Forest Ecology and Management 417 (2018) 154–166

Contents lists available at ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

The imprint of logging on tropical forest carbon stocks: A Bornean case-study

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ARTICLE INFO

Keywords:
Above- and below-ground carbon
Carbon stock
Dipterocarp forests
Logged forest

ABSTRACT

In tropical forests, selective logging generates a significant reduction of above-ground carbon stocks, due to direct removal of a few large merchantable individuals, and the death of smaller injured or smashed trees following harvesting. Several studies have shown a strong correlation between logging intensity and a reduction of biodiversity, wood production, and biomass stocks. However, little is known about the long-term effects of logging on the main forest carbon (C) stocks in above and below-ground tree biomass, deadwood, litter, and soil. In this study we quantified C stocks in 28 0.25-ha plots located in a mixed Dipterocarp forest, Borneo, Indonesia, logged 16 years ago at different intensities ranging from 0 to 57% of initial biomass removed. We investigated the effect of logging intensity, topography, and soil variables on each C stock using linear mixed models. Sixteen years after logging, total C stocks ranged from 218 to 554 Mg C ha^{-1} with an average of 314 ± 21 Mg C ha^{-1}, of which more than 75% were found in live trees. Logging intensity was found to be the main factor explaining the variability in carbon stored in above- and below- ground biomass of tree DBH > 20 cm and deadwood. Simultaneously, the proportion of deadwood increased with logging intensity reaching 13.5% of total C stocks in intensively logged plots (> 20% removal of initial biomass). This study confirmed, therefore, the need to limit logging intensity to a threshold of 20% of initial biomass removal in order to limit the long-term accumulation of deadwood after logging, probably due to high post-logging mortality. With more than half of all Bornean forests already logged, accounting for total C post-logging is key to better assess the long-term carbon footprint of commercial logging in the region, and is a necessary step towards the development of C-oriented forest management in the tropics.

1. Introduction

Bornean forests have mainly been exploited since the 1960s and with little concerns on ecological drawbacks and no implementation of appropriate logging and management practices (Nasi and Frost, 2009; Nicholson, 1979; Putz et al., 2008). With increasing awareness on the fast degradation of Bornean forests, guidance to reduce the negative impacts of logging have been proposed since the 1990s, but remains poorly implemented in practice (Nasi and Frost, 2009). In 2010, almost half of the Bornean forests had been affected by commercial timber extraction (Gaveau et al., 2014) and deforestation is still ramping up at high rate due to fast expansion of commercial plantations, such as oil palm (Margono et al., 2014). The remaining tropical forests, not only in Borneo, but all around the tropics, are under increasing anthropogenic pressure (Potapov et al., 2017) and logged forests are likely to play a key role in the future provision of ecosystem services, such as the production of wood, sequestration of carbon and maintenance of biodiversity (Edwards et al., 2014; Sist et al., 2015).

Even though reduced-impact logging techniques have been proposed and applied in the tropics (Miller et al., 2011; Putz et al., 2008), poor implementation of these prescriptions still makes selective logging largely detrimental for tropical forest ecosystems. Widespread damages to residual stands and soils (e.g. Picard et al., 2012; Pinard et al., 2000) induced long-lasting reduction of both biomass (Rutishauser et al., 2015) and timber (Vidal et al., 2016) stocks. Incidental damages are unavoidable, being directly related to logging intensity (Sist et al.,

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https://doi.org/10.1016/j.foreco.2018.03.007
Received 22 January 2018; Received in revised form 2 March 2018; Accepted 5 March 2018

2003b) and to the methods of tree felling and skidding (Pinard and Putz, 1996; Sist and Nguyen-Thé, 2002). Carbon (C) emissions induced by incidental damages, log wastes, and infrastructures can be up to 2–3 times higher than the C emissions related directly to extracted logs (Pearson et al., 2014). Recent studies showed that commercial logging was found to be a major source of green-house gas emission, forming up to 50% of annual emissions related to forest degradation (Pearson et al., 2017).

While timber is generally exported, incidentally killed trees, along with logging residues, remain in the forest as deadwood and slash in the forest floor and can form up to 50% of total C stocks in logged forests (Osone et al., 2016; Pfeifer et al., 2015). By creating large canopy gaps, logging also affects the production of litter (Prasetyo et al., 2015). In logging gaps, the increased temperature on the forest floor was shown to enhance the decomposition of deadwood and litter (Zhang et al., 2008; Zhou et al., 2007). Further, increased availability of C in soil may accelerate the decomposition of deeper organic material in the soil where the micro-fauna is nutrient limited (Fontaine et al., 2004). This phenomenon is called priming effect (Fontaine et al., 2003) and may explain the sharp decrease of SOC observed 50 years after logging in a tropical logged African forest (Chiti et al., 2015).

Most C studies investigating the effects of logging in Bornean forests have focused on above-ground biomass (e.g. Ioki et al., 2014; Kenzo et al., 2010; Morel et al., 2011) with a few exceptions also looking at other C pools (e.g. Osone et al., 2016; Pfeifer et al., 2015; Saner et al., 2012). A better understanding of the distribution and variability of C stocks in logged forests is required to accurately estimate the carbon footprint of logging activities. The present study offers to quantify carbon stocks in five major pools, namely above and below-ground tree biomass, deadwood, litter, and organic carbon in soil at Malinau Research Forest, Borneo, Indonesia. Based on the hypothesis that logging has a significant influence on C stocks after 16 years, this study specifically aims to: a) estimate total C stocks and the proportion of each C pool along a gradient of logging intensity (ranging from 0 to 57% of initial biomass removed), and b) identify the factors influencing the variability in these C pools. Getting detailed estimates of C stocks post-logging and knowing the effect of logging intensity on total C stocks will help refine the carbon budget of managed forests and develop C-oriented forest management.

2. Materials and methods

2.1. Study site

Malinau Research Forest (MRF) was established in 1998/1999 with the aim to develop a sustainable forest management program that reduces logging-impacts and preserves the biodiversity along with the wellbeing of local communities (Cifor and ITTO, 2002; Gunarso et al., 2007; Sist et al., 2003b). MRF is located in a logging concession owned by PT Inhutani II in Malinau, North Kalimantan (2°45′N, 116°30′E). The area is 100–300 m above sea level with 10–70% slope and an annual rainfall of around 3790 mm. The forest is mainly composed of Dipterocarps, of which most species are prized commercial species, and stands among the most diverse Indonesian forests with 205 tree species inventoried (Sheil et al., 2010). MRF was selectively logged in 1999/2000 with different intensities, ranging from 3 to 13 trees harvested per hectare (Sist et al., 2003b). The Indonesian selective logging and planting system (TPTI) allows all commercial trees with diameter at breast height (DBH) over 50 or 60 cm (depending on the forest type) to be harvested within a felling cycle of 35 years. In MRF, the targeted commercial tree species were *Agathis borneensis*, *Dipterocarpus* spp., and *Shorea* spp. (Sist et al., 2003b).

