b,j} + \gamma_{b,A} f(A) + \gamma_{b,T} f(T) + \gamma_{b,R} f(R) \tag{5}$$

We assumed a hierarchical structure for the model defining first-level priors for the plot random effects: $\beta_{\{a,b\}} \sim N(0, V_{\{a,b\},\beta})$ and for the annual random effects: $\delta_{a,d} \sim N(0, V_{a,\delta})$. Second-level priors were assumed to be non-informative with large variances. For parameters denoted $\alpha : \alpha \sim N(0, 1.0 \times 10^6)$, for parameters denoted $\gamma : \gamma \sim N(0, 1.0 \times 10^6)$, for variance parameters denoted V and $\sigma^2 : V, \sigma^2 \sim IG(1.0 \times 10^{-3}, 1.0 \times 10^{-3})$.

Model fitting

Conditional posterior for each parameter was obtained using a Gibbs sampler (Gelfand 1990) available through the JAGS software (http://www-fis.iarc.fr/~martyn/software/jags/http://www-fis.iarc.fr/∼martyn/software/jags/). We ran two MCMC simulations of 200 000 iterations. The 'burn-in' period was set to 100 000 iterations and the 'thinning' to 1/200. We then obtained 1 000 estimations for each parameter. We checked chain convergence using the Gelman Rubin statistic (Gelman 2003).

Model comparison

We compared the full Model (Model 1) with two simpler models, denoted Model 2 and Model 3. Model 2 included only (i) fixed effects $\alpha_{\{a,b\},S}$ of plot status S on the slope and intercept and (ii) random plot effects $\beta_{\{a,b\}}$ on the slope and the intercept. In Model 2 covariates for Altitude, Precipitation and Temperature were not included, and neither was the random effect on the year of measurement. Model 3 included only fixed effects $\alpha_{\{a,b\},S}$ of the plot status S on the slope and intercept. Model 3 did not include any random effects and is analogous to a classical approach.

The DIC (Deviance Information Criterion) was used to compare models. The DIC is the sum of the mean deviance (with Deviance = -2 log(Likelihood)) and the number of parameters pD. A difference of more than 10 is taken as a rough index of difference between two models and rules out the model with the higher DIC (Spiegelhalter 2002). When DIC difference is less than 10, the best model is the one with the lower number of parameters pD, in accordance with the parsimony principle.

Parameter significance

From the posterior distribution of each parameter, we computed a credible 95% confidence interval. If the interval included zero, we assumed that the parameter was not significantly different from zero.

Predictive posterior of the carbon stock

We computed the predictive posterior π of $c(t)$, the carbon stock at time t (6). The predictive posterior included variability in the process (e.g. plot variability) and parameter uncertainty. We denoted Θ the vector of parameters.

$$\pi(C(t)) = \int_{\Theta} \pi(C(t)|\Theta)\pi(\Theta)d\Theta \qquad (6)$$

Results

PNG PSP data structure

There were a range of trends in C stock observed on the PSPs. For example, there was an exponential trend for Giluwe01 and Oomsi02 (Figure 2); a concave curvature with increasing sequestration after disturbance for Pasma01 and Umbuk01; and a linear trend for Mokol01 and Wasap01. Some PSPs exhibited high rates of C sequestration (above 3 MgC $ha^{-1}yr^{-1}$; Wasap01, Mokol01, Oomsi02), while others (Giluw01, Pasma01, Umbuk01) indicated lower rates below 1.7 MgC $ha^{-1}yr^{-1}$. A simple linear model was found to provide the best generalised fit for C stock change.

Figure 2 near here

PSPs that were affected by ENSO induced fires in 1997/1998 generally had reduced C stock in live biomass in subsequent measures due to mortality; some PSPs recovered from fire (UMBOI01, WCOST04, VAILA02), while other PSPs continued to degrade after fire (KAPUL02, IVAIN02, ORLAK01, Figure 3).

Figure 3 near here

To examine mean trends and variability in the PNG PSP data we constructed a graph (Figure 4) with measurements benchmarked against either the first measurement for primary plots or the date of disturbance (selective-harvesting or 1998 for fire affected plots) for disturbed plots.

Figure 4 near here

C stock and sequestration is highly variable across the PSPs. C stock in primary forest PSPs is generally (but not uniformly) higher than in selectively-harvested and burnt PSPs. C sequestration is generally positive on selectively-harvested PSPs and negative on PSPs burnt in 1997 or 1998 (Figure 4).

HBM Model selection

The estimated variation (assessed using DIC) is equivalent for models 1 and 2, which both include random effects, but is far larger for Model 3, which only includes fixed effects (Table 1). Despite having the same DIC, Model 2 is superior to Model 1 because it is more parsimonious, having fewer parameters (pD=210). None of the parameters for Altitude, Rainfall and Temperature, nor random effects on the year of measurement (temporal autocorrelation), were significantly different to zero. Therefore Model 2 was the preferred model for estimating C stock and sequestration.

