Forest Ecology and Management 391 (2017) 246–255

Contents lists available at ScienceDirect

Forest Ecology and Management

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

Quantifying uncertainty about forest recovery 32-years after selective logging in Suriname

Anand Roopsind[a,b,*], Verginia Wortel[c], Wedika Hanoeman[d], Francis E. Putz[a]

[a] Department of Biology, University of Florida, Gainesville, Florida, FL 32611-8525, USA
[b] Iwokrama International Centre, Georgetown, Guyana
[c] Department of Forest Management, Centre for Agricultural Research in Suriname (CELOS), Paramaribo, Suriname
[d] Greenheart (Suriname) N.V., Paramaribo, Suriname

ARTICLE INFO

Article history:
Received 24 August 2016
Received in revised form 9 February 2017
Accepted 10 February 2017
Available online 21 February 2017

Keywords:
Reduced-impact logging
Sustainable forest management
REDD+
Timber stocks
Cutting cycles
Allometric models

ABSTRACT

The inclusion of managed tropical forests in climate change mitigation has made it important to find the sustainable sweet-spot for timber production, carbon retention, and the quick recovery of both. Here we focus on recovery of aboveground carbon and timber stocks over the first 32 years after selective logging with the CELOS Harvest System in Suriname. Our data are from twelve 1-ha permanent sample plots in which growth, survival, and recruitment of trees $\geq$15 cm diameter were monitored between 1978 and 2012. We evaluate plot-level changes in basal area, stem density, aboveground carbon, and timber stock in response to average timber harvests of 15, 23, and 46 $m^3\ ha^{-1}$. We use a linear mixed-effects model in a Bayesian framework to quantify recovery time for aboveground carbon and timber stock, as well as annualized increments for both. Our statistical models accounted for the uncertainty associated with the height and biomass allometries used to estimate aboveground carbon and increased precision of annualized aboveground carbon increments by including data from forty-one plots located elsewhere on the Guiana Shield. The probabilities of aboveground carbon recovery to pre-logging levels 32 years after harvests of 15, 23 and 46 $m^3\ ha^{-1}$ were 45%, 40%, and 24%, respectively. Net aboveground carbon increment for logged forests across all harvest intensities was 0.64 $Mg\ C\ ha^{-1}\ yr^{-1}$, more than twice the rate observed in unlogged forests (0.26 $Mg\ C\ ha^{-1}\ yr^{-1}$). The probabilities of timber stock recovery at the end of the 32-year period were highest after harvest intensities of 15 and 23 $m^3\ ha^{-1}$ (with 80% probability) and lowest after the harvest of 46 $m^3\ ha^{-1}$ (with 70% probability). Timber stock recovery across all harvest intensities was driven primarily by residual tree growth. Application of the legal cutting limit of 25 $m^3\ ha^{-1}$ will require more than 70 and 40 years to recover aboveground carbon and timber stocks, respectively, with 90% probability. Based on the low recruitment rates of the twelve species harvested, the 25 year cutting cycle currently implemented in Suriname is too short for long-term timber stock sustainability. We highlight the value of propagating uncertainty from individual tree measurements to statistical predictions of carbon stock recovery. Ultimately, our study reveals the trade-offs that must be made between timber and carbon services as well as the opportunity to use carbon payments to enable longer cutting rotations to capture carbon from forest regrowth.

1. Introduction

Technological advancements (e.g., development of chainsaws and bulldozers) coupled with growth of global shipping industries and increased demand for tropical timbers during the mid-20th Century led to the degradation of large expanses of tropical forests by unnecessarily destructive logging (Dawkins and Philip, 1998). Concerns about sustained timber production and the environmental degradation caused by bad logging practices motivated research to identify management prescriptions for improved tropical forest management. These logging studies aimed to reconcile tropical timber production with the provision of other ecosystem services, and to ensure continued timber production with economically viable cutting cycles (FAO, 2004; Jonkers, 1987; Nicholson, 1958, 1979; van der Hout, 1999).

The CELOS Harvest System experiments in Suriname, the results of which were recently reviewed by Werger (2011), are among the

* Corresponding author.
E-mail address: aroopsind@ufl.edu (A. Roopsind).

http://dx.doi.org/10.1016/j.foreco.2017.02.026
0378-1127/

oldest on-going studies of improved forest management in the tropics. The CELOS approach involves the selective removal of a few trees per hectare in a manner that minimizes collateral damage to the residual forest and improves recovery of utilizable timber. The specific logging practices employed include: (1) mapping all trees of commercial timber species $\geq$35 cm measured at 1.3 m above the ground (DBH); (2) selecting trees to be felled to avoid aggregations that would result in large felling gaps; (3) planning and construction of roads and skid trails prior to felling; (4) directional felling to facilitate log extraction; and, (5) winching of logs during extraction and the use of wheeled skidders for long-distance log yarding (de Graaf, 1986; Jonkers, 1987). These practices are common components of what are now referred to as reduced-impact logging (RIL) systems (e.g., Putz et al., 2008). The full CELOS Management System also includes the release of future crop trees from competition through poison girdling of non-marketable stems, but no post-harvest silvicultural treatments were applied in the plots we studied.

Although the primary goal of the CELOS Management System was to sustain timber stocks, reduction in residual stand damage relative to unplanned or conventional logging also has positive effects on standing stocks of forest carbon and rates of post-logging recovery (Pinard and Putz, 1996; Putz et al., 2012; Vidal et al., 2016). By reporting on the post-logging dynamics of aboveground carbon stocks (ACS) and timber stocks, we hope that this study helps inform the management of Suriname's forest for both, the former associated with the country's commitment to climate change mitigation (e.g., REDD+, Intended Nationally Determined Contribution (INDCs) associated with COP12; UFCCC, 2016). In particular, with permanent sample plot data for the first 32-years after logging, we evaluate changes in tree density, basal area, ACS, and timber stocks.

We use permanent sample plot data collected between 1978 and 2012 to build statistical models in a Bayesian framework to predict recovery time and forest stand increments as a function of harvest intensity ($m^3\ ha^{-1}$ of commercial timber). Our Bayesian analytical approach also provided a means to address the long and irregular census intervals that would otherwise result in underestimated aboveground carbon increments (Clark et al., 2001; Sheil and May ,1996; Talbot et al., 2014). Specifically, we include results from previous research on aboveground carbon increments for the Guiana Shield as informed priors to reduce uncertainty in our model predictions (Crome et al., 1996; McCarthy and Masters, 2005; Morris et al., 2013). In addition to leveraging knowledge gained from other studies, our Bayesian approach enabled us to propagate uncertainty associated with our height and biomass allometries into our ACS recovery predictions.

2. Methods

2.1. Study site

The experimentally logged plots are in a 1150 ha research area (hereafter Kabo; 5°15′N, 55°43′W) in north-central Suriname (Fig. S1). Common canopy tree species in this lowland moist tropical forest are *Dicorynia guianensis* Amshoff (Fabaceae), *Qualea rosea* Aubl. (Vochysiaceae), and *Dendrobangia boliviana* Rusby (Cardiopteridaceae). The understory is composed mainly of palms, with *Astrocaryum sciophyllum* Pulle and *Astrocaryum paramaca* Mart. the most abundant (Jonkers, 1987). The soil is an ultic haplorthox, a low pH sandy loam that is characteristic of the highly weathered Precambrian Guiana Shield (Hammond, 2005; Poels, 1987; Quesada et al., 2010). Annual precipitation is 2385 mm with a mean of 98 mm in each of the driest months of September and October (Dekker and de Graaf, 2003).

2.2. Experimental design and logging treatments

Trees of commercial timber species (DBH $\geq$ 15 cm; Table S1) were marked, mapped, and measured across a 140-ha forest compartment in 1978. Experimental logging treatments designed to remove 1, 2, and 4 $m^2\ ha^{-1}$ of basal area were applied between 1979 and 1980 based on a randomized block design. Each logging treatment was applied to 4 ha with 3 replicates per logging treatment (Table 1; Fig. S1). The basal areas removed corresponded to average harvests of 15, 23, and 46 $m^3\ ha^{-1}$ of commercial log volumes (hereafter low, medium, and high-intensity timber harvests; Jonkers, 1987, 2011). Trees of commercial timber species $\geq$ 15 cm DBH were re-censused immediately after logging in 1980 in 1 ha permanent sample plots established within each of the 4 ha treatment blocks.

Growth, recruitment, and mortality of trees $\geq$15 cm DBH of all species, commercial and non-commercial, were subsequently monitored in these 1-ha plots (100 $\times$ 100 m) for each replicated treatment four times (1981, 1983, 2000 and 2012). Unlogged control plots of 1-ha were established within the study site in 1983 and remeasured in 2000 and 2012 (Fig. S1). Censuses adhered to protocols established by Jonkers (1983) based on standards set out in Synnott (1979). Tree species were identified by parabotanists (tree-spotters) based on common names and converted to their scientific names by a trained botanist. In instances where species were unknown, botanical collections were made for comparison with herbarium specimens. In cases of irregular stem form associated with buttresses and bole deformities, the point of measurement was moved to 1 m above the end of the deformity to continue growth monitoring.