2.2. Experimental design

Twenty-four 1-ha plots (100 m × 100 m) were randomly established in 1998/1999 before logging occurred (Sist et al., 2003b). In each plot, all trees with a DBH > 20 cm ($DBH_{>20}$) were mapped, tagged, and identified to the lowest taxonomic level. Trees were identified by a professional botanist in 1999/2000 and herbarium vouchers were deposited in Herbarium Bogoriense. A total of 6696 trees were identified at species (85.1%), genus (10.7%), and family (4.2%) levels. Logging took place in 1999/2000. An overview of logging intensity and techniques used in MRF is given elsewhere (Sist et al., 2003b). Before logging (1999), all trees $DBH_{>20}$ were systematically recorded, girth at breast height measured and crown forms and positions recorded. Tree status (live or dead), stem damages, and cause of death of all trees were recorded in all plots 8 months after logging (Sist et al., 2003b). In 2015, 7 out of 24 1-ha plots were surveyed and diameter of all trees $DBH_{>20}$ was measured at 130 cm or 50 cm above any buttress or deformity. Additionally, in 2016, ten quadrats of 10 m × 10 m were randomly placed in each of those 7 plots to measure trees with DBH between 5 and 20 cm ($DBH_{5\text{-}20}$), deadwood, and litter. For 2015 and 2016 measurements, trees were identified by an experienced parabotanist at species (74.9%), genus (25%), and family (0.1%) levels. Tree girths were measured at 130 cm using a tape meter and converted into diameter, while total and trunk heights were measured using a laser rangefinder (Bushnell G-Force 1300 ARC). After data collection, a soil pit was dug in 2 quadrats chosen randomly in each plot (except in plot C09 where 3 pits were dug) leading to a total of 15 soil pits.

2.3. Logging intensity and C stocks

Logging intensity is defined as the ratio between the biomass lost at first post-logging measurement and pre-logging biomass stock (expressed as a percentage of pre-logging biomass). Biomass lost corresponds to the summed biomass of timber harvested and injured trees that died before the first post-logging census. Usually injured trees will die during the first 2 years after logging (Shenkin et al., 2015; Sist et al., 2014) and damages will be concentrated around gaps created by harvested trees (Pearson et al., 2014). Logging intensity was estimated at 0.25-ha scale (each plot was divided into 4 subplots (50 m × 50 m) giving 28 subplots in total) to account for the large heterogeneity in logging treatment and damages within 1-ha plots. Logging intensity ranged from 0 to 57% of initial biomass lost (Table A1). Neither tree biomass, nor logging intensity was not found spatially correlated above 30 m (Figs. A1 and A2), avoiding pseudo-replication among subplots.

Five main C stocks were assessed as recommended by IPCC (2006), and quantified within each subplot: C stored in (i) live trees with a DBH between 5 and 20 cm, hereinafter $AGC_{5\text{-}20}$, and larger than 20 cm DBH ($AGC_{>20}$), (ii) coarse roots of trees DBH 5–20 and > 20 cm (referred to as $BGC_{5\text{-}20}$ and $BGC_{>20}$, respectively), (iii) deadwood composed of coarse woody debris (CWD) having a diameter > 10 cm and standing dead trees DBH > 10 cm, (iv) litter, and (v) soil organic carbon in the top 1 m (SOC). Carbon stocks were calculated using a nested design: $AGC_{>20}$ and $BGC_{>20}$ were estimated across the whole 0.25-ha subplot, whereas $AGC_{5\text{-}20}$, $BGC_{5\text{-}20}$, CWD, litter, and SOC were estimated in the 10 × 10 m quadrats and then averaged by subplot. For the sake of simplicity, a default ratio of 47% was used to estimate the carbon content of both live and dead biomass (IPCC, 2006). Total C stocks correspond to the sum of all five C stocks at subplot level expressed in Mg C ha^{-1}.

2.3.1. Above- and below ground biomass (AGB and BGB)

AGB was estimated using a generic allometric model including DBH, wood density (ρ) and a climate index (E) (Chave et al., 2014). Such generic allometric models were shown to be more accurate and less biased than local models, notably in Dipterocarp forests (Rutishauser et al., 2013). Wood densities arise from the Global Wood Density Database (Chave et al., 2009; Zanne et al., 2009) using the lowest taxonomic level available. For species not present in the database, a wood density of $\rho = 0.58\ g\ cm^{-3}$ were used. Root biomass ($BGB_{>20}$ and

$BGB_{5\text{-}20}$) were estimated based on DBH using an allometric model developed in a mixed Dipterocarp forest (Niiyama et al., 2010). $AGB_{5\text{-}20}$, $AGB_{>20}$, $BGB_{5\text{-}20}$, and $BGB_{>20}$ were calculated using 2015 and 2016 data.

2.3.2. Deadwood

All fallen and standing deadwood with diameter > 10 cm in each 100 m^2 quadrat were measured. For fallen deadwood, diameters at both ends and length (L) of each piece of deadwood lying in or crossing the quadrat were measured (Gove and Van Deusen, 2011). For deadwood expanding outside the quadrat's boundaries, diameters were measured at the point of intersection with any boundary, and the piece wood length is the distance between these two points, representing the portion lying in the quadrat. The volume of each fallen deadwood (V_f) was calculated using conic-paraboloid formula (Fraver et al., 2007), as follows:

$$V_f = \frac{L_d}{12}\cdot(5\cdot A_s + 5\cdot A_l + 2\cdot\sqrt{A_s\cdot A_l})$$

where L, A_s and A_l are the length (m) and the cross-sectional area (m^2) at the small- and large-end diameter of a CWD, respectively. CWD mass is generally obtained by multiplying the volume of each piece by its respective wood density (ρ_{DW}, gr cm^{-3}). The volume of a standing deadwood was considered as a cylinder (V_s), of which height and DBH were measured and multiplied by a generic form factor (0.48) for broadleaved tree species (Cannell, 1984). Deadwood density (ρ_{DW}, Table A2) was estimated visually using the three following decay classes (Walker et al., 2014):

Class 1 (Solid): little decay, extensive bark cover, leaves and fine twigs present, logs relatively undecayed.
Class 2 (Intermediate): No bark and few branch stubs (not moving when pulled), sapwood decaying
Class 3 (Rotten): Wood largely decayed, often scattered across the soil surface, logs elliptical in cross-section.

For each class, average dry wood density was determined by collecting 40 wood samples randomly for class 1, 2, and 3, respectively. Wood samples were weighed fresh in the field and oven-dried (at 80° C until constant weight) to compute dry weight per wet volume.

2.3.3. Litter

The litter layer is defined as all dead organic material on the top of the mineral soil (Walker et al., 2014). Dead material with diameter < 10 cm is included in this layer. The litter sample was collected in a 1 m × 1 m subplot randomly chosen in each quadrat, and weighed wet. A sub-sample (≤0.5 kg) was then dried until constant weight in the laboratory to estimate the dry weight. Dry mass of litter was calculated based on the wet-to-dry weight ratio of sub-samples.

2.3.4. Soil organic carbon (SOC)

Soil samples were collected volume based using metal rings of known volume (*c.* 92 cm^3) at five depth intervals (0–5, 5–15, 15–30, 30–50, and 50–100 cm) in each soil pit to determine chemical and physical properties. Soil bulk density (g cm^{-3}) and a fraction of gravel (%) for each depth were determined after sieving the dried soil using a 2-mm mesh. Organic carbon concentration (mg g^{-1}) of the sample was estimated using a wet oxidation method (Walkley and Black, 1934). Other soil properties, such as texture, pH (H_2O), CEC, available phosphorus (Bray I/II), and nitrogen (Kjeldahl) were also determined. SOC stocks (Mg ha^{-1}) for each depth were calculated as the function of soil bulk density, carbon concentration, and coarse fragment for each depth (Batjes, 1996). Total SOC stocks (Mg ha^{-1}) were then calculated as the sum of SOC stocks of each depth.