Table 1 near here

Parameter estimates

Table 2 and Figure 5 near here

The HBM approach was used to determine C stock at t_0 and the average C sequestration across re-measurements for primary, harvested and ENSO burnt PSPs (Table 2 and Figure 5). C stock in primary forest (137 ± 9 MgC ha^{-1}) is significantly higher than in harvested (62 ± 18 MgC ha^{-1}) and burnt (70 ± 26 MgC ha^{-1}) forest (Table 2). C sequestration in harvested forest (1.12 ± 3.41 MgC $ha^{-1}yr^{-1}$) is higher than C sequestration in primary forest (0.23 ± 1.70), but neither were significantly different to zero. C sequestration in burnt forest (-6.87 ± 3.98) is significantly negative. If we assume that primary and selectively-harvested forest C stock are representative averages across forest types and regions, then the change in C stock due to selective-harvesting (ΔC_{SH}) is on average 75 MgC ha^{-1} (55%). We can construct an additive 95% CI for ΔC_{SH} as 75 ± 25 MgC ha^{-1} (or 55% ± 18%)

There was a significant variance in the plot random effect for both the intercept (C stock at t_0; $\boldsymbol{V_{a,\beta}}$ = 641.4) and the slope (C sequestration rate; $\boldsymbol{V_{b,\beta}}$ = 1.29) indicating that plot to plot variation in C stock at t_0 and C sequestration was high. The insignificance of covariates for temperature, rainfall, and altitude suggest that this was not driven by environmental conditions, but rather differences in forest types and species composition and the degree of disturbance from selective-harvesting or fire.

Comparing confidence intervals for the parameters (Table 2) when random plot effects are included (Model 2) and excluded (Model 3) indicates that confidence intervals are narrower for all parameters for Model 3. This creates a false impression of precision in parameter estimates. When hierarchical variability is included in Model 2, confidence intervals that reflect the true precision of parameter estimates result. Model 2 also explained far more variability in the data as indicated by the lower deviance (Table 1).

This is due to the high plot to plot variability in the intercept and slope which is captured using random parameters.

Discussion

Selective-harvesting results in the displacement of living forest biomass to non-living biomass, a component of which is taken off site as wood products with the remaining displacement termed collateral damage and becoming decomposing residue on the forest floor (Blanc et al. 2009). Collateral damage in tropical forest harvesting can be large and consists of crown material, peripheral trees that are damaged during tree felling and that subsequently die, and tree boles used for bridge, road and deck construction (Johns et al. 1996; Feldpausch 2005). The enhanced pool of decomposing residue resulting from collateral damage in disturbed forest can be a significant source of CO_2 emissions (Keller et al. 2004, Feldpausch 2005).

Although our sample of primary forest plots is small, we can estimate the change in C stock due to selective-harvesting (75 ± 25 MgC ha^{-1}). This provides an estimate of the displacement of living aboveground biomass to collateral damage and wood products. However, our comparison is unbalanced and unmatched; we have far more observations in selectively-harvested forest, and plots were not designed for this comparison; matched plots in adjoining primary and selectively-harvested forest would provide a more valid comparison. Nevertheless, an initial estimate of 55% reduction in AGLB could be a useful indicative figure for calculations of reductions in forest C due to commercial selective-harvesting in PNG. Similar reductions have been observed elsewhere, with surprising consistency; Lasco et al. (2006); Tangki and Chappell (2008); Faldpausch et al. (2005); and Gerwing (2002) all observed 50% reductions in AGB in the Philippines, Borneo, Southern Amazon, and Brazilian Amazon respectively.

Estimated change in C stock due to selective-harvesting can be used for preliminary national estimates of harvesting related emissions. PNG Forest Authority estimate that the area subject to selectively-harvesting between 1961, when commercial selective-harvesting commenced, and 2002 is approximately 3.4 million (M) hectares (PNGFA 2007). Based on our estimate of C reduction due to harvesting this equates to a total and average annual displacement of 255 ± 85 MtC and 6 ± 2 MtC yr^{-1} from living to non-living AGB respectively. Over this period approximately 43 M m^3 of logs have been removed from PNG's native forests (Bank of PNG (various); SGS (various)). If we assume 33% recovery of raw logs into timber products, and an average wood density of 0.58 g cm^{-3} (Fox et al. 2010), then approximately 5 MtC will have been stored in timber products over this time. By this supposition, approximately 250 ± 85 MtC is either collateral damage left in the forest to decompose or is sawmilling residue. Decomposition of biomass in tropical forests occurs rapidly with woody material completely decomposed with the C fraction emitted as CO_2 after 15 years (Keller et al. 2004; Chambers et al. 2000). Assuming complete decomposition of collateral damage and sawmilling residue (which is often combusted), approximately 917 ± 312 Mt CO_2 has been emitted due to selective-harvesting in PNG between 1961 and 2002. The year to year variability in emissions will be high due to variability in the rate of timber harvesting, particularly over the last 10 years (Bank of PNG 2009).