When the forest was selectively logged by trained and closely supervised crews, the main skid trails were opened with a D6 bulldozer within 25-m wide strips between the 1-ha permanent sample plots. Trees were directionally felled to aid extraction with wheeled skidders. Tree location maps developed from a 100% pre-harvest inventory of harvestable trees, together with topographic maps, were used to inform the selection of trees to be harvested and to plan the most appropriate routes for extraction. There were a total of six skid trail entry points into the 1-ha permanent sample plots, three on the western side and three located on the east.

2.3. Stem densities and basal areas ($m^2\ ha^{-1}$)

We report changes over time in basal area, stem density, and diameter class distributions for the twelve 1-ha permanent sample plots. As pre-logging data were only available for commercial stems prior to logging, we track the changes in forest structure for the logged plots between the first census completed post-logging (1981) when all stems, commercial and non-commercial species, were recorded to the last census in 2012, except for timber stocks where we use the plot census data from 1980. We also report on the observed changes for the control plots between 1983 and 2012 as well as the basal area-weighted average wood density across censuses and diameter classes for all plots. We acknowledge that forest structure can vary greatly across small spatial scales, and the use of only three 1-ha control plots as baseline reference values is not ideal. We address this limitation in our statistical models for ACS recovery through the estimation of plot-level ACS prior to logging based on an emissions factor associated with logging intensity (Appendix 2).

2.4. Aboveground carbon stocks (ACS; $Mg\ C\ ha^{-1}$)

To estimate aboveground biomass for each tree across censuses we applied the pan-tropical allometric model of Chave et al. (2014;

Table 1
Stem density, basal area ($m^2\ ha^{-1}$), and ACS ($Mg\ C\ ha^{-1}$) by stem diameter class in 1981 (2-years post-logging) and 2012 (32-years post-logging). Commercial timber stocks ($m^3\ ha^{-1}$) are reported for 1978 (pre-logging) and 2012. ACS values reported are the mean from 1350 posterior predictions based on uncertainty associated with our allometric models. Control plot values are from 1983 to 2012.

Plot ID	41		42		43		19		28		34		14		26		38		12		22		32	
Logging intensity (basal area - $m^2\ ha^{-1}$)	0.00		0.00		0.00		1.19		1.61		1.74		2.81		2.74		2.60		3.51		4.04		3.82	
Logging intensity ($m^3\ ha^{-1}$)	0.00		0.00		0.00		14.30		15.30		14.60		22.50		30.30		22.50		49.10		56.40		42.20	
Logging intensity (stems ha^{-1})	0		0		0		4		3		3		7		6		6		13		11		12	
Census year	1983	2012	1983	2012	1983	2012	1981	2012	1981	2012	1981	2012	1981	2012	1981	2012	1981	2012	1981	2012	1981	2012	1981	2012
(1) Stem density (ha^{-1})																								
15–30	170	150	180	153	147	137	142	139	158	145	182	184	172	186	140	178	165	187	131	134	132	157	135	154
30–45	54	71	60	73	54	44	48	53	58	45	64	65	50	65	34	56	62	50	52	57	51	48	61	47
45–60	22	24	24	25	18	22	22	31	19	29	18	26	21	16	23	20	22	32	15	40	17	25	18	32
>60	20	22	28	27	18	14	18	23	17	23	9	20	22	17	18	18	15	20	10	13	19	25	15	29
Total	266	267	292	278	237	217	230	246	252	242	273	295	265	284	215	272	264	289	208	244	219	255	229	262
(2) Basal area ($m^2\ ha^{-1}$)																								
15–30	6.41	5.50	6.45	5.85	5.49	5.29	5.56	5.32	5.42	5.18	6.51	6.57	5.96	6.72	4.61	6.45	5.84	6.76	4.83	5.16	4.68	5.58	4.83	5.64
30–45	5.53	7.62	6.10	7.68	5.61	4.90	5.41	5.42	6.16	4.91	6.68	6.58	5.39	6.59	3.45	5.99	6.37	5.38	5.44	6.13	5.54	5.45	6.26	4.86
45–60	4.53	5.09	5.33	5.21	3.83	4.60	4.99	6.48	3.90	5.99	3.61	5.34	4.32	3.46	5.00	4.42	4.57	7.00	3.30	8.60	3.51	5.32	3.84	6.86
>60	8.53	10.12	13.43	15.16	10.43	9.76	7.73	11.09	9.53	12.06	4.66	8.79	10.25	7.51	9.26	9.81	6.04	8.98	3.28	5.38	8.77	11.75	9.07	13.56
Total	25.01	28.34	31.31	33.90	25.37	24.55	23.68	28.31	25.02	28.15	21.45	27.29	25.91	24.28	22.33	26.67	22.82	28.12	16.86	25.27	22.50	28.09	23.99	30.92
(4) Wood specific gravity ($g\ cm^{-3}$)																								
15–30	0.64	0.64	0.66	0.65	0.62	0.63	0.66	0.63	0.64	0.65	0.62	0.62	0.64	0.59	0.61	0.62	0.66	0.64	0.63	0.60	0.63	0.62	0.63	0.60
30–45	0.65	0.64	0.68	0.68	0.63	0.61	0.66	0.65	0.64	0.65	0.60	0.62	0.60	0.59	0.68	0.61	0.68	0.65	0.69	0.64	0.64	0.60	0.62	0.65
45–60	0.63	0.63	0.66	0.66	0.63	0.65	0.66	0.66	0.66	0.60	0.67	0.63	0.63	0.61	0.63	0.66	0.68	0.66	0.65	0.68	0.69	0.65	0.62	0.60
>60	0.62	0.62	0.68	0.65	0.62	0.60	0.68	0.65	0.63	0.66	0.59	0.58	0.59	0.68	0.63	0.66	0.60	0.67	0.73	0.63	0.69	0.66	0.71	0.67
Mean plot level wood density	0.63	0.63	0.67	0.66	0.62	0.62	0.66	0.65	0.64	0.64	0.62	0.61	0.61	0.62	0.64	0.64	0.66	0.65	0.68	0.64	0.66	0.63	0.65	0.63
(4) ACS ($Mg\ ha^{-1}$)																								
15–30	25.98	22.08	26.60	24.18	21.60	21.38	23.45	21.51	21.36	21.15	25.11	25.67	23.52	24.76	17.34	25.13	24.04	27.14	18.79	19.46	18.74	21.57	19.37	21.34
30–45	28.29	38.39	32.24	40.91	27.99	23.90	28.22	27.71	30.69	25.36	31.76	31.92	25.88	30.70	18.54	29.23	33.71	27.63	28.75	31.30	28.22	26.27	30.77	24.98
45–60	25.79	29.18	32.27	31.21	21.65	27.25	30.31	39.32	23.47	32.33	21.20	30.34	24.70	19.58	28.96	26.89	27.76	40.84	19.04	52.82	21.89	31.47	21.76	37.10
>60	55.26	67.93	99.28	110.68	73.28	70.21	56.28	76.04	67.87	88.13	29.91	54.34	65.60	54.51	64.77	72.78	37.07	61.79	24.16	36.36	65.68	85.04	74.46	100.92
Total	135.32	157.57	190.39	206.97	144.52	142.75	138.26	164.58	143.39	166.97	107.98	142.28	139.70	129.56	129.61	154.03	122.57	157.40	92.38	140.11	134.53	164.35	146.36	184.34
(5) Timber stocks ($m^3\ ha^{-1}$)	1983	2012	1983	2012	1983	2012	1978	2012	1978	2012	1978	2012	1978	2012	1978	2012	1978	2012	1978	2012	1978	2012	1978	2012
15–30	9.33	4.30	8.72	5.35	2.25	0.34	8.14	0.82	11.55	6.64	15.83	6.98	8.99	5.13	5.62	1.15	5.68	7.61	5.32	1.77	11.19	5.57	15.12	11.94
30–45	21.10	27.96	12.56	18.71	9.49	7.14	13.15	12.59	32.88	22.84	21.62	29.07	17.10	14.15	9.64	11.03	15.58	18.72	18.99	15.64	23.92	25.27	32.52	27.43
45–60	30.05	27.53	22.62	23.91	7.37	10.25	25.14	25.92	20.46	31.21	11.30	26.30	29.09	13.42	30.04	13.00	27.37	31.15	32.21	42.60	26.03	31.95	44.02	56.20
>60	60.88	89.74	80.52	109.88	32.61	23.00	15.83	64.33	80.38	106.00	40.08	64.47	51.13	36.70	67.64	47.90	60.09	68.58	53.22	48.52	77.57	88.00	76.15	126.48
Total	121.36	149.53	124.43	157.84	51.71	40.73	62.26	103.66	145.27	166.69	88.83	126.83	106.31	69.40	112.94	73.09	108.72	126.06	109.73	108.53	138.70	150.78	167.81	222.05

Eq. 4): $aboveground\ biomass = \beta_0 * (pD^2H)^{\beta_1}$, where p is species-specific wood density (g cm^{-3}), D is stem diameter (cm), and H is total tree height (m). Tree heights were not measured so we estimated them with the diameter-height allometry model also proposed by Chave et al. (2014; Eq. 6a), $\ln(H) = \theta_0 - E + \theta_1 * \ln(D) - \theta_2 * (\ln(D))^2$. The E parameter is a site-specific bioclimatic stress variable that includes temperature seasonality, precipitation seasonality, and climatic water deficit. We estimate the β_i and θ_i parameters in the allometric equations using the Chave et al. (2014) destructive harvest dataset (Appendix 3). We propagate the uncertainty around the β_i and θ_i parameters into 1350 posterior predictions of biomass for each individual tree in our census data. Aboveground carbon stocks (ACS) were estimated by multiplying aboveground tree biomass by 0.47 (IPCC, 2003).