2.4. Data analyses

Linear mixed models were developed to test the relationship between logging intensity, topography (i.e. slope), and soil variables on each C stock (Y). The effect of logging intensity and topography on the different C pools were tested across all subplots (n = 28), while the effect of soil could be tested only in 15 subplots where a pit was dug. To avoid collinearity of the soil variables, only three soil variables (clay, nitrogen, and available phosphorus) were included in the model based on correlation with the first two axes of a Principal Component Analysis (see SI). Initial forest structure within each plot was accounted for as random effect (u) to lower spatial correlation. $AGC_{>20}$, deadwood, total C stocks, logging intensity, and available phosphorus content were normalized by log-transformation to fulfill assumption of normality, and therefore to avoid heteroscedasticity of residuals. The initial linear mixed model for each C pool is therefore defined as follows:

$$Y = \beta_0 + \beta_1\cdot logging\ intensity + \beta_2\cdot slope + \beta_3\cdot clay + \beta_4\cdot nitrogen + \beta_5\cdot available\ phosphorus + u + \varepsilon_a$$

with $\varepsilon_a \sim N(0,\sigma_a^2)$ and β are the coefficients of the fixed effects tested. All analyses were carried on in R (R Core Team, 2017). The *lmer* function in the 'lme4' package was used to fit linear mixed-effects models (Bates et al., 2015), the "MuMIn" package to estimate marginal (the proportion of variance explained by the fixed factors) and conditional (the proportion of variance explained by both fixed and random factors) R^2 of the model (Barton, 2016), the "glmulti" package to predict the best fit model based on the lowest Bayesian Information Criterion (BIC) as well as to estimate the relative importance value for each variable used in the model (Calcagno and de Mazancourt, 2010), the 'car' package to analyze significant difference between the predictor variables included in the model (Fox and Weisberg, 2011), and the "PMCMR" package to analyze the difference between artificial logging intensity classes based on 0-33rd (0–2.1%), 34-66th (2.1–19%), and 67-100th (19–56.9%) percentiles of the logging intensity distribution using Kruskal-Wallis test followed by Dunn's test (Pohlert, 2016).

3. Results

3.1. Total C stocks in a logged forest

Sixteen years after logging, total C stocks at MRF ranged from 218 to 554 Mg C ha^{-1} (Fig. 1) with an average of 314 ± 21 Mg C ha^{-1}, of which more than 75% were found in live trees DBH > 5 cm (Fig. 2B, Table A4). Total C stocks generally decreased when logging intensity increased (Fig. 1, adj-R^2 = 0.42, slope = −0.07, p-value < 0.01), driven by the strong effect of logging intensity on $AGC_{>20}$ (Fig. 1, adj-R^2 = 0.60, slope = −57.90, p-value < 0.01). Excluding 0% logging intensity, slope and adjusted R^2 of linear model were slightly changed without affecting the result (Fig. 1, the solid blue line). Areas affected by high logging intensity had in average 33% less $AGC_{>20}$ and $BGC_{>20}$ than unmanaged areas or logged at low intensity (Fig. 2). Deadwood stocks were positively correlated with logging intensity (adj-R^2 = 0.36, slope = 0.35, p-value < 0.05), increasing significantly in areas with high logging intensity where it formed 13.5% of total C stock (Fig. 2). No trend along gradient of logging intensity was found on $AGC_{5\text{-}20}$, $BGC_{5\text{-}20}$, SOC stock, and litter C stock (Fig. 1, all p-value > 0.1).

3.2. Drivers of C pools

The explanatory variables explained between 25 and 63% of the total variance among the C pools (Table 1, marginal R^2). Logging intensity was found to be the main driver explaining variation in $AGC_{>20}$, $BGC_{>20}$, deadwood, and total C stocks when initial forest structure and key environmental variables were included (Table 1). The

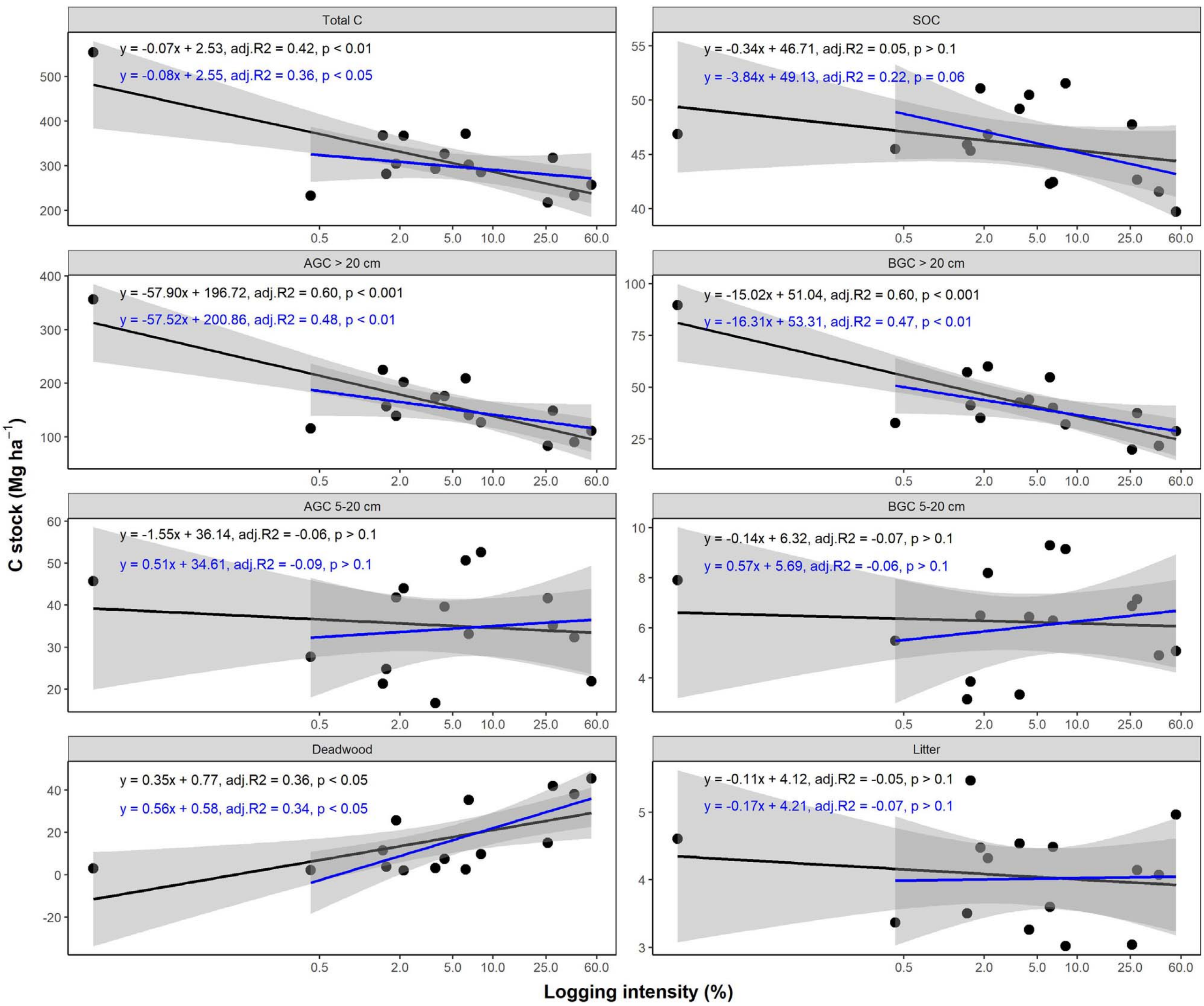

Fig. 1. C stocks for each C pool and total C stocks along a gradient of logging intensity (n = 15 subplots). The solid black line is a linear model with 95% confidence interval. The solid blue line is a linear model excluding 0% logging intensity with 95% confidence interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