There is high variability in previous estimates of C sequestration in secondary tropical forest. Some studies indicate less than 2.5 MgC $ha^{-1}yr^{-1}$ (Brown and Lugo 1990);

while others indicate sequestration of between 7.5 and 10 MgC $ha^{-1}yr^{-1}$ (Hughes et al. 1999; Scatena et al. 1996); with many studies falling in the middle of this range with sequestration between 2.5 and 7.5 MgC $ha^{-1}yr^{-1}$ (Fehse et al. 2002; Uhl and Jordan 1984). Many of these studies were for heavily disturbed forest in early successional phases where sequestration is dominated by the growth of pioneers (Fehse et al. 2002). Our analysis included species-specific wood densities (Fox et al. 2010) to capture the true C contribution of low wood density pioneers (Baker et al. 2004a). A very large 95% CI (± 3.41) on the parameter indicated similar variability in C sequestration after selective-harvesting, possibly due to variation in successional stage, forest type, level of disturbance, edaphic conditions and the climatic regime in the period following disturbance. On average, observed C sequestration in regrowth in PNG was at the lower end of the range described above (1.12 ± 3.41 MgC $ha^{-1}yr^{-1}$, generally below 5 MgC $ha^{-1}yr^{-1}$). This may be due to the lower levels of disturbance relative to secondary forest resulting from agriculture. Selective-harvesting will have resulted in variability in successional stages between, and also within, the large one hectare PSPs. Gaps created due to selective-harvesting will experience regeneration that can result in high sequestration, while undisturbed areas of latter successional forest may experience little C sequestration, or even negative sequestration due to mortality (Feeley et al. 2007). We also need to be mindful of a possible bias in our sample of secondary forest toward forest that contains future merchantable timber; heavily harvested secondary forest may have been avoided (Fox et al. 2010).

The PSPs represent a valuable sample of selectively-harvested forest in the Oceania region with good spatial and temporal representation (Fox et al. 2010). We contend therefore that the average sequestration (1.12 MgC $ha^{-1}yr^{-1}$), despite high uncertainty (± 3.41), is a sound estimate for C recovery rates after selective-harvesting. If we assume that the 3.4 M ha harvested between 1961 and 2002 is harvested at the annual rate of 0.083 M ha, then the net C sequestered since harvesting began can be calculated as (41*1.12*0.083 + 40*1.12*0.083 + 39*1.12*0.083….. 1*1.12*0.083) and is approximately equal to 80 MtC or 294 MtCO_2 over this period. If we include parameter uncertainty in this estimate the 95% CI for sequestered C is 80 ± 244 MtC. Despite this high uncertainty, if the average sequestration occurred across selectively-harvested forest it would offset approximately one third of the emissions from decomposition of collateral damage and sawmilling residue (917 MtCO_2).

The observed uptake of C by primary tropical forests (Phillips et al. 1998) has become a point of contention in recent years (Clark 2001b; Wright 2005). Results for the limited number of plots in this study indicated a mean sequestration rate in primary forest of 0.23 ± 1.57 MgC $ha^{-1}yr^{-1}$. This figure is lower than biome averages for primary forest (0.44 MgC $ha^{-1}yr^{-1}$, Phillips et al. (1998); 0.61 MgC $ha^{-1}yr^{-1}$, Baker et al. (2004b)). These higher than expected C sequestration rates for primary forest have led several authors to suggest a pervasive alteration of primary tropical forest dynamics from global environmental changes such as increased atmospheric CO_2 (Phillips et al. 1998; Baker et al. 2004b; Lewis et al. 2009). Our limited sample suggests that PNG's primary forests are not a net C sink, however, more samples are required to verify this.

The ENSO event of 1997/1998 caused a drying out of lowland tropical forests in PNG, with large-scale wildfires causing widespread tree mortality. The estimated annual C emission in AGLB after this event is -6.87 (± 3.98) MgC $ha^{-1}yr^{-1}$. Balch et al. (2008)

report a similar loss of AGLB of -8.5 MgC $ha^{-1}yr^{-1}$ for a large-scale fire experiment in Amazonian forests. Some of the PSPs in this study were measured for 10 years after ENSO-induced fires, and indicated that ΔC_B is ongoing with net C emissions 10 years after the fire disturbance. Shearman et al. (2008) estimate that 350,000 ha has been affected by fire between 1972 and 2002. Assuming that fire impacts the forest C dynamic for 10 years, then emissions from fire affected forest over this period are approximately 24 ± 14 MtC or 88 ± 51 $MtCO_2$. Considering that ENSO events are predicted to become more frequent and more severe under climate change, the significant emissions as observed here have implications for global C cycles.