Stem wood densities [p] used in our biomass allometry were extracted from a global pan-tropical database (Chave et al., 2009); in the absence of species-level p values (9% of trees), the mean wood density was used for congeneric trees in tropical South America; if genus-level wood density data were unavailable (2% of trees), we used mean family values; and, for a single stem for which we had no taxonomic information, we used the basal area-weighted average wood density for the plot (Baker et al., 2004).

2.5. Timber stocks (m^3 ha^{-1})

We applied in-country derived species-specific allometric equations to estimate timber stocks when available, but otherwise used a generic equation (Table S1). Our estimates of rates of post-logging timber stock recovery are restricted to the 12 species harvested in 1979 (Table S1) and to trees ≥35 cm DBH, the legal minimum cutting diameter in Suriname. Only stems of commercial value, as indicated by log quality assessments made at each census were included in our timber stock estimation. We retained class code 1 stems (trees with straight and long boles without defects), and class code 2 stems (trees slightly leaning, somewhat crooked, or with minor defects) for reporting timber stocks (Alder and Synnott, 1992). To account for the lower timber stock recovery associated with minor defects for trees with stem class code 2, we reduced our timber stock estimates by 20% for those trees. We were not able to propagate uncertainty associated with our allometric equations used to estimate timber stock, as we did for ACS, because the original destructive harvest data used to build the timber stock allometric equations were not available.

2.6. Statistical models: ACS and timber stock recovery

We weighted our response variables, ACS and timber stock, by their respective plot-level initial values (i.e., prior to logging). This proportional approach facilitates interpretation of model predictions; values ≥1 indicate full plot recovery to the initial forest state. As we did not have initial ACS values for the logged plots, we estimate these values by applying a carbon emissions factor based on logging intensity from a study conducted in Guyana on the same weathered Precambrian Guiana Shield substrate as our study site in Suriname (Pearson et al., 2014). The emissions factor of 1.52 Mg C m^{-3} ha^{-1} accounted for carbon emissions associated with the extracted log, damage to the residual stand, and logging infrastructure associated with skid trails (Appendix 2). The weighted ACS values we consider to be conservative estimates of recovery as the emissions factors reported in the Pearson et al., (2014) included stems with DBH ≥ 10 cm, whilst our census data are restricted to stems with DBH ≥ 15 cm. We estimate ACS stored in stems 10–15 cm DBH to be approximately 1.97 Mg C ha^{-1} (SD ± 0.37), based on permanent sample plot data from Guyana (unpublished data).

We used a linear mixed-model approach to predict the time needed for ACS and timber stocks to recover to pre-logging values. Our mixed-model approach allows us to account for correlations among repeated measures at the plot level that would otherwise violate the assumption of independence. We incorporated plot-level random effects in our models to account for these correlations under the assumption of heterogeneous variance (Barnett et al., 2010).

We partitioned the additional variation in our models into fixed effects for harvest intensity (timber volume extracted) and time-since-logging (years), which are continuous covariates:

$$\mu_{ij} = \alpha_o + \beta_1 * harv.intensity + \beta_2 * time.since.logged + (\beta_3 * harv.intensity * time.since.logged) + plot[i]$$

where μ_{ij} represents the mean from a normal distribution for the i^{th} plot and j^{th} census. α_o is the intercept term that represents the unlogged forest state; and, β_1, β_2 and β_3 capture the effect of harvest intensity, time-since-logging, and the interaction between harvest intensity and time, respectively. Plot level variance is captured by $plot[i]$. We explored several models that included different combinations of covariates and also treated censuses as a fixed categorical random effect. We use the Deviance Information Criterion (DIC) to select the best model and present results from those models (Spiegelhalter et al., 2002). We also assessed the goodness-of-fit of our models based on the variance explained (R^2), and partitioned the explained variance into fixed and random factors (Nakagawa and Schielzeth, 2013; Appendix 1).

Our final model predictions accounts for uncertainty associated with our model parameters as well as sampling uncertainty based on a Gaussian distribution. The flexibility of our Bayesian modeling framework also enabled us to propagate the uncertainty associated with our height and biomass allometries into our statistical model for estimation of ACS. We ran all our models for 300,000 iterations, discarded the first 20,000 draws, and thinned our remaining posterior samples by 2000 using JAGS in R (Plummer, 2011; R Development Core Team, 2015).

2.7. Annualized increments for aboveground carbon and timber

We calculated annualized increments for aboveground carbon and timber based on the methodology recommended by Clark et al. (2001) for forest stands that are re-measured after long intervals. We estimated the difference in carbon stock from all surviving trees at the plot-level between censuses, subtracted carbon gained from newly recruited trees and added the biomass of trees that died between censuses (Clark et al., 2001). To account for uncertainty in aboveground carbon increments due to the long census intervals, we used aboveground carbon increments (Mg C ha^{-1} yr^{-1}) reported from forty-one plots across the Guiana Shield in our statistical model. Failure to correct for the long census intervals would otherwise result in underestimates of annualized aboveground carbon increments due to (1) unobserved growth of residual trees that died between censuses and (2) trees that grew to exceed 15 cm DBH but died before they were recorded (Clark et al., 2001).We incorporate the results from the Johnson et al., (2016) as informative priors for the unlogged forest state in our statistical model because we were unable to implement the parametric technique recommended by Malhi et al. (2004). That approach partitions sequential censuses into increasing time intervals, but we are limited by two census intervals, 1983–2000 and 2000–2012, that averages 15 years between censuses. We also did not use the method recommended by Talbot et al. (2014) to deal with the same problem, which estimates the number of unobserved recruits based on mean annual mortality and recruitment rates, because it seems more suited for shorter time spans between censuses.

Instead of the Malhi et al. (2004) and Talbot et al. (2014) corrections for underestimated aboveground productivity, we rely on Bayes' principle that allows us to include published rates of aboveground carbon increments for the Guiana Shield in the form of a prior distribution to increase the precision of our model predictions for aboveground carbon productivity. The combination of this prior information, with the likelihood function that relates our observed data to the statistical model, enables us to obtain a posterior distribution that characterizes the parameter of interest under Bayes' theorem. If the prior information specified does not reduce the model fit, the model DIC value (which is analogous to the AIC in a likelihood framework) will improve (Spiegelhalter et al., 2002). Improvements indicate that the prior information specified is consistent with the data and that the data had an overwhelmingly large influence on the posterior distribution (Morris et al., 2013). Bayes' principle is especially suited to our needs given that we aim to quantify and communicate uncertainty around post-logging recovery in a probabilistic manner, and overcome data limitations with a quantitatively rigorous approach to better inform forest managers (Hobbs and Hooten, 2015; McCarthy and Masters, 2005).

3. Results

3.1. Stem density and basal area (m^2 ha^{-1}) recovery

Average density of trees ≥15 cm DBH in the control plots declined by 4% over the 29-year observation period, from 265 stems ha^{-1} in 1983 to 254 stems ha^{-1} in 2012. After logging at medium and high intensities, stem densities increased by 14% and 16% between 1981 and 2012, from 248 to 282 stems ha^{-1} and from 218 to 254 stems ha^{-1}, respectively; average density after low intensity logging increased by 4%, from 251 to 261 stems ha^{-1} (Table 1; Fig. 1).