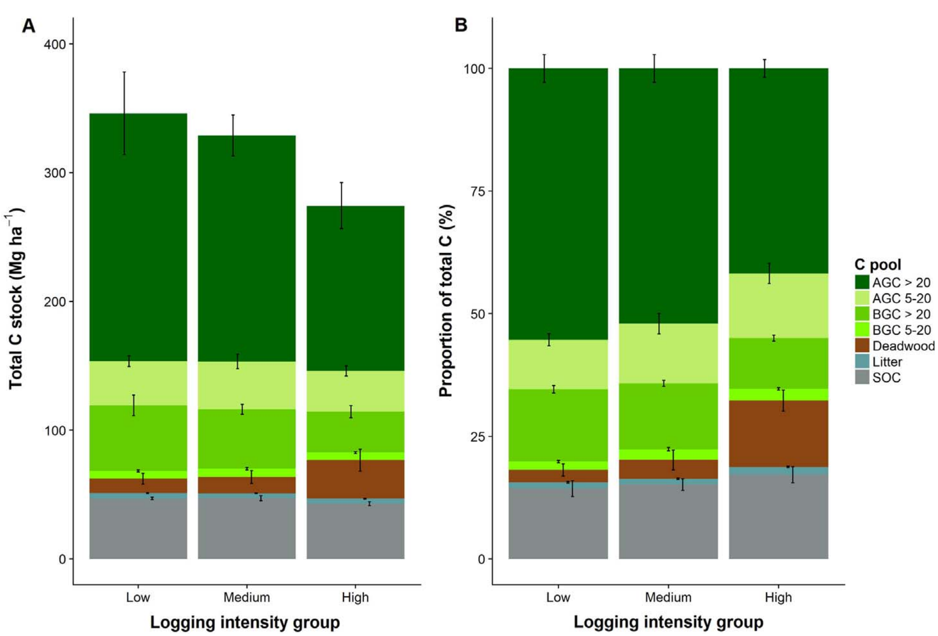

Fig. 2. Total C stocks (A) and its proportion (B) for each pool in different logging intensity group 16 years after logging. Logging intensity was grouped into 3 classes corresponding to 0–33rd (0–2.1%), 34–66th (2.1–19%), and 67–100th (19–57%) percentiles of the logging intensity distribution, respectively. The stocks and proportions of $AGC_{>20}$, $BGC_{>20}$, $AGC_{5\text{-}20}$, $BGC_{5\text{-}20}$, deadwood, and litter were averaged from 28 subplots, while SOC from 15 subplots. Error bars indicate one standard error of the mean.

Table 1
Goodness of fit (BIC, marginal and conditional R^2) of the best model, coefficients (β), standard error (SE), and p-values (significant values are in bold) of explanatory variables retained for each C pool. In all cases, logging intensity range between 0 and 55% of initial biomass removed (n = 15).

C pools	BIC	Marginal R^2	Conditional R^2	Predictor	β	SE	p-value
$AGC_{>20}$	163.8	0.61	0.61	Intercept	196.7	12.14	< **0.001**
				Logging intensity	−57.9	11.4	< **0.001**
$BGC_{>20}$	123.3	0.63	0.65	Intercept	51.04	3.15	< **0.001**
				Logging intensity	−15.02	2.96	< **0.001**
Deadwood	24.5	0.38	0.41	Intercept	0.77	0.12	< **0.001**
				Logging intensity	0.35	0.11	**0.006**
Litter	35.7	0.51	0.51	Intercept	5.64	0.84	< **0.001**
				Logging intensity	−0.25	0.14	0.095
				Slope	0.03	0.01	**0.034**
				Clay	0.09	0.02	**0.003**
SOC	84.1	0.25	0.46	Intercept	36.91	3.42	< **0.001**
				Nitrogen	88.16	32.21	0.054
Total C	−25.4	0.48	0.53	Intercept	2.53	0.02	< **0.001**
				Logging intensity	−0.07	0.02	**0.003**

influence of logging intensity on $AGC_{>20}$, $BGC_{>20}$, deadwood, and total C stocks was corroborated by high relative importance value (> 65%, Table A7).

4. Discussion

Our study aimed at investigating the effects of logging on C stocks in Dipterocarp logged forests. Focusing on the most significant C pools generally reported to form > 80% of total C stored in tropical forests (Malhi et al., 2009), we found that total C stocks were significantly influenced by logging intensity 16 years after timber harvest and therefore confirms our hypothesis. The main result is the transfer from live biomass ($AGC_{>20}$ – $BGC_{>20}$) to the dead material. While dead neotropical trees have been reported to lose 90% of their mass within two decades (Hérault et al., 2010), deadwood stocks were about 3 times higher in intensively logged areas (> 20% removal of initial biomass) than in low logging intensity areas (Fig. 2A). Large logging wastes (e.g. forgotten logs) and large incidental killed trees might explain this difference 16 years after logging. Furthermore, another explanation lies in increased post-logging mortality of residuals trees in intensively logged stands. Mortality rates post-logging were shown to peak shortly after logging, and remain high after a decade compared to unlogged forests (Blanc et al., 2009; Sist et al., 2014). This reflects long-term effects of logging on forest ecosystems, and somehow lowered resilience with increasing logging intensity. A key challenge will be to know how long do these negative side effects last and how do they affect the ecosystem functioning. We found that several C pools can be relatively well predicted through the sole logging intensity, expressed as a percentage of initial biomass lost (Table 1). Unfortunately, information about logging intensity is usually unavailable in the field. With rapid development of remote sensing technique enabling to capture fine change in live biomass stocks (Coomes et al., 2017), a correlative approach using logging intensity as explanatory variable could provide an efficient surrogate to estimate total C stocks and other C pools (especially for $AGC_{>20}$ and $BGC_{>20}$, marginal R^2 > 60%). Our results also corroborate the previous finding on the importance of deadwood in degraded forests (Pfeifer et al., 2015) and the need to account for other C pools when accurate calculations of C stocks and fluxes have to be done in human-modified tropical forests.

4.1. C stocks in logged forests and its driver

Sixteen years after logging, areas where high logging intensity occurred have lost around a third of their C stocks (Fig. 2). Total C stocks in our study site were within the range of C stocks reported in secondary and primary Dipterocarp forests in Singapore (Ngo et al., 2013). The stocks of $AGC_{>20}$ in our site were also comparable with the same type of logged forests in Malaysian Borneo when the generic allometric model was used (Morel et al., 2011). The very high variation of total C stocks in MRF along the gradient of logging intensity (Fig. 1) showed that logging intensity should be accounted for as explanatory variable rather than logged forests are seen as a whole ecosystem (Morel et al., 2011; Saner et al., 2012).