There has been speculation (Shearman et al. 2009) that PNG's secondary forests are degraded to the extent that they are incapable of recovery. The present study suggests otherwise, indicating that selectively-harvested forests are reasonably stocked after harvesting (62 ± 18 MgC ha^{-1}), and are recovering C at the rate of 1.12 ± 3.41 MgC $ha^{-1}yr^{-1}$. The high variability indicates that some plots are degrading but the bulk of plots are either maintaining or increasing biomass and carbon stock. If the average sequestration rate is maintained at a linear rate, it would take approximately 65 years for harvested forest to recover the 75 MgC ha^{-1} that was displaced during selective-harvesting.

We have used HBM model parameters inclusive of valid parameter uncertainties for some initial estimates of CO_2 emissions from harvesting and fires. These estimates can provide a quantitative basis for forest C accounting systems for PNG, and constitute country specific information required for Tier 3 compliant greenhouse gas inventories of forested land (IPCC 2006). Analysis of carbon dynamics in PNG forests can be based on these estimates, published carbon book-keeping methods (e.g. Ramankutty et al. 2007;

Blanc et al. 2009) and elements of the Voluntary Carbon Standard (VCS 2008) to construct an appropriate forest C accounting system for PNG. Note that the initial emission estimates detailed in this paper include only aboveground C dynamics. A full C account would need to be inclusive of under-storey plants, lianas and vines, woody debris, litter, coarse and fine roots and soil C (Blanc et al. 2009).

In this study, hierarchical autocorrelation was highly significant due to high plot to plot variability in both the intercept (C stock at t_0) and the slope (C sequestration). This has important implications for carbon dynamic models. Deterministic model structures fail to effectively explain these plot to plot differences, despite the inclusion of environmental variables (altitude, rainfall, and temperature). Explaining structural complexity and temporal variability in tropical forests is an ongoing scientific challenge (Chambers et al. 2001). As our understanding of this complexity improves there will be opportunities to include covariates in deterministic model structures that better explain site to site and plot to plot variability. Until this occurs it seems prudent to use model structures, such as HBM, that account for high site to site variability.

The HBM model structure used in this study has several advantages over reporting averages and 95% confidence intervals. It avoided the presence of autocorrelation in model residuals that result in biased estimates of standard errors of parameter estimates (Johnston 1972), and bias in inference on averages or parameter estimates such as 95% CIs. When we excluded plot level random effects (in Model 3) the CIs for different parameters were considerably lower, creating a false impression of precision. This is statistically well known. When positive autocorrelation is present among residuals located on the same sampling unit (for example; several remeasurements of a plot) then parameter CIs will be underestimated and hypothesis tests on the significance will be biased upwards and the type I error rate will be inflated, i.e. too often it will be concluded that the value is different from zero. Inferences on the parameters and averages are particularly important in light of controversies on the C balance of tropical forests. Many studies that have observed significant net C sequestration in primary tropical forest have failed to account for autocorrelation resulting from hierarchical data structures. When autocorrelation is incorporated, estimation efficiency is improved, as each measurement is bringing information to the model, independent of other measurements. Efficiency considerations are important in light of the cost of tropical forest census. Given the importance of discussions on the global carbon balance and the climate mitigation potential of tropical forests, we need improved statistical methodology such as hierarchical Bayesian models which are more appropriate for tropical forest data from repeated plot measurements.

In conclusion, we have reported defensible estimates of aboveground C and C sequestration in primary, selective-harvested, and ENSO burnt forest using a HBM. These estimates have improved our understanding of the forest C cycle in PNG, and provide quantitative inputs for climate change mitigation initiatives such as REDD+.