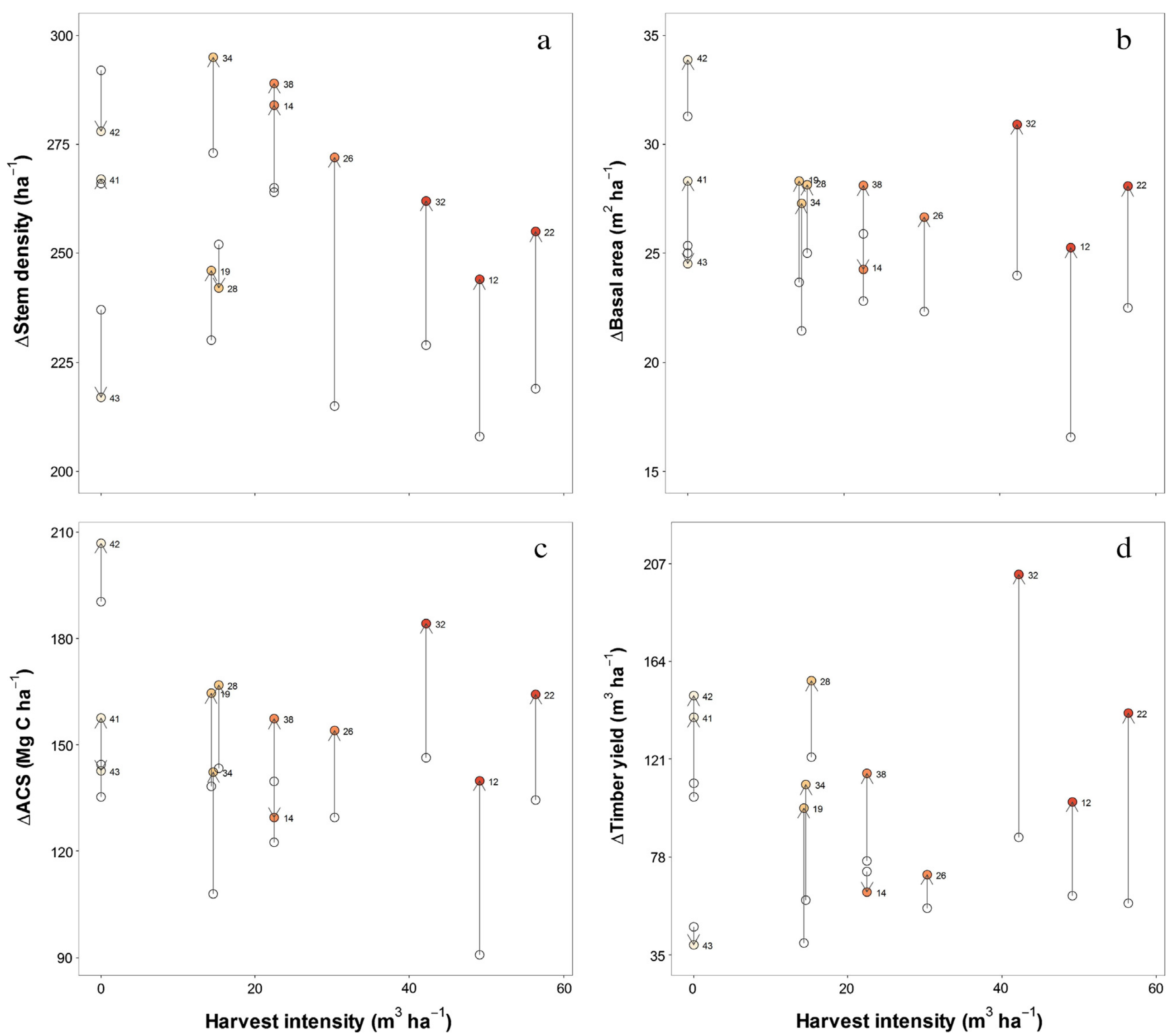

Fig. 1. Changes (Δ) in stem density (*a*), basal area (*b*), and ACS (*c*) from 2 years (1981) to 32 years (2012) after selective logging. Changes in timber stock (*d*) are from 1 year (1980) to 32 (2012) years after selective logging. Numbers on graph identify the plots and corresponds to the meta-data presented in Table 1 with arrows indicating direction of change over the period reported. Changes across the unlogged forest plots are located at the zero point of the x-axis (plots 41, 42, and 43) and are from 1983 to 2012. We propagate the uncertainty of our allometric models used to estimate ACS (*c*) and plotted the mean values.

Basal area in the control plots increased by 6% between 1983 (27.23 m^2 ha^{-1}) and 2012 (28.93 m^2 ha^{-1}). On average high intensity logged plots had the lowest basal area in 1981 (21.12 m^2 ha^{-1}) after logging with the largest increase of 33% by 2012 (28.09 m^2 ha^{-1}). Basal area in the low intensity logged plots increased by 19% (from 23.38 to 27.92 m^2 ha^{-1}) and medium intensity logged plots by 11% (from 23.69 to 26.36 m^2 ha^{-1}; Table 1; Fig. 1). Between 1981 and 2012, basal area-weighted average wood density for control, low, and medium intensity logged plots remained relatively constant at 0.64 g cm^{-3} whereas it declined by 4% after the highest intensity of logging, from 0.66 g cm^{-3} in 1981 to 0.63 g cm^{-3} in 2012 (Table 1).

3.2. ACS (Mg C ha^{-1}) and timber stock (m^3 ha^{-1}) recovery

Average control plot ACS increased by 8% over the 29-year observation period, from 156.75 Mg C ha^{-1} in 1983 to 169.10 Mg C ha^{-1} in 2012. On average, ACS in low, medium, and high intensity logged plots 32 years after the harvest were below the 2012 control plot mean values by 7% (157.94 Mg C ha^{-1}), 13% (146.99 Mg C ha^{-1}), and 4% (162.94 Mg C ha^{-1}), respectively, with highly variable plot-level ACS gains (Fig. 1).

Commercial timber in stems $\geq$35 cm DBH that were judged to have merchantable boles (Grade 1 plus 80% of Grade 2) was estimated at 100 m^3 ha^{-1} (SE ± 9.2) prior to logging in 1978 across the entire harvest block. Control forest stands recorded an increase in standing stocks of timber of 25% from 1983 (87.4 m^3 ha^{-1}) to 2012 (109.30 m^3 ha^{-1}). Plots logged at low and high intensity had recovered their initial (1978) commercial timber of 81.56 m^3 ha^{-1} and 120.21 m^3 ha^{-1}, respectively; in 2012 their commercial timber stocks were 49% (121.62 m^3 ha^{-1}) and 24% (148.57 m^3 ha^{-1}) higher than their initial commercial timber stocks. Over the same 32-year period, plots logged at medium intensity recovered to 84% of commercial timber stocks measured in 1978, from 98.22 m^3 ha^{-1} before the harvest to 82.58 m^3 ha^{-1} in 2012.

3.3. Model predictions of ACS and timber stock recovery

The probability of ACS recovery 32 years post-logging was 45%, 40% and 24% after low, medium, and high logging intensity (Fig. 2). At the currently instituted legal harvest intensity of 25 m^3 ha^{-1}, more than 70 years will be required to recover ACS with 90% probability. The mean predicted time to recover initial ACS, estimated at 184.95 Mg C ha^{-1} across all plots, after 25 m^3 ha^{-1} harvest intensity is 37 years (95%; CI, 140.56 to 229.34 Mg C ha^{-1}). Logging intensity (β_1) had a negative effect on ACS recovery with time-since-logging (β_2) and the interaction term (β_3) with positive but non-significant effects (Fig. 3).

Model predictions of timber stock recovery at the end of 32 years after logging was 82%, 80% and 70% after low, medium, and high logging intensity. The mean recovery time needed at harvest intensity of 25 m^3 ha^{-1} was estimated at 20 years (95% CI: 60.00 to 137.00 m^3 ha^{-2}). For more than 90% probability that timber stock would have recovered to pre-logged values, 40 years will be required. Logging intensity had a negative effect on timber stock recovery with small positive effects for time-since-logging and the interaction term (Fig. 3).

Our ACS and timber stock models explained 0.74 (95% CI, 0.60 to 0.86) and 0.84 (95% CI, 0.75 to 0.91) of the variance captured by our fixed and random effects (conditional R^2; Figs. S2 and S3). Fixed factors (i.e. logging intensity, time-since-logging, and an interaction term) accounted for 85% and 65% of the explained variance (marginal R^2) in our ACS and timber stock recovery models, respectively. Our random-effects (plot identity) accounted for 15% and 33% of the variance explained by our ACS and timber stock recovery models, respectively.