Most of the ecosystem C stocks was found in live tree biomass (77%), followed by SOC (15%) and deadwood (6%). Litter formed only a minor fraction (1.4%) (Table A4) and was only slightly affected by logging (Table 1). Logging shifts the ratio of live and dead materials after more than a decade, decreasing $AGC_{>20}$ by up to 14% and increasing deadwood stocks by 11% (Table A4). Thus, sustainable forest management should primarily focus on avoiding incidental damages through improving the ecological sustainability (Sist et al., 2003a), notably in preserving large trees (Sist et al., 2014).

Deadwood stock was correlated to logging intensity, and was three times higher in highly logged than in lowly logged areas. However, the best model only captured 38% of the total variance (Table 1), revealing the large heterogeneity of deadwood stocks in logged forests. Average deadwood stock (18 ± 3 Mg C ha^{-1}) was in range with the result from a previous study (Pfeifer et al., 2015). However, comparing deadwood stock among forests is difficult because its stock depends on the amount of incidental damages (Pinard and Putz, 1996; Sist and Nguyen-Thé, 2002), environmental factors (Garbarino et al., 2015; Osone et al., 2016; Weedon et al., 2009), decomposition rates among species (Harmon et al., 1995; Hérault et al., 2010), and methodology used to assess deadwood volume (Fraver et al., 2007).

4.2. Implications for sustainable forest management

Our result revealed that logging's imprint is still largely perceptible after 16 years specifically on $AGC_{>20}$, $BGC_{>20}$, deadwood, and total C stocks (Table 1). Controlling logging intensity and combining it with silvicultural guidelines (Sist, 2001; Sist et al., 2003b) are still relevant to minimize the impact of logging intensity to AGB and stand damage. More than half of C emissions from logging are related to logged trees forgotten in the field and incidentally killed trees (Griscom et al., 2014). Strengthening and monitoring the adoption of reduced-impact logging (RIL) would help prevent logging damages and C emissions.

While 46% of Bornean forests were already logged in 2010 (Gaveau et al., 2014), these forests, if preserved, are likely to play an important role in the region for biodiversity conservation and providing other ecosystem services. Even though several studies have shown many benefits provided by logged forests (Bicknell et al., 2014; Meijaard and Sheil, 2007), these forests are still disappearing due to illegal logging and forest conversion. Forest law enforcement, such as EU support for Indonesian government in accordance with Forest Law Enforcement Governance and Trade (FLEGT) policy (Schmitz, 2016), was created to promote sustainable timber extraction.

Forests at Malinau are among the most diverse of Indonesia (Sheil et al., 2010) and our results revealed that they also harbor high C stocks. While biodiversity and C stocks seem only poorly related at the global scale (Sullivan et al., 2017), our study site combines both, as for some African forest sites (Day et al., 2014). Furthermore, the inclusion of carbon enhancement into forest management and REDD+ strategies remain to be done, either as interventions aimed at reducing emissions, or as parts of REDD+ investment frameworks (Hein and van der Meer, 2012).

5. Conclusions

Total C stocks in unmanaged forests or logged at low intensity were on average higher than those found in areas with high logging intensity. Simultaneously, the proportion of deadwood was multiplied by 5 to reach 13.5% of total C in heavily logged areas. While C pool responded differently to logging and a few key environmental variables, logging intensity solely was found to be the main factor explaining the variability in $AGC_{>20}$, $BGC_{>20}$, deadwood, and total C stocks. Living trees remain the main C pool 16 years after logging, followed by a significant amount of C in deadwood and SOC. As logging intensity affect C pools in our site, it will have consequences for C stocks in the future. Considering that 32% of 114.1 million ha of permanent forest estate are designated as permanent production forest in Indonesia (Blaser et al., 2011), narrowing down C stock estimates in logged forests will be an important step for the Indonesian National Carbon Accounting System (The Ministry of Environment and Forestry, 2013). Our findings, therefore, shed new light on the long-term imprint of logging on the carbon cycle in production forests of Indonesia and confirmed the need to limit logging intensity to a threshold of 20% of initial biomass removal in order to limit the long-term accumulation of deadwood after logging, probably due to high post-logging mortality.

Acknowledgements

We would like to thank the Management of PT Inhutani II in Jakarta and Malinau for their support for this research. We would also to thank Pak Rustandi, Pak Martinus, Jesly, and Ari for their essential help during the fieldwork. This study was carried out in the framework of the Tropical managed Forest Observatory (TmFO) project, supported by CIRAD and the Forest, Tree, and Agroforestry Research Program of the Consultative Group on International Agricultural Research (CGIAR). AHR was supported by the Education, Audiovisual and Culture Executive Agency of the European Commission under the Erasmus Mundus Joint Doctorate (EMJD) programme – Forest and Nature for Society (Fonaso) contract no. 2014-2, CIRAD, and ITTO Fellowship Program 2015 Reference Number 008/15A.

Appendix A

See Figs. A1, A2 and Tables A1–A8.