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Figure 1

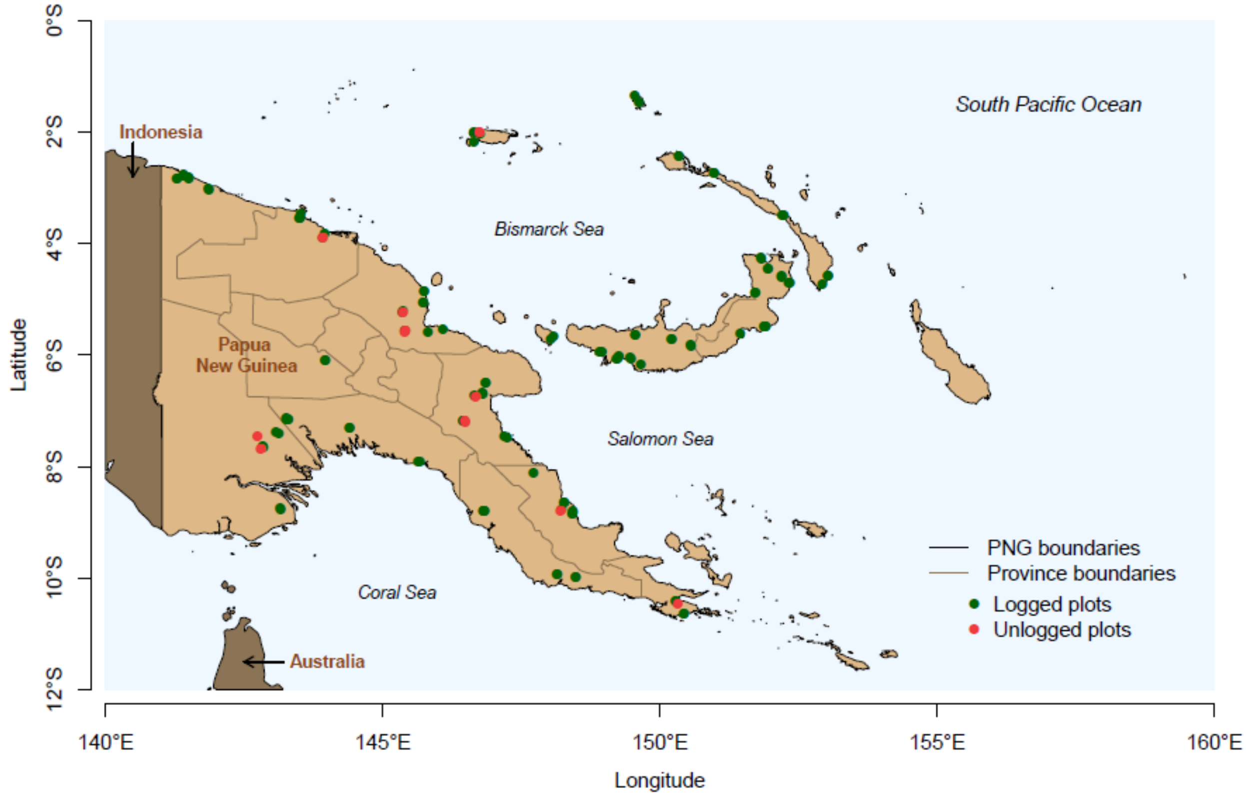

South Pacific Ocean
Indonesia
Bismarck Sea
Papua
New Guinea
Salomon Sea
Coral Sea
Australia
PNG boundaries
Province boundaries
Logged plots
Unlogged plots
0°S
2°S
4°S
6°S
8°S
10°S
12°S
Latitude
140°E
145°E
150°E
155°E
160°E
Longitude