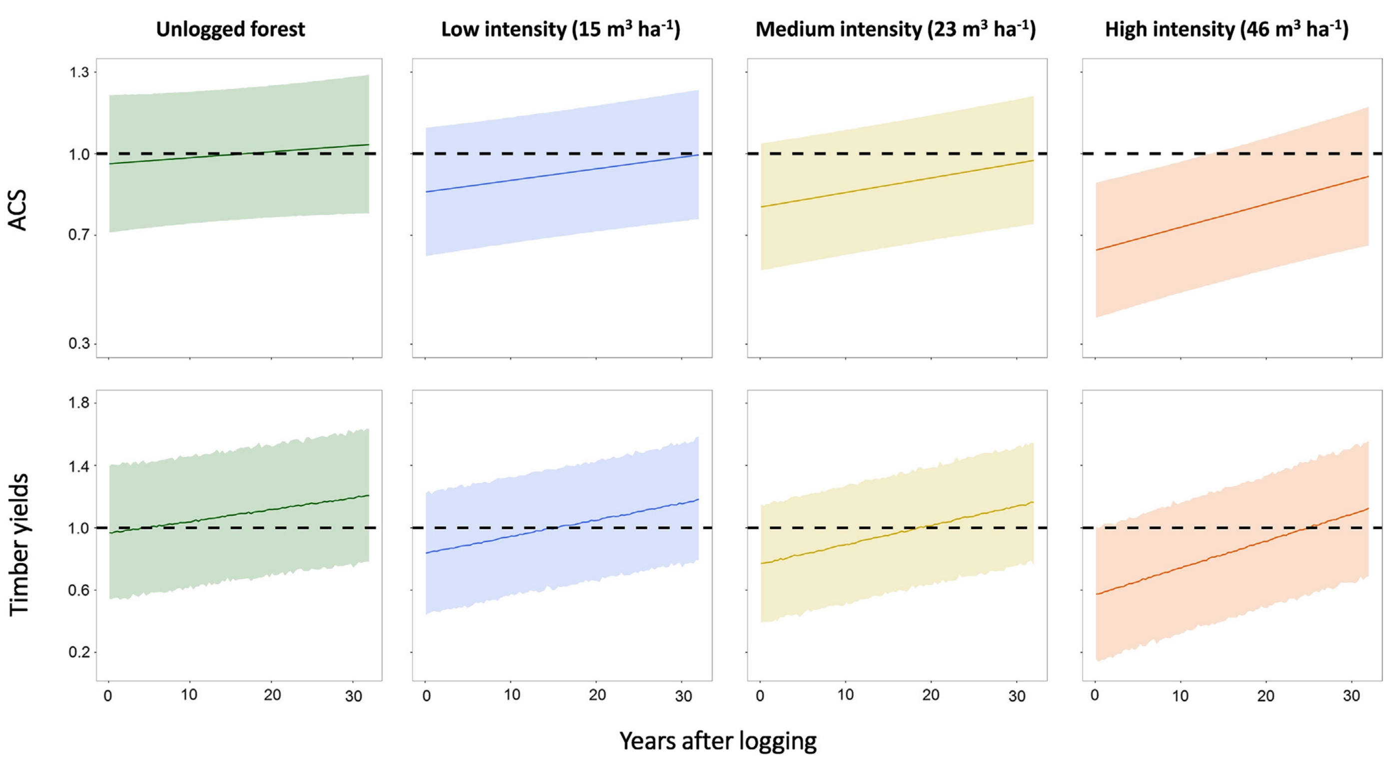

Fig. 2. Model predictions of recovery of ACS (*a*, *b*, and *c*) and timber stock (*d*, *e*, and *f*) at low, medium and high logging intensities. Observed ACS post-logging is weighted by initial ACS (Mg C ha^{-1}) and timber stock (m^3 ha^{-1}). Solid lines are the mean predictions based on parameter and sampling uncertainly, with 95% credible intervals represented by the lighter colored ribbons. Predictions above the dashed horizontal line (*y-intercept* = *1.0*) indicate recovery to pre-logging values.

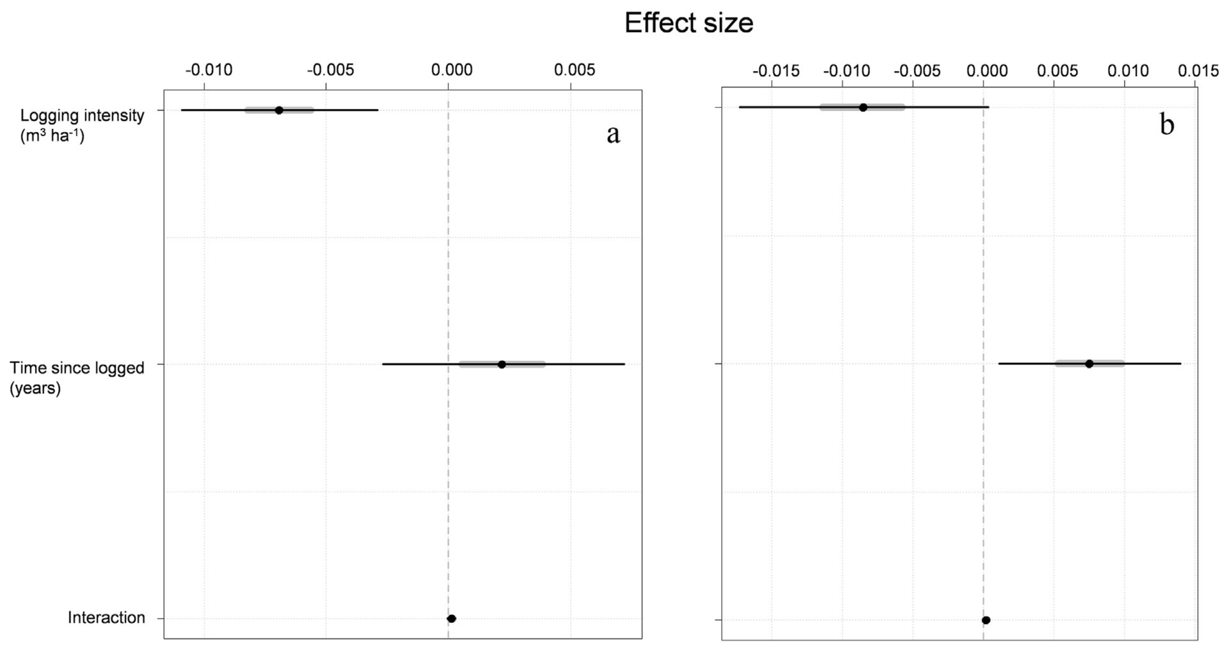

Fig. 3. Regression coefficients from recovery models for ACS (*a*) and timber (*b*) based on logging intensity (m^3 ha^{-1}), time-since-logging (years), and an interaction-term for logging intensity and time-since-logging. Thin vertical lines indicate the 95% credible intervals (CIs), thicker lines capture the 50% CIs based on posterior draws, and points indicate the mean effect size. Coefficients with 95% CIs that do not cross the zero value (dashed line) can be considered statistically significant.

3.4. Annualized increments for aboveground carbon (Mg C ha^{-1} yr^{-1}) and timber (m^3 ha^{-1} yr^{-1})

Predicted increments of aboveground carbon were highest for plots logged at 46 m^3 ha^{-1} (2.91 Mg C ha^{-1} yr^{-1}; CI, 1.99 to 3.82) and slowest in the unlogged forests (2.39 Mg C ha^{-1} yr^{-1}; CI, 1.51 to 3.26; Table 2). Observed carbon losses were highest in medium intensity logged plots, with annual mortality rates of 2.26 Mg C ha^{-1} yr^{-1}, resulting in the slowest net increase of ACS. The model that used results from previous research as informed priors was indistinguishable from the model that had vague priors based on their DIC metric. Predictions for aboveground carbon increments for unlogged forests were 4% higher in the model with informative priors compared to the model with noninformative priors.

Increases in timber stocks were faster in plots logged at 46 m^3 ha^{-1} (3.56 m^3 ha^{-1} yr^{-1}; 95% CI, 1.44 to 3.56). Net timber stock increments were slowest in unlogged forests (0.86 m^3 ha^{-1} yr^{-1}) with residual tree growth driving timber stock recovery, with little or no recruitment of stems of commercial value (Table 3).

Table 2

Components of aboveground woody carbon production and model predictions with uninformed and informed priors for stand-level increments (Mg C ha^{-1} yr^{-1}) at logging intensities of 15, 23, and 46 m^3 ha^{-1}. We estimated aboveground carbon increment at the plot level as: ($\sum$*ACS at* $t_{i+1} - \sum$*ACS at* t_i = *residual growth*) + ($\sum$*ACS mortality between* t_i *and* t_{i+1}) − (*ACS of tree at 15 cm DBH* ∗ *number of new recruits between* t_i *and* t_{i+1}) for the 1983–2000 and 2000–2012 census intervals to account for unobserved increments. We used these values to estimate ACS increments across logging intensities, with both vague Gaussian priors [N ∼ (μ = 0, sd = 0.0001)]and informative priors [N ∼ (μ = 3.51, sd = 4.04; Johnson et al., 2016].

Logging intensity	Mg C ha^{-1} yr^{-1}			Aboveground carbon increments Mg C ha^{-1} yr^{-1} (95% CI)	
	ΣACS t_{i+1} - ΣACS t_i (±SE)	Recruits - 15 cm DBH (±SE)	Mortality (±SE)	Uniformed priors	Informed priors
15 m^3 ha^{-1}	2.39 (±0.09)	0.14 (±0.03)	1.91 (±0.32)	2.54 (1.68 to 3.44)	2.55 (1.71–3.46)
23 m^3 ha^{-1}	2.25 (±0.20)	0.27 (±0.03)	2.26 (±0.35)	2.65 (1.73 to 3.51)	2.65 (1.71–3.52)
46 m^3 ha^{-1}	2.65 (±0.22)	0.31 (±0.10)	2.10 (±0.39)	2.93 (2.04 to 3.83)	2.91 (1.99–3.82)
Control	2.23 (±0.19)	0.11 (±0.02)	2.13 (±0.21)	2.35 (1.47 to 3.22)	2.39 (1.51–3.26)

Table 3

Timber stock increments (m^3 ha^{-1} yr^{-1}) for stems ≥15 cm DBH and classified as having commercial log value. We applied the stand increment formula presented in Clark et al. (2001): ($\sum$*ACS at* $t_{i+1} - \sum$*ACS at* t_i = *residual growth*) + ($\sum$*ACS mortality between* t_i *and* t_{i+1}) − (*ACS of tree at 15 cm DBH* ∗ *number of new recruits between* t_i *and* t_{i+1}) to estimate timber stock recovery rates.