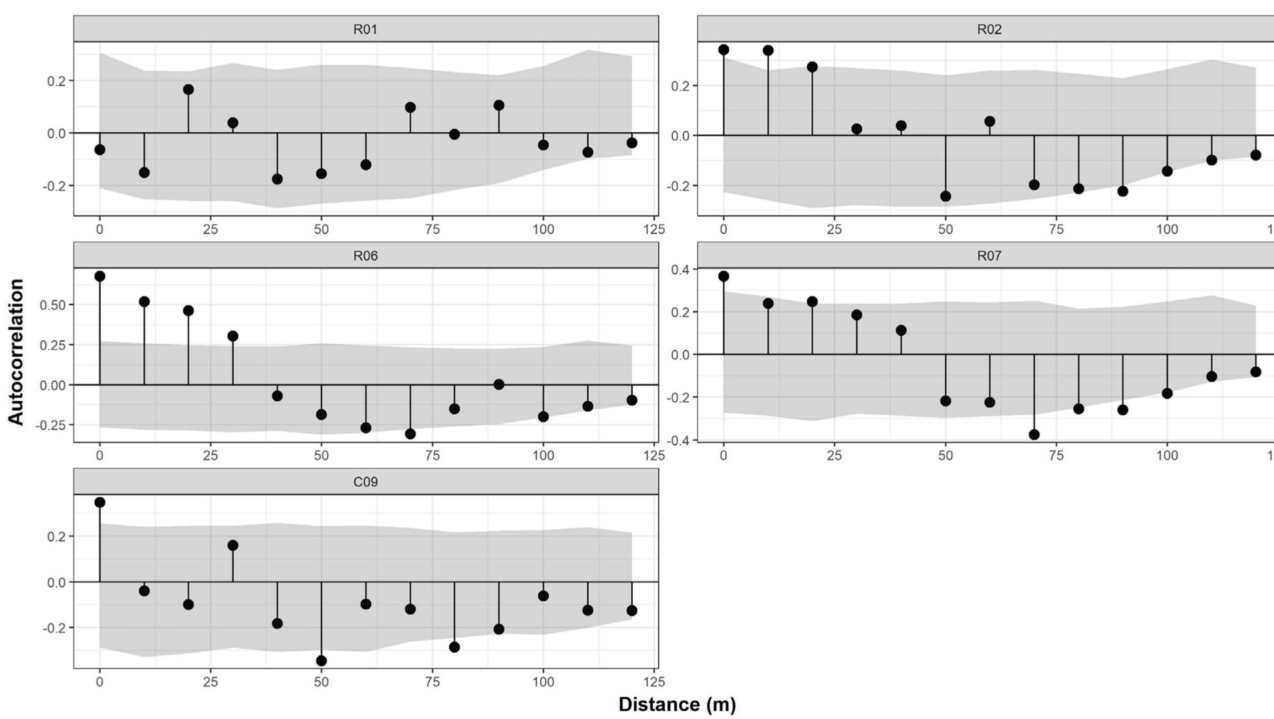

Fig. A1. Spatial autocorrelation of logging intensity for each plot. In plot R06, there was a quite strong autocorrelation for the first 30 m distance class as the values were larger than expected the null hypothesis of no autocorrelation (95% CI). After 30 m, logging intensity appears to be independent.

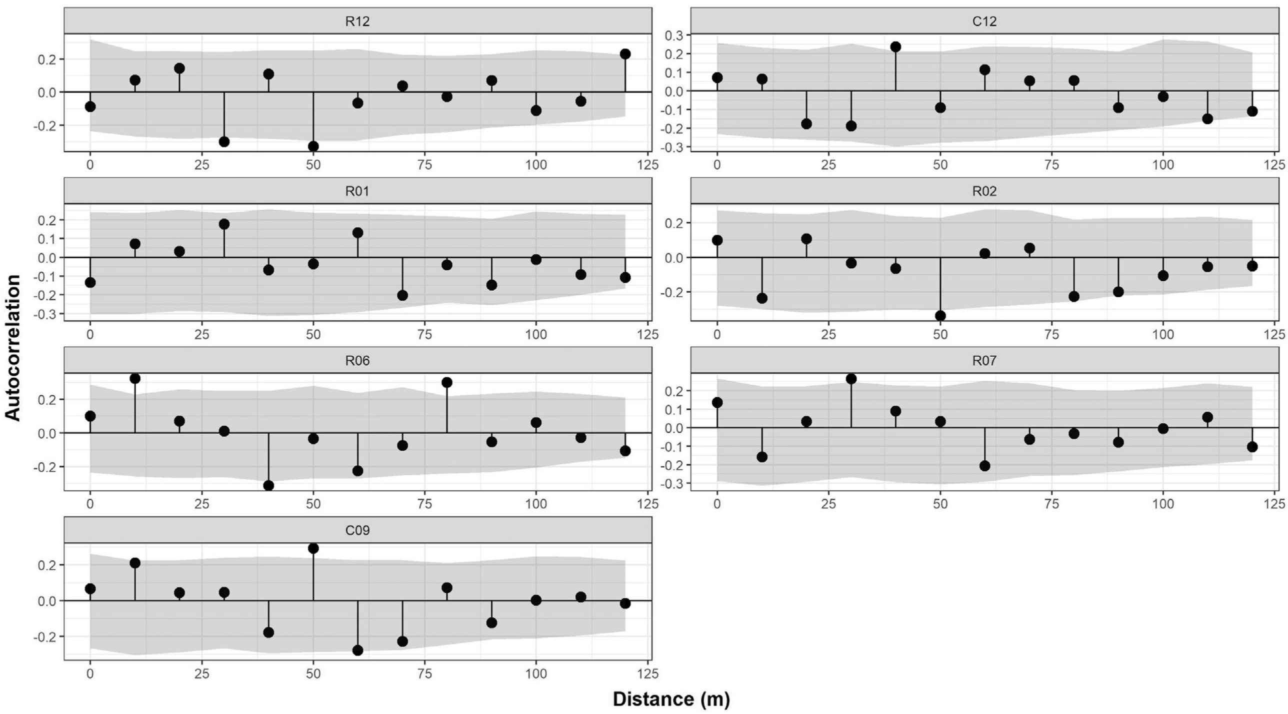

Fig. A2. Spatial autocorrelation of above-ground tree biomass for each plot. Grey areas show 95% CI.

Table A1
Pre-logging forest structure and logging intensity at 0.25-ha subplot scale: number of pre-logging stem (tree), pre-logging basal area (m^2) pre-logging biomass (Mg), number of tree harvested (tree), tree biomass harvested (Mg), number of tree killed (tree), tree biomass killed (Mg) due to logging, and logging intensity (%) in 0.25-ha subplot level.

Plot	Subplot	Number of stems	Basal area	Pre-logging biomass	Number of trees harvested	Biomass harvested	Number of trees killed	Biomass killed	Logging intensity
MRF-C12	MRF-C12-1	66	7.22	81.75	0	0.00	1	3.06	3.75
	MRF-C12-2	82	11.65	134.46	0	0.00	0	0.00	0
	MRF-C12-3	62	8.23	104.75	0	0.00	1	3.86	3.69
	MRF-C12-4	75	10.95	121.83	0	0.00	1	2.59	2.12
MRF-R12	MRF-R12-1	57	6.27	68.56	0	0.00	1	0.29	0.42
	MRF-R12-2	55	8.84	118.36	0	0.00	0	0.00	0
	MRF-R12-3	82	12.34	165.49	0	0.00	0	0.00	0
	MRF-R12-4	74	8.38	103.62	0	0.00	0	0.00	0
MRF-R01	MRF-R01-1	54	7.18	83.25	0	0.00	1	1.55	1.87
	MRF-R01-2	93	10.61	116.10	1	1.72	0	0.00	1.48
	MRF-R01-3	45	4.54	46.37	0	0.00	0	0.00	0
	MRF-R01-4	79	10.24	121.25	2	7.56	11	7.85	9.71
MRF-R02	MRF-R02-1	65	6.73	72.99	2	9.53	1	0.51	8.14
	MRF-R02-2	49	6.50	68.30	0	0.00	1	1.51	2.21
	MRF-R02-3	80	6.66	70.96	0	0.00	10	3.44	4.33
	MRF-R02-4	69	7.28	82.14	2	6.35	14	15.44	25.90
MRF-R06	MRF-R06-1	56	7.71	101.69	1	20.10	3	1.61	21.35
	MRF-R06-2	46	4.28	47.15	1	3.74	9	8.42	25.80
	MRF-R06-3	76	9.50	111.56	3	10.47	31	52.59	56.86
	MRF-R06-4	62	7.89	84.89	2	5.37	6	3.20	6.57
MRF-R07	MRF-R07-1	60	7.80	99.59	4	32.24	12	9.16	40.87
	MRF-R07-2	61	6.25	63.08	0	0.00	1	0.99	1.57
	MRF-R07-3	78	8.09	95.47	2	18.76	19	11.23	31.41
	MRF-R07-4	78	9.57	114.58	1	6.76	1	0.51	5.90
MRF-C09	MRF-C09-1	75	13.64	182.31	5	36.34	19	18.57	28.15
	MRF-C09-2	55	7.90	98.21	0	0.00	13	7.05	6.22
	MRF-C09-3	83	11.30	117.99	5	36.08	31	30.95	54.83
	MRF-C09-4	85	9.28	107.01	0	0.00	26	23.64	19.02

Table A2
Decay classes and corresponding wood density (± standard error). Letters figure out significant difference among classes at p-value < 0.05.