Figure 2

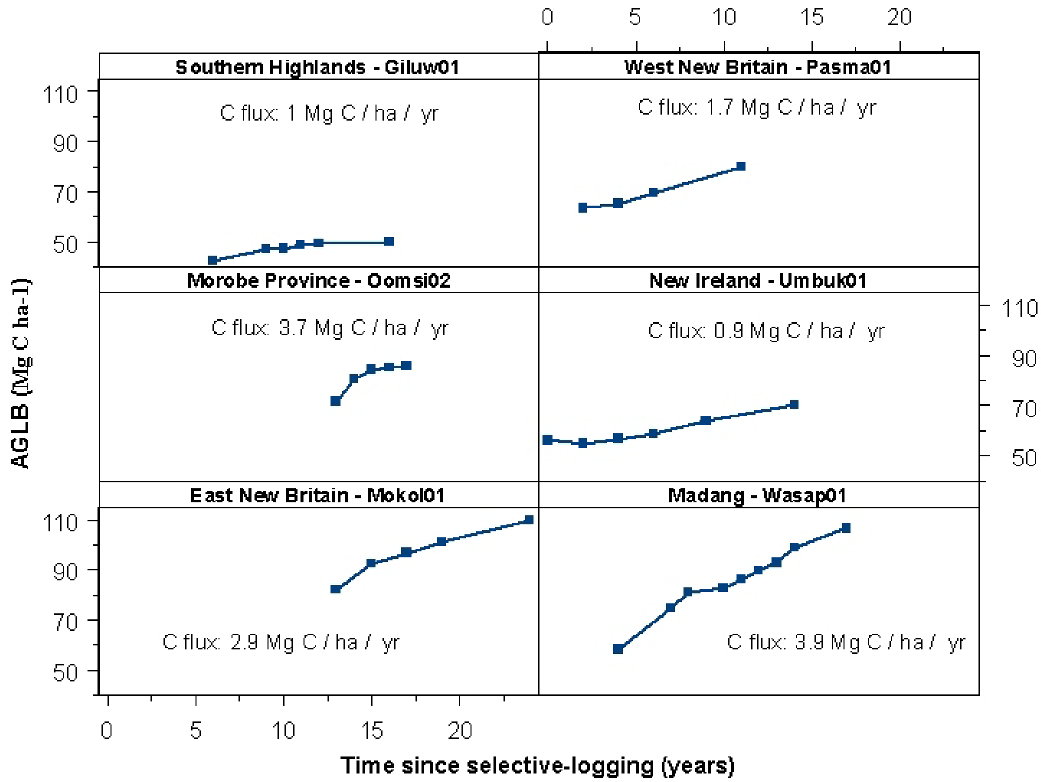

Southern Highlands - Giluw01
C flux: 1 Mg C / ha / yr
West New Britain - Pasma01
C flux: 1.7 Mg C / ha / yr
Morobe Province - Oomsi02
C flux: 3.7 Mg C / ha / yr
New Ireland - Umbuk01
C flux: 0.9 Mg C / ha / yr
East New Britain - Mokol01
C flux: 2.9 Mg C / ha / yr
Madang - Wasap01
C flux: 3.9 Mg C / ha / yr
AGLB (Mg C ha-1)
Time since selective-logging (years)
0
5
10
15
20
50
70
90
110