Logging intensity	m^3 ha^{-1} yr^{-1}			Timber stock increment (95% credible interval)
	ΣACS t_{i+1} - ΣACS t_i (± SE)	Recruits - 15 cm DBH (± SE)	Mortality (± SE)	
15 m^3 ha^{-1}	2.35 (±0.19)	0.000 (±0.00)	1.35 (±0.20)	2.62 (1.16 to 4.06)
23 m^3 ha^{-1}	1.86 (±0.31)	0.006 (±0.00)	1.20 (±0.31)	2.25 (0.72 to 3.83)
46 m^3 ha^{-1}	3.22 (±0.48)	0.023 (±0.02)	0.91 (±0.30)	3.56 (1.44 to 3.56)
Control	1.58 (±0.36)	0.003 (±0.00)	1.04 (±0.18)	1.90 (−0.13 to 3.57)

4. Discussion

Model predictions for recovery time after careful selective logging in Suriname revealed a 55% probability that forests logged at the lowest harvest intensity (15 m^3 ha^{-1}) would not recover initial ACS within 32 years (Fig. 2). At an estimated loss of 14% of initial ACS associated with the lowest logging intensity, we expected a higher probability of recovery after 32 years based on a recent Amazon-wide study on ACS that found recovery time (years) is close to the proportional losses in ACS due to logging (Rutishauser et al., 2015; $[100 * ACS_{loss}/ACS_{intial}]^{1.106}$]). Similarly, 60% and 76% of model predictions at 32 years after logging indicated that ACS would not have recovered after medium and high logging intensity, with average losses of 22% and 37% of initial ACS, respectively. As our study lacked pre-logging plot-level ACS data, we applied an emissions factor based on harvested timber volume to estimate initial ACS prior to logging in 1979 and weighted our post-logging ACS data by their respective plot-level initial ACS estimates (Appendix S2). Our recovery predictions may thus be conservative as the carbon emissions factor (1.52 Mg C m^{-3} ha^{-1}) accounted for tree mortality for stems $\geq$10 cm DBH, whilst our census data includes stems $\geq$15 cm DBH. Additionally, the logging emissions factor reported by Pearson et al. (2014) could be higher than those at our study site as it spanned a wide range of logging practices, whilst the CELOS System was designed to reduce collateral damage to the forest based on RIL principles.

In contrast to the low confidence in ACS recovery, confidence about timber stock recovery was higher. There is an 80% probability that plots logged at intensities of 15–23 m^3 ha^{-1} would have recovered initial timber stocks within 32 years after logging. Recovery was slower for forests logged at 46 m^3 ha^{-1}, with 30% of model predictions at 32 years indicating failure to recover initial timber stocks (Fig 2). However, recovery of timber stocks was driven primarily by biomass accumulation from residual tree growth (Table 1), as reported for a forest in Eastern Amazonia after RIL (Mazzei et al., 2010). The low recruitment of commercial species may not be sufficient to sustain timber stocks beyond a third harvest. Perversely, if market preferences change to favor additional timber species beyond those harvested during the study, timber stocks could be sustained beyond a third harvest (Keller et al., 2007). Stand improvement interventions such as liberation thinning that stimulates recruitment and growth of commercial timber species (Gourlet-Fleury et al., 2004; Peña-Claros et al., 2008) or enrichment planting (Ruslandi et al., 2017) can also be used to promote long-term timber yield sustainability.

The average net recovery rate of aboveground carbon across all nine of our logged plots was 0.62 Mg C ha^{-1} yr^{-1} (95% CI, 0.24 to 1.01), half of the 1.3 Mg C ha^{-1} yr^{-1} for Amazonia reported by Rutishauser et al. (2015) study. The net rate of change in aboveground carbon (residual growth and recruitment minus mortality) in our unlogged forest was similar to those reported for old-growth Amazonian forests (0.28 Mg C ha^{-1} yr^{-1}; Brienen et al. 2015) but slower than observed rates reported for Guiana Shield old-growth forests (0.45 Mg C ha^{-1} yr^{-1}; Johnson et al., 2016). The slower carbon increments relative to other studies in the Brazilian Amazon, which dominated the Rutishauser et al., (2015) was also found in a nearby logging study in Paracou, French Guiana. In that study, at harvest intensity of 23 m^3 ha^{-1}, the average time to recover initial ACS was 45 years with conventional logging (Blanc et al., 2009). In our study, average predicted time to recover initial ACS based on logging intensity of 25 m^3 ha^{-1} was 37 years, 8 years less than at the Paracou research site. The shorter recovery time with the CELOS system could be associated with the lower reduction in ACS losses associated with logging, estimated to be one fifth of initial ACS. In Paracou, ACS loss immediately after logging with conventional logging was estimated at one third of initial ACS.

Analytically, the Bayesian framework employed in our analysis enabled us to make probabilistic statements about recovery at different time points after logging. In particular, the use of data from forty-one plots across the Guiana Shield helped address two major shortcomings of our dataset that would otherwise have resulted in lower precision and less confidence in our annualized increments: (1) long census intervals that lead to unrecorded growth of trees that die between censuses as well as the contributions of trees that recruited but died before being measured (Clark et al., 2001); and, (2) our small sample size (N = 12) of small (1-ha) plots that can lead to prediction bias due to failure to capture much of the characteristic spatial heterogeneity of carbon stocks in tropical forests (Phillips et al., 2002). We found the mean rate of aboveground carbon productivity in unlogged forests to be 4% higher in the model with informative priors, which is similar to the ~1–3% underestimates caused by not accounting for growth and recruitment of trees that die between censuses (Carey et al., 1994). The combination of the results from other studies with our own data represents a cost-effective statistical method to improve confidence associated with model inferences when census intervals are long and there is high uncertainty associated with carbon stocks across the landscape (McCarthy and Masters, 2005).

4.1. Forest management implications

Our model predictions indicate a 67% probability that timber stocks will recover in 25 years to pre-logging levels after careful harvests of 25 m^3 ha^{-1}; in Suriname, 25 years is the minimum cutting cycle duration and 25 m^3 ha^{-1} is the maximum harvest intensity. Similarly, we estimate the probability of ACS recovery under these same rules as only 27%. If forest managers want >90% confidence in both ACS and timber stock recovery to pre-logged levels, cutting cycles will have to be set at 70 and 40 years, respectively. These results indicate a trade-off between carbon and timber values, with longer cutting cycles needed to recover initial ACS compared to timber stocks. Carbon payments can potentially be used to extend the cutting cycle, thereby enabling additional carbon sequestration and storage.

The CELOS system, though intended to be environmentally good logging, may not ensure long term profitable timber management alone due to the low recruitment of commercial timber species. To sustain timber yields and profits across multiple cutting cycles, timber stand improvements aimed at increasing growth rates and recruitment of commercial timber species could be used (Putz and Ruslandi, 2015). The application of stand improvement treatments to increase timber stocks could however further decrease carbon storage and sequestration between cutting cycles (Blanc et al., 2009). Nevertheless, adoption of the CELOS harvest system that is guided by RIL practices improves post-logging recovery rates of both timber stocks and ACS compared to conventional logging (Sasaki et al., 2016).

Acknowledgements

We thank the University of Hamburg for financial support for the 2012 census; Jonker W.B.J for access to the previous census data; and the dedicated members of the field crew that collected those data. The foresight and careful work of the original research team also deserves acknowledgement. A.R is a WWF Russel E. Train Fellow.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foreco.2017.02.026.

References

Alder, D., Synnott, T.J., 1992. Permanent sample plot techniques for mixed tropical forest. Trop. For. Papers.

Baker, T., Phillips, O., Malhi, Y., Almeida, S., Arroyo, L., Di Fiore, A., Erwin, T., Killeen, T.J., Laurence, S.G., Laurance, W.F., Lewis, S.L., Lloyd, J., Monteagudo, A., Neill, D.A., Patiño, S., Pitman, N.C., Silva, J.N.M., Martínez, R.V., 2004. Variation in wood density determines spatial patterns in Amazonian forest biomass. Glob. Chang. Biol. 10, 545–562. http://dx.doi.org/10.1111/j.1529-8817.2003.00751.x.

Barnett, A.G., Koper, N., Dobson, A.J., Schmiegelow, F., Manseau, M., 2010. Using information criteria to select the correct variance–covariance structure for longitudinal data in ecology. Meth. Ecol. Evol. 1, 15–24. http://dx.doi.org/10.1111/j.2041-210X.2009.00009.x.

Blanc, L., Echard, M., Herault, B., Bonal, D., Marcon, E., Chave, J., Baraloto, C., 2009. Dynamics of aboveground carbon stocks in a selectively logged tropical forest. Ecol. Appl. 19, 1397–1404.