Decay class	Description	Average deadwood density (g cm^{-3})
1	Little decay, bark cover extensive, leaves and fine twigs present, logs relatively undecayed	0.537 ± 0.025[a]
2	No bark and few branch stubs (not moving when pulled), sapwood decaying	0.377 ± 0.010[b]
3	Wood often scattered across the soil surface, logs elliptical in cross-section	0.291 ± 0.010[c]

Table A3
The average (± standard error) of C stocks (Mg C ha^{-1}) by C pools and logging intensity group. Logging intensity was grouped into 3 classes corresponding to 0–33rd, 34–66th, and 67–100th percentiles of the logging intensity distribution, respectively. Letters figure out significant differences at p-value < 0.05 after pairwise comparisons using Dunn's test.

C pool	Number of subplots	Logging intensity			Average
		Low (0–2.1%)	Medium (2.1–19%)	High (19–56.9%)	
$AGC_{>20}$	28	192.5 (24.9)[a]	175.5 (11.9)a	128.3 (13.3)[b]	166.4 (11.5)
$BGC_{>20}$	28	50.9 (6.2)[a]	46.1 (2.9)[a]	31.8 (3.5)[b]	43.2 (3)
$AGC_{5\text{-}20}$	28	34.3 (3.3)[a]	37.2 (4.2)[a]	31.6 (3)[a]	34.4 (2)
$BGC_{5\text{-}20}$	28	6.1 (0.6)[a]	6.5 (0.8)[a]	5.9 (0.6)[a]	6.2 (0.4)
Deadwood	28	11.2 (3.3)[a]	12.6 (3.7)[a]	29.8 (6.3)[b]	17.7 (3)
Litter	28	4.2 (0.2)[a]	3.8 (0.2)[a]	3.9 (0.2)[a]	4 (0.1)
SOC	15	46.9 (0.8)[a]	47.2 (1.8)[a]	42.9 (1.5)[a]	45.9 (0.9)
Total C	15	351.3 (42.3)[a]	315.8 (14.3)[a]	256.2 (19.6)[a]	314.1 (21.3)

Table A4
The average (± standard error) of proportion C pools by total C stocks (%) for each logging intensity group. Logging intensity was grouped into 3 classes corresponding to 0–33rd, 34–66th, and 67–100th percentiles of the logging intensity distribution, respectively. Letters figure out significant differences at *p-value* < 0.05 after pairwise comparisons using Dunn's test.

C pool	Logging intensity group			Average
	Low (0–2.1%)	Medium (2.1–19%)	High (19–56.8%)	
$AGC_{>20}$	55.3 (2.6)[a]	52 (2.6)[ab]	41.8 (1.8)[b]	50.6 (1.5)
$BGC_{>20}$	14.7 (0.7)[a]	13.4 (0.6)[ab]	10.4 (0.6)[b]	13.1 (0.4)
$AGC_{5\text{-}20}$	10.1 (1.1)[a]	12.2 (1.9)[a]	13.1 (2)[a]	11.6 (0.7)
$BGC_{5\text{-}20}$	1.7 (0.2)[a]	2.2 (0.3)[a]	2.4 (0.2)[a]	2.1 (0.1)
Deadwood	2.5 (1.2)[a]	3.8 (1.8)[a]	13.5 (2.1)[b]	5.9 (1.2)
Litter	1.3 (0.2)[a]	1.2 (0.1)[a]	1.6 (0.1)[a]	1.4 (0.1)
SOC	14.4 (1.5)[a]	15.1 (1.1)[a]	17.2 (1.6)[a]	15.4 (0.9)

Table A5
Model fit statistics for mixed-effect models of C pools included logging intensity, mean slope, clay content, phosphorus content, and nitrogen content as fixed effects and plot as a random effect. Bold number on *p-value* shows significant variables (*p-value* < 0.05).

C pools	BIC	Marginal R^2	Conditional R^2	Predictor	β	SE	p-value
$AGC_{>20}$	−7.2	0.701	0.985	Intercept	1.69	0.28	< **0.001**
				Logging intensity	−0.20	0.06	**0.006**
				Slope	−0.00	0.00	0.659
				Clay	0.01	0.01	**0.047**
				Phosphorus	−0.06	0.17	0.707
				Nitrogen	3.18	2.19	0.173
$BGC_{>20}$	133.7	0.660	0.660	Intercept	34.52	30.61	0.277
				Logging intensity	−13.31	4.83	**0.015**
				Slope	0.08	0.29	0.796
				Clay	0.02	0.61	0.979
				Phosphorus	2.61	21.78	0.906
				Nitrogen	103.05	190.23	0.596

(*continued on next page*)

Table A5 (*continued*)

C pools	BIC	Marginal R^2	Conditional R^2	Predictor	β	SE	p-value
$AGC_{5\text{-}20}$	133.2	0.145	0.145	Intercept	14.04	30.18	0.648
				Logging intensity	−0.81	4.76	0.867
				Slope	0.06	0.29	0.826
				Clay	0.68	0.60	0.273
				Phosphorus	−4.37	21.47	0.841
				Nitrogen	34.45	187.51	0.857
$BGC_{5\text{-}20}$	80.5	0.176	0.176	Intercept	1.47	5.21	0.781
				Logging intensity	−0.47	0.82	0.574
				Slope	0.03	0.05	0.553
				Clay	0.16	0.10	0.143
				Phosphorus	1.31	3.71	0.728
				Nitrogen	−14.03	32.36	0.671
Deadwood	26.8	0.559	0.990	Intercept	−5.41	0.79	< **0.001**
				Logging intensity	−0.71	0.18	**0.002**
				Slope	−0.03	0.00	**0.000**
				Clay	0.09	0.01	**0.000**
				Phosphorus	0.49	0.46	0.314
				Nitrogen	18.80	6.17	**0.012**
Litter	40.6	0.602	0.602	Intercept	6.37	1.38	< **0.000**
				Logging intensity	0.35	0.22	0.129
				Slope	0.03	0.01	**0.030**
				Clay	−0.09	0.03	**0.005**
				Phosphorus	0.19	0.98	0.846
				Nitrogen	5.09	8.55	0.561
SOC	91.8	0.519	0.519	Intercept	28.55	7.57	**0.002**
				Logging intensity	−1.13	1.19	0.360
				Slope	−0.08	0.07	0.279
				Clay	0.08	0.15	0.603
				Phosphorus	3.40	5.39	0.538
				Nitrogen	138.84	47.05	**0.009**
Total C	183.0	0.583	0.583	Intercept	233.72	158.60	0.161
				Logging intensity	−63.90	25.03	**0.022**
				Slope	−1.04	1.50	0.500
				Clay	1.73	3.14	0.590
				Phosphorus	13.63	112.85	0.906
				Nitrogen	224.45	985.51	0.822

Table A6
The most three parsimonious models for each C pool explaining the variability of C stocks in MRF ranked according to increasing of BIC.