Figure 3

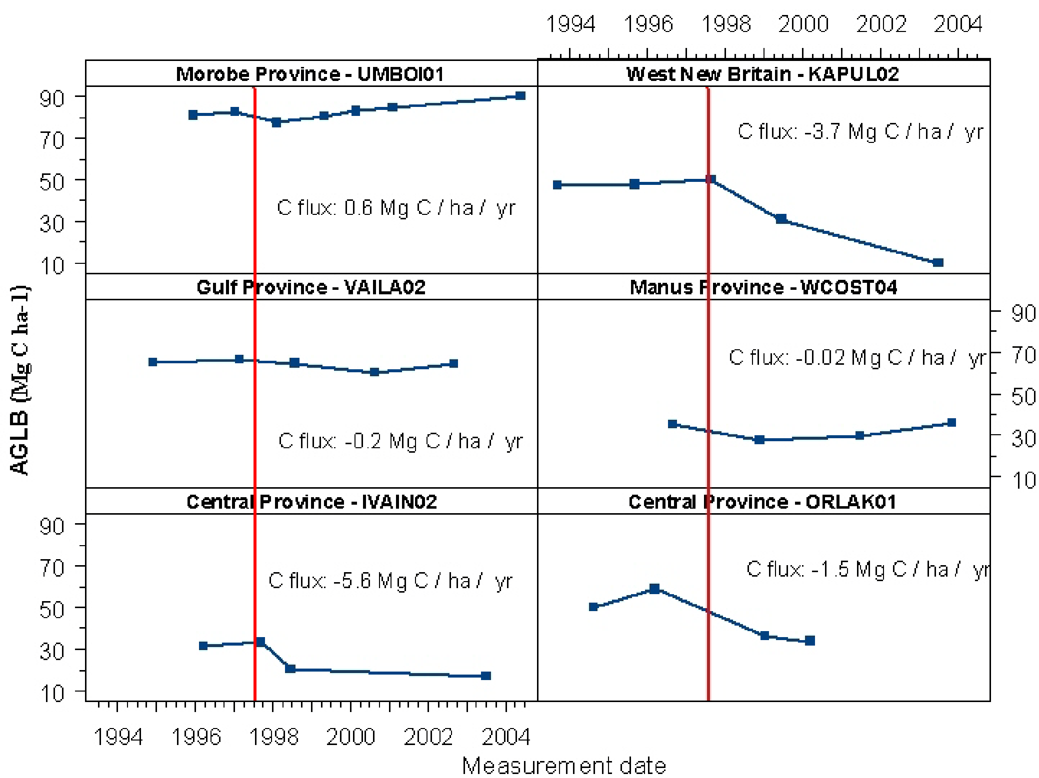
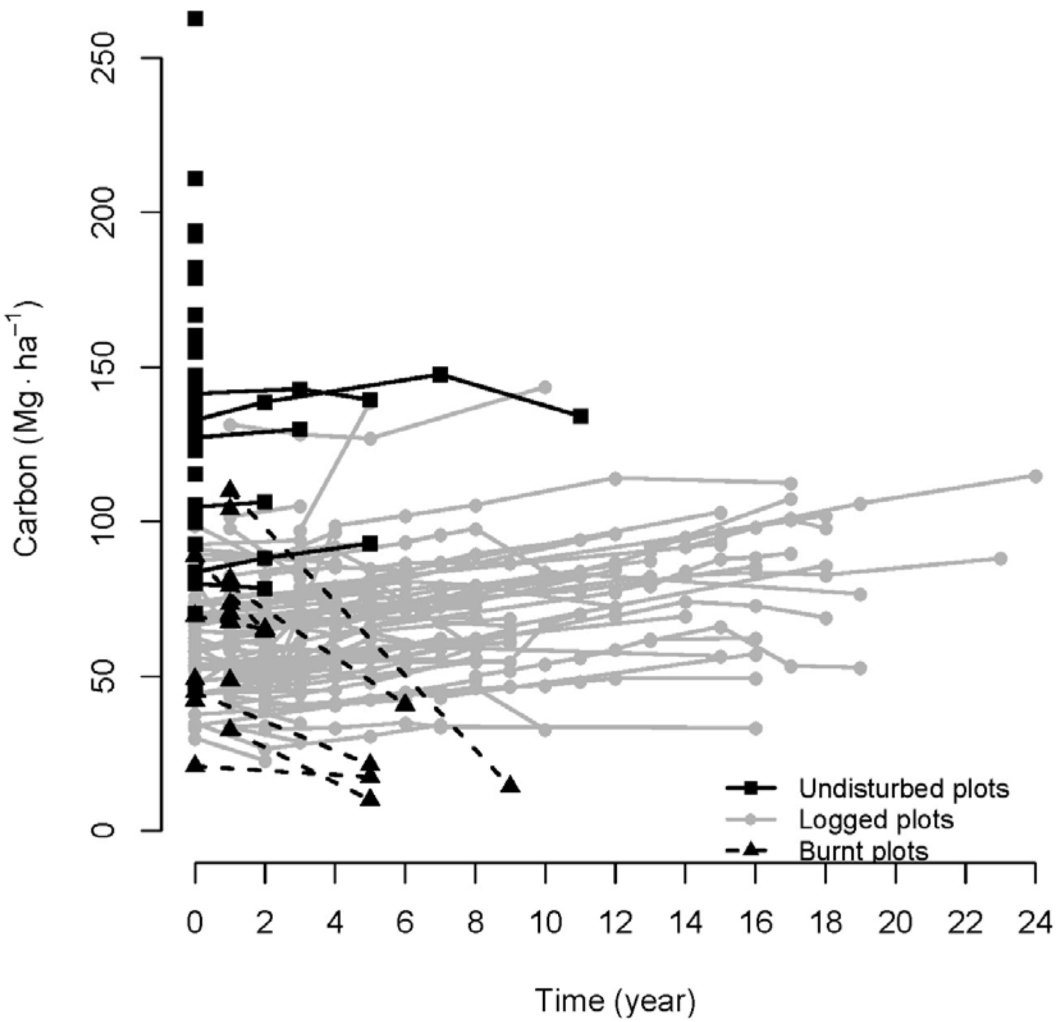
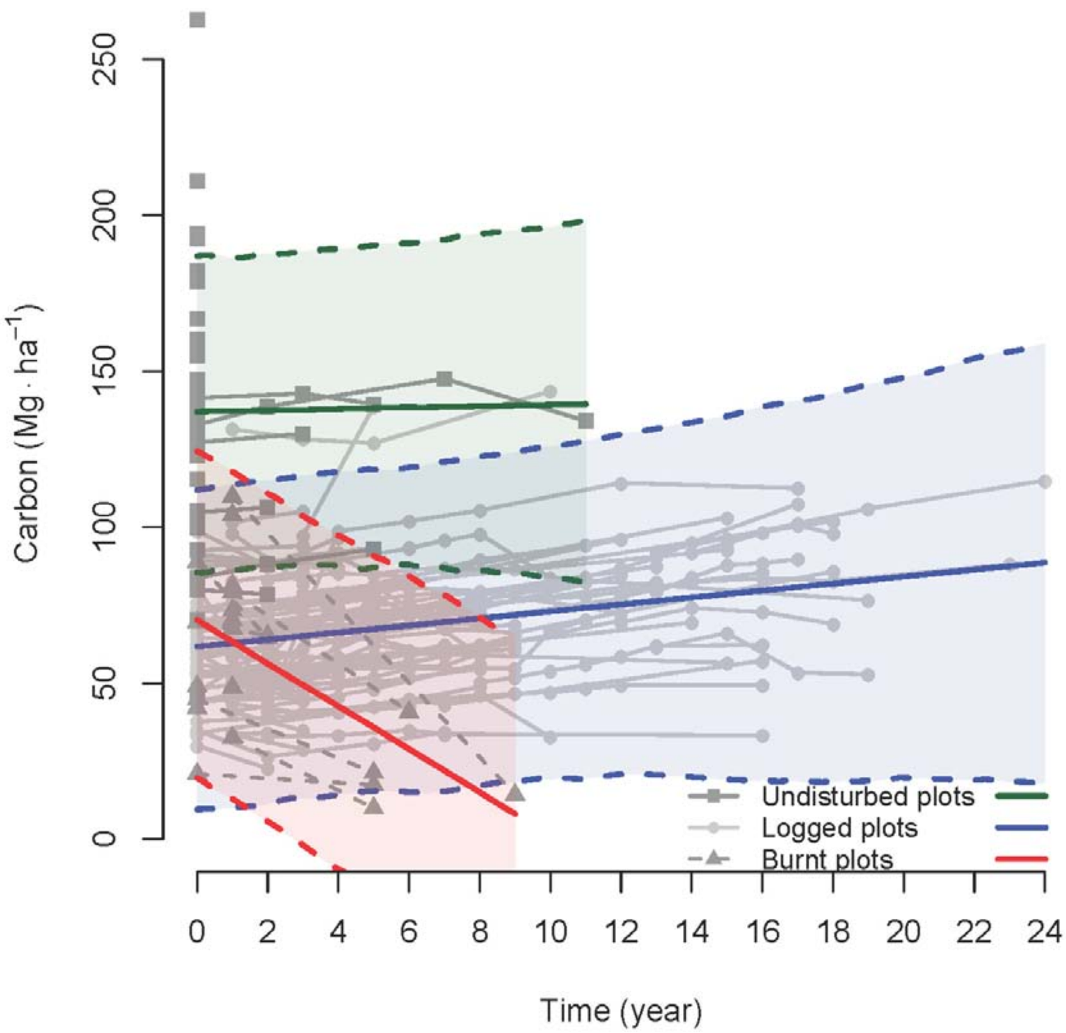