Brienen, R.J.W., Phillips, O.L., Feldpausch, T.R., Gloor, E., Baker, T.R., Lloyd, J., Lopez-Gonzalez, G., Monteagudo-Mendoza, A., Malhi, Y., Lewis, S.L., Vásquez Martinez, R., Alexiades, M., Álvarez Dávila, E., Alvarez-Loayza, P., Andrade, A., Aragão, L.E. O.C., Araujo-Murakami, A., Arets, E.J.M.M., Arroyo, L., Aymard, C.G.A., Bánki, O.S., Baraloto, C., Barroso, J., Bonal, D., Boot, R.G.A., Camargo, J.L.C., Castilho, C.V., Chama, V., Chao, K.J., Chave, J., Comiskey, J.A., Cornejo Valverde, F., da Costa, L., de Oliveira, E.A., Di Fiore, A., Erwin, T.L., Fauset, S., Forsthofer, M., Galbraith, D.R., Grahame, E.S., Groot, N., Hérault, B., Higuchi, N., Honorio Coronado, E.N., Keeling, H., Killeen, T.J., Laurance, W.F., Laurance, S., Licona, J., Magnussen, W.E., Marimon, B.S., Marimon-Junior, B.H., Mendoza, C., Neill, D.A., Nogueira, E.M., Núñez, P., Pallqui Camacho, N.C., Parada, A., Pardo-Molina, G., Peacock, J., Peña-Claros, M., Pickavance, G.C., Pitman, N.C.A., Poorter, L., Prieto, A., Quesada, C.A., Ramírez, F., Ramírez-Angulo, H., Restrepo, Z., Roopsind, A., Rudas, A., Salomão, R. P., Schwarz, M., Silva, N., Silva-Espejo, J.E., Silveira, M., Stropp, J., Talbot, J., ter Steege, H., Teran-Aguilar, J., Terborgh, J., Thomas-Caesar, R., Toledo, M., Torello-Raventos, M., Umetsu, R.K., van der Heijden, G.M.F., van der Hout, P., Guimarães Vieira, I.C., Vieira, S.A., Vilanova, E., Vos, V.A., Zagt, R.J., Vasquez Martinez, R., Alexiades, M., Alvarez Davila, E., Alvarez-Loayza, P., Andrade, A., Aragao, L.E.O.C., Araujo-Murakami, A., Arets, E.J.M.M., Arroyo, L., Aymard, C.G.A., Banki, O.S., Baraloto, C., Barroso, J., Bonal, D., Boot, R.G.A., Camargo, J.L.C., Castilho, C.V., Chama, V., Chao, K.J., Chave, J., Comiskey, J.A., Cornejo Valverde, F., da Costa, L., de Oliveira, E.A., Di Fiore, A., Erwin, T.L., Fauset, S., Forsthofer, M., Galbraith, D.R., Grahame, E.S., Groot, N., Herault, B., Higuchi, N., Honorio Coronado, E.N., Keeling, H., Killeen, T.J., Laurance, W.F., Laurance, S., Licona, J., Magnussen, W.E., Marimon, B.S., Marimon-Junior, B.H., Mendoza, C., Neill, D.A., Nogueira, E.M., Nunez, P., Pallqui Camacho, N.C., Parada, A., Pardo-Molina, G., Peacock, J., Pena-Claros, M., Pickavance, G.C., Pitman, N.C.A., Poorter, L., Prieto, A., Quesada, C.A., Ramirez, F., Ramirez-Angulo, H., Restrepo, Z., Roopsind, A., Rudas, A., Salomao, R. P., Schwarz, M., Silva, N., Silva-Espejo, J.E., Silveira, M., Stropp, J., Talbot, J., ter Steege, H., Teran-Aguilar, J., Terborgh, J., Thomas-Caesar, R., Toledo, M., Torello-Raventos, M., Umetsu, R.K., van der Heijden, G.M.F., van der Hout, P., Guimaraes Vieira, I.C., Vieira, S.A., Vilanova, E., Vos, V.A., Zagt, R.J., 2015. Long-term decline of the Amazon carbon sink. Nature 519, 344–348. http://dx.doi.org/10.1038/nature14283.

Carey, E.V., Brown, S., Gillespie, A.J.R., Lugo, A.E., 1994. Tree mortality in mature lowland tropical moist and tropical lower montane moist forests of Venezuela. Biotropica 26, 255–265. http://dx.doi.org/10.2307/2388846.

Chave, J., Coomes, D., Jansen, S., Lewis, S.L., Swenson, N.G., Zanne, A.E., 2009. Towards a worldwide wood economics spectrum. Ecol. Lett. 12, 351–366. http://dx.doi.org/10.1111/j.1461-0248.2009.01285.x.

Chave, J., Réjou-Méchain, M., Búrquez, A., Chidumayo, E., Colgan, M.S., Delitti, W.B. C., Duque, A., Eid, T., Fearnside, P.M., Goodman, R.C., Henry, M., Martnez-Yrzar, A., Mugasha, W.A., Muller-Landau, H.C., Mencuccini, M., Nelson, B.W., Ngomanda, A., Nogueira, E.M., Ortiz-Malavassi, E., Pélissier, R., Ploton, P., Ryan, C.M., Saldarriaga, J.G., Vieilledent, G., 2014. Improved allometric models to estimate the aboveground biomass of tropical trees. Glob. Chang. Biol. 20, 3177–3190. http://dx.doi.org/10.1111/gcb.12629.

Clark, D.A., Brown, S., Kicklighter, D.W., Chambers, J.Q., Thomlinson, J.R., Ni, J., 2001. Measuring net primary production in forest concepts and field methods. Ecol. Appl. 11, 356–370. http://dx.doi.org/10.1890/1051-0761(2001) 011[0356:MNPPIF]2.0.CO;2.

Crome, F.H.J., Thomas, M.R., Moore, L.A., 1996. A novel bayesian approach to assessing impacts of rain forest logging. Ecol. Appl. 6, 1104–1123.

Dawkins, H.C., Philip, M.S., 1998. Tropical Moist Forest Silviculture and Management: a History of Success and Failure, Agroforestry Systems. CAB Internationa, Wallingford.

de Graaf, N.R., 1986. A Silvicultural System for Natural Regeneration of Tropical Rain Forest in Suriname., Agricultural University. Ecology and Management of Tropical Rain Forest in Suriname. Agricultural University, Wageningen, The Netherlands. doi:10.1016/0006-3207(89)90020-7.

Dekker, M., de Graaf, N.R., 2003. Pioneer and climax tree regeneration following selective logging with silviculture in Suriname. For. Ecol. Manage. 172, 183–190. http://dx.doi.org/10.1016/S0378-1127(01)00801-5.

FAO, 2004. Reduced impact logging in tropical forests. Literature synthesis, analysis and prototype statistical framework, Forest Harvesting and Engineering Working Paper. Rome, Italy.

Gourlet-Fleury, S., Guehl, J.M., Laroussinie, O., 2004. Ecology and management of a neotropical rainforest : lessons drawn from Paracou, a long-term experimental research site in French Guiana., Ecology and Manegement of a Neotropical Rainforest. Elsevier, Paris.

Hammond, D.S., 2005. Tropical forests of the Guiana shield: ancient forests in a modern world, Forestry. CABI. doi:10.1079/9780851995366.0000.

Hobbs, N.T., Hooten, M.B., 2015. Bayesian Models: A Statistical Primer for Ecologists. Princeton University Press, Oxford, UK.

IPCC, 2003. Good practice guidance for land use, landuse change and forestry (GPG-LULUCF), in: Good Practice Guidance for Land Use, Land-Use Change and Forestry.

Johnson, M.O., Galbraith, D., Gloor, E., De Deurwaerder, H., Guimberteau, M., Rammig, A., Thonicke, K., Verbeeck, H., von Randow, C., Monteagudo, A., Phillips, O.L., Brienen, R.J.W., Feldpausch, T.R., Lopez Gonzalez, G., Fauset, S., Quesada, C.A., Christoffersen, B., Ciais, P., Gilvan, S., Kruijt, B., Meir, P., Moorcroft, P., Zhang, K., Alvarez, E.A., Alves de Oliveira, A., Amaral, I., Andrade, A., Aragao, L.E.O.C., Araujo-Murakami, A., Arets, E.J.M.M., Arroyo, L., Aymard, G.A., Baraloto, C., Barroso, J., Bonal, D., Boot, R., Camargo, J., Chave, J., Cogollo, A., Cornejo, F.V., Costa, L.Da., di Fiore, A., Ferreira, L., Higuchi, N., Honorio, E., Killeen, T.J., Laurance, S.G., Laurance, W.F., Licona, J., Lovejoy, T., Malhi, Y., Marimon, B., Marimon, B.H.J., Matos, D.C.L., Mendoza, C., Neill, D.A., Pardo, G., Peña-Claros, M., Pitman, N.C.A., Poorter, L., Prieto, A., Ramirez-Angulo, H., Roopsind, A., Rudas, A., Salomao, R.P., Silveira, M., Stropp, J., Ter Steege, H., Terborgh, J., Thomas, R., Toledo, M., Torres-Lezama, A., van der Heijden, G.M.F., Vasquez, R., Vieira, I., Vilanova, E., Vos, V.A., Baker, T.R., 2016. Variation in stem mortality rates determines patterns of aboveground biomass in Amazonian forests: implications for dynamic global vegetation models. Glob. Chang. Biol. 44, 1–18. http://dx.doi.org/10.1111/gcb.13315.

Jonkers, W.B., 1983. Exploitation, Natural regeneration and increment-experiment plan and progress report on Experiment 78/5. doi:CELOS Rapporten no.141.

Jonkers, W.B., 2011. Tree growth, recruitment and mortality after logging and refinement. In: Werger, M. (Ed.), Sustainable Management of Tropical Rainforests: The CELOS Management System. Tropenbos International, Paramaribo, Suriname.