No	Model	Marginal R^2	Conditional R^2	BIC
$AGC_{>20}$				
1	$AGC_{>20}$ ~ logging intensity	0.61	0.61	163.8
2	$AGC_{>20}$ ~ logging intensity + nitrogen	0.64	0.70	166.2
3	$AGC_{>20}$ ~ logging intensity + slope	0.60	0.60	166.4
$BGC_{>20}$				
1	$BGC_{>20}$ ~ logging intensity	0.63	0.65	123.3
2	$BGC_{>20}$ ~ logging intensity + nitrogen	0.65	0.73	125.6
3	$BGC_{>20}$ ~ logging intensity + phosphorus	0.60	0.60	125.9
$AGC_{5\text{-}20}$				
1	$AGC_{5\text{-}20}$ ~ 1	0	0	121.9
2	$AGC_{5\text{-}20}$ ~ clay	0.11	0.11	122.7
3	$AGC_{5\text{-}20}$ ~ phosphorus	0.03	0.03	124.1
$BGC_{5\text{-}20}$				
1	$BGC_{5\text{-}20}$ ~ 1	0	0	69.7
2	$BGC_{5\text{-}20}$ ~ clay	0.12	0.12	70.3
3	$BGC_{5\text{-}20}$ ~ phosphorus	0.01	0.01	72.2

(*continued on next page*)

Table A6 (*continued*)

No	Model	Marginal R^2	Conditional R^2	BIC
CWD				
1	Deadwood ~ logging intensity	0.38	0.41	24.5
2	Deadwood ~ logging intensity + clay	0.44	0.51	24.8
3	Deadwood ~ nitrogen	0.35	0.35	25.2
Litter				
1	Litter ~ logging intensity + slope + clay	0.51	0.51	35.7
2	Litter ~ clay	0.36	0.36	35.8
3	Litter ~ slope + clay	0.44	0.44	35.9
SOC				
1	SOC ~ nitrogen	0.25	0.46	84.1
2	SOC ~ 1	0	0.60	85.0
3	SOC ~ slope + nitrogen	0.30	0.48	85.4
Total C stocks				
1	C stocks ~ logging intensity	0.48	0.53	−25.4
2	C stocks ~ logging intensity + clay + phosporus + nitrogen	0.62	0.99	−24.2
3	C stocks ~ logging intensity + slope	0.44	0.44	−23.1

Table A7
The relative importance value (%) of logging intensity, mean slope, clay, nitrogen, and available phosphorus content in the soil for each C stock. In all cases, logging intensity range between 0 and 55% of initial biomass removed (n = 15).

Stock	Fixed factor	Estimate	Unconditional variance	Number of models	Importance value (%)	± (alpha = 0.05)
$AGC_{>20}$	Intercept	171.99	3624.74	32	100	118.02
	Logging Intensity	−54.43	227.08	16	96	29.54
	Nitrogen	169.62	134575.85	16	26	719.09
	Slope	0.10	0.12	16	22	0.67
	Available Phosphorus	2.06	368.84	16	22	37.65
	Clay	0.01	0.21	16	21	0.89
$BGC_{>20}$	Intercept	44.56	248.80	32	100	30.92
	Logging Intensity	−14.01	15.58	16	96	7.74
	Nitrogen	46.60	9541.16	16	27	191.47
	Available Phosphorus	0.72	25.08	16	22	9.82
	Slope	0.02	0.01	16	21	0.15
	Clay	0.00	0.01	16	21	0.23
Deadwood	Intercept	0.61	1.62	32	100	2.50
	Logging Intensity	0.22	0.04	16	67	0.38
	Nitrogen	−4.20	47.54	16	50	13.52
	Clay	0.02	0.00	16	49	0.05
	Slope	0.01	0.00	16	36	0.02
	Available Phosphorus	−0.09	0.12	16	31	0.68
Litter	Intercept	5.78	1.98	32	100	2.76
	Clay	−0.08	0.00	16	89	0.07
	Slope	0.02	0.00	16	61	0.04
	Logging Intensity	−0.11	0.02	16	42	0.31
	Nitrogen	0.17	5.54	16	25	4.61
	Available Phosphorus	−0.04	0.01	16	23	0.60
SOC	Intercept	39.32	70.32	32	100	16.44
	Nitrogen	64.64	3416.70	16	62	114.58
	Slope	0.03	0.00	16	32	0.09
	Logging Intensity	0.11	0.28	16	29	1.03
	Clay	−0.01	0.01	16	28	0.15
	Available Phosphorus	−0.61	3.23	16	24	3.52
Total C	Intercept	2.34	0.06	32	100	0.46
	Logging Intensity	−0.07	0.00	16	85	0.08
	Nitrogen	0.95	1.76	16	46	2.60
	Clay	0.00	0.00	16	35	0.01
	Available Phosphorus	−0.01	0.00	16	35	0.10
	Slope	0.00	0.00	16	24	0.00

Table A8
The relative importance value (%) of logging intensity, mean slope, clay, nitrogen, and available phosphorus content in the soil for each C stock. Logging intensity range between 1.5 and 55% of initial biomass removed (excluding 0% of logging intensity, n = 13).

Stock	Fixed factor	Estimate	Unconditional variance	Number of models	Importance value (%)	± (alpha = 0.05)
$AGC_{>20}$	Intercept	232.41	3615.98	32	100	117.87
	Logging Intensity	−64.29	312.10	16	97	34.63
	Slope	−1.13	0.80	16	70	1.75
	Clay	0.44	0.80	16	29	1.75
	Nitrogen	−62.76	57126.67	16	26	468.51
	Available Phosphorus	7.39	390.52	16	25	38.74
$BGC_{>20}$	Intercept	54.74	488.71	32	100	43.33
	Logging Intensity	−25.92	74.66	16	98	16.94
	Slope	−0.37	0.05	16	79	0.45
	Clay	0.85	0.60	16	63	1.52
	Available phosphorus	13.66	288.77	16	52	33.31
	Nitrogen	−146.70	44412.56	16	49	413.10
Deadwood	Intercept	0.57	0.70	32	100	1.64
	Logging Intensity	0.49	0.05	16	88	0.44
	Clay	0.01	0.00	16	40	0.03
	Available Phosphorus	−0.18	0.16	16	31	0.78
	Nitrogen	−2.05	15.58	16	31	7.74
	Slope	0.00	0.00	16	27	0.01
Litter	Intercept	6.11	1.67	32	100	2.53
	Clay	−0.09	0.00	16	93	0.06
	Slope	0.01	0.00	16	55	0.03
	Logging Intensity	−0.02	0.01	16	24	0.17
	Available Phosphorus	−0.07	0.10	16	24	0.62
	Nitrogen	−0.37	4.36	16	22	4.10
SOC	Intercept	34.58	63.22	32	100	15.59
	Nitrogen	100.22	3193.89	16	80	110.78
	Slope	0.05	0.00	16	43	0.13
	Clay	0.02	0.01	16	31	0.16
	Available Phosphorus	−0.91	4.81	16	26	4.30
	Logging Intensity	−0.22	0.45	16	26	1.31
Total C	Intercept	2.44	0.02	32	100	0.30
	Logging Intensity	−0.14	0.00	16	97	0.07
	Clay	0.01	0.00	16	75	0.01
	Slope	0.00	0.00	16	69	0.00
	Available Phosphorus	0.03	0.00	16	34	0.10
	Nitrogen	−0.14	0.29	16	29	1.06

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foreco.2018.03.007.

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