Morobe Province - UMBOI01
C flux: 0.6 Mg C / ha / yr
West New Britain - KAPUL02
C flux: -3.7 Mg C / ha / yr
Gulf Province - VAILA02
C flux: -0.2 Mg C / ha / yr
Manus Province - WCOST04
C flux: -0.02 Mg C / ha / yr
Central Province - IVAIN02
C flux: -5.6 Mg C / ha / yr
Central Province - ORLAK01
C flux: -1.5 Mg C / ha / yr
AGLB (Mg C ha-1)
Measurement date
1994 1996 1998 2000 2002 2004
10 30 50 70 90

Figure 4



Carbon (Mg · ha⁻¹)
0
50
100
150
200
250
0 2 4 6 8 10 12 14 16 18 20 22 24
Time (year)
Undisturbed plots
Logged plots
Burnt plots

Figure 5



Carbon (Mg · ha^{-1})
0
50
100
150
200
250
0
2
4
6
8
10
12
14
16
18
20
22
24
Time (year)
Undisturbed plots
Logged plots
Burnt plots

Figure Legends

Figure 1. Spatial distribution of PNGFRI PSPs across PNG

Figure 2. Trends in C stock after selective-harvesting

Figure 3. Trends in C stock for plots affected by ENSO induced fires of 1997 and 1998

Figure 4. PNG PSP data structure

Figure 5. Predicted posterior for Model 2 with 95% confidence intervals inclusive of random plot variability on the intercept and slope

Table 1. Model comparison

	Deviance	pD	DIC
Model 1	2762	217	3060
Model 2	2777	210	3060
Model 3	4100	7	4107

Table 2. Parameter estimates for Model 2

Parameter	Explanation	Parameter estimate	95% CI M2*	95% CI M3**
a_P	C stock t_0 – Primary	137.00#	± 8.62	± 6.90
a_H	C stock t_0 – Harvested	61.74#	± 18.34	± 7.53
a_B	C stock t_0 – Burnt	70.17#	± 25.93	± 13.91
b_P	C sequestration - Primary	0.23	± 1.70	± 1.11
b_H	C sequestration - Harvested	1.12	± 3.41	± 2.93
b_B	C sequestration - Burnt	-6.87#	± 3.98	± 3.10
$V_{a,\beta}$	Variance on plot random effect on intercept	641.40#	± 140.17	
$V_{b,\beta}$	Variance on plot random effect on slope	1.29#	± 0.85	
σ^2	Variance	30.92#	± 6.26	± 63.47

Parameter estimate is significantly different to zero *Credible 95% confidence interval CI for Model 2 inclusive of random plot effects **95% for Model 3 with no random effects

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