Jonkers, W.B.J., 1987. Vegetation structure, logging damage and silviculture in a tropical rain forest in suriname, Biological Conservation. Wageningen, The Netherlands. doi:10.1016/0006-3207(89)90022-0.

Keller, M., Asner, G.P., Blate, G., Mcglocklin, J., Merry, F., Peña-claros, M., Zweede, J., 2007. Timber production in selectively logged tropical forests in South America. Front. Ecol. Environ. 5, 213–216.

Malhi, Y., Baker, T.R., Phillips, O.L., Almeida, S., Alvarez, E., Arroyo, L., Chave, J., Czimczik, C.I., Di Fiore, A., Higuchi, N., Killeen, T.J., Laurance, S.G., Laurance, W.F., Lewis, S.L., Montoya, L.M.M., Monteagudo, A., Neill, D.A., Vargas, P.N., Patino, S., Pitman, N.C.A., Quesada, C.A., Salomao, R., Silva, J.N.M., Lezama, A.T., Martínez, R.V., Terborgh, J., Vinceti, B., Lloyd, J., 2004. The above-ground coarse wood productivity of 104 Neotropical forest plots. Glob. Chang. Biol. 10, 563–591. http://dx.doi.org/10.1111/j.1529-8817.2003.00778.x.

Mazzei, L., Sist, P., Ruschel, A., Putz, F.E., Marco, P., Pena, W., Ferreira, J.E.R., 2010. Above-ground biomass dynamics after reduced-impact logging in the Eastern Amazon. For. Ecol. Manage. 259, 367–373. http://dx.doi.org/10.1016/j.foreco.2009.10.031.

McCarthy, M.A., Masters, P., 2005. Profiting from prior information in Bayesian analyses of ecological data. J. Appl. Ecol. 42, 1012–1019. http://dx.doi.org/10.1111/j.1365-2664.2005.01101.x.

Morris, W.K., Vesk, P.A., McCarthy, M.A., 2013. Profiting from pilot studies: Analysing mortality using Bayesian models with informative priors. Basic Appl. Ecol. 14, 81–89. http://dx.doi.org/10.1016/j.baae.2012.11.003.

Nakagawa, S., Schielzeth, H., 2013. A general and simple method for obtaining R2 from generalized linear mixed-effects models. Methods Ecol. Evol. 4, 133–142. http://dx.doi.org/10.1111/j.2041-210x.2012.00261.x.

Nicholson, D., 1958. An analysis of logging damage in tropical rain forest. North Borneo. Malaysian For. 21, 235–245.

Nicholson, D.I., 1979. The Effects of Logging and Treatment on the Mixed Dipterocarp Forests of Southeast Asia, Report FAO MISC/79/8. FAO, Rome.

Pearson, T.R.H., Brown, S., Casarim, F.M., 2014. Carbon emissions from tropical forest degradation caused by logging. Environ. Res. Lett. 9, 34017. http://dx.doi.org/10.1088/1748-9326/9/3/034017.

Peña-Claros, M., Fredericksen, T.S., Alarcón, A., Blate, G.M., Choque, U., Leaño, C., Licona, J.C., Mostacedo, B., Pariona, W., Villegas, Z., Putz, F.E., 2008. Beyond reduced-impact logging: Silvicultural treatments to increase growth rates of tropical trees. For. Ecol. Manage. 256, 1458–1467. http://dx.doi.org/10.1016/j.foreco.2007.11.013.

Phillips, O.L., Malhi, Y., Vinceti, B., Baker, T., Lewis, S.L., Higuchi, N., Laurance, W.F., Vargas, P.N., Martinez, R.V., Laurance, S., 2002. Changes in growth of tropical forests: evaluating potential biases. Ecol. Appl. 12, 576–587.

Pinard, M.A., Putz, F.E., 1996. Retaining forest biomass by reducing logging damage. Biotropica 28, 278–295. http://dx.doi.org/10.2307/2389193.

Plummer, M., 2011. JAGS Version 3.1. 0 user manual. Int. Agency Res. Cancer.

Poels, R.L., 1987. Soils, Water, and Nutrients in a Forest Ecosystem in Suriname. Agricultural University, Wageningen. http://dx.doi.org/10.1016/0022-1694(89)90087-5.
Putz, F.E., Ruslandi, 2015. Intensification of tropical silviculture. J. Trop. For. Sci. 27, 285–288.
Putz, F.E., Sist, P., Fredericksen, T., Dykstra, D., 2008. Reduced-impact logging: challenges and opportunities. For. Ecol. Manage. 256, 1427–1433. http://dx.doi.org/10.1016/j.foreco.2008.03.036.
Putz, F.E., Zuidema, P.A., Synnott, T., Peña-Claros, M., Pinard, M.A., Sheil, D., Vanclay, J.K., Sist, P., Gourlet-Fleury, S., Griscom, B., Palmer, J., Zagt, R., 2012. Sustaining conservation values in selectively logged tropical forests: the attained and the attainable. Conserv. Lett. 5, 296–303. http://dx.doi.org/10.1111/j.1755-263X.2012.00242.x.
Quesada, C.A., Lloyd, J., Schwarz, M., Patiño, S., Baker, T.R., Czimczik, C., Fyllas, N.M., Martinelli, L., Nardoto, G.B., Schmerler, J., Santos, A.J.B., Hodnett, M.G., Herrera, R., Luizão, F.J., Arneth, A., Lloyd, G., Dezzeo, N., Hilke, I., Kuhlmann, I., Raessler, M., Brand, W.A., Geilmann, H., Filho, J.O.M., Carvalho, F.P., Filho, R.N.A., Chaves, J.E., Cruz, O.F., Pimentel, T.P., Paiva, R., 2010. Variations in chemical and physical properties of Amazon forest soils in relation to their genesis. Biogeosciences 7, 1515–1541. http://dx.doi.org/10.5194/bg-7-1515-2010.
R Development Core Team, 2015. R: A language and environment for statistical computing.
Ruslandi, Cropper, W.P., Putz, F.E., 2017. Effects of silvicultural intensification on timber yields, carbon dynamics, and tree species composition in a dipterocarp forest in Kalimantan, Indonesia: an individual-tree-based model simulation. For. Ecol. Manage. 390, 104–118. http://dx.doi.org/10.1016/j.foreco.2017.01.019.
Rutishauser, E., Hérault, B., Baraloto, C., Blanc, L., Descroix, L., Sotta, E.D., Ferreira, J., Kanashiro, M., Mazzei, L., D'Oliveira, M.V.N., De Oliveira, L.C., Peña-Claros, M., Putz, F.E., Ruschel, A.R., Rodney, K., Roopsind, A., Shenkin, A., Da Silva, K.E., De Souza, C.R., Toledo, M., Vidal, E., West, T.A.P., Wortel, V., Sist, P., 2015. Rapid tree carbon stock recovery in managed Amazonian forests. Curr. Biol. 25, R787–R788. http://dx.doi.org/10.1016/j.cub.2015.07.034.
Sasaki, N., Asner, G.P., Pan, Y., Knorr, W., Durst, P.B., Ma, H.O., Lowe, A.J., Koh, L.P., Putz, F.E., 2016. Sustainable management of tropical forests can reduce carbon emissions and stabilize timber production. Front. Environ. Sci. http://dx.doi.org/10.3389/fenvs.2016.00050.
Sheil, D., May, R.M., 1996. Mortality and recruitment rate evaluations in heterogeneous tropical forests. J. Ecol. 84, 91–100.
Spiegelhalter, D.J., Best, N.G., Carlin, B.P., Van Der Linde, A., 2002. Bayesian measures of model complexity and fit. J. R. Stat. Soc. Ser. B Stat. Methodol. 64, 583–616. http://dx.doi.org/10.1111/1467-9868.00353.
Synnott, T.J., 1979. A manual of permanent plot procedure for tropical rainforests Commonweal.
Talbot, J., Lewis, S.L., Lopez-Gonzalez, G., Brienen, R.J.W., Monteagudo, A., Baker, T.R., Feldpausch, T.R., Malhi, Y., Vanderwel, M., Araujo Murakami, A., Arroyo, L.P., Chao, K.J., Erwin, T., van der Heijden, G., Keeling, H., Killeen, T., Neill, D., Núñez Vargas, P., Parada Gutierrez, G.A., Pitman, N., Quesada, C.A., Silveira, M., Stropp, J., Phillips, O.L., 2014. Methods to estimate aboveground wood productivity from long-term forest inventory plots. For. Ecol. Manage. 320, 30–38. http://dx.doi.org/10.1016/j.foreco.2014.02.021.
UFCCC, 2016. Aggregate effect of the intended nationally determined contributions : an update.
van der Hout, C., 1999. Reduced impact logging in the tropical rain forest of Guyana. Tropenbos-Guyana Series 6.
Vidal, E., West, T.A.P., Putz, F.E., 2016. Recovery of biomass and merchantable timber volumes twenty years after conventional and reduced-impact logging in Amazonian Brazil. For. Ecol. Manage. 376, 1–8. http://dx.doi.org/10.1016/j.foreco.2016.06.003.
Werger, M. (Ed.), 2011. Sustainable Management of Tropical Rainforests: The CELOS Management System, Tropenbos Series. Tropenbos International, Paramaribo, Suriname.