

Assessing impacts of selective logging on water, energy, and carbon budgets and ecosystem dynamics in Amazon forests using the Functionally Assembled Terrestrial Ecosystem Simulator [MS No.: bg-2019-129]

Responses to review comments

Associate Editor's comment:

I have now received a new referee report on your revised manuscript. This report is fairly positive but also raises a few questions. Please read this report carefully and revise your manuscript as needed in order to address the questions and comments from this referee.

Response:

We greatly appreciate the associate editor and reviewers for their insightful and encouraging comments. We have made the suggested changes to the manuscript in response to these comments, and believe that the revised manuscript have addressed all of the reviewers' concerns.

Reviewer comments are shown in *Italic*. Author responses are shown in plain text.

Anonymous Referee #2

The authors clearly improved the calibration since the previous version.

Response: Thanks for your encouragement.

In the response letter, the authors mentioned that they updated the model to a new version of FATES. This is not clear in section 2. Did you only reduce the penalty for establishing leaf biomass from the old version?

Response: We did not emphasize the change between versions because it is a little strange to refer to an unaccepted version of the same manuscript and elaborate the version changes there. Nevertheless, the new simulations in the revised manuscript were performed using the FATES version https://github.com/NGEET/fates/releases/tag/sci.1.27.2_api.7.3.0, in which the penalty for establishing leaf biomass is significant reduced based. In the revised manuscript, the model version has been provided in the *Code and data availability* section with a user's guide to show how to check out the codes and run the simulations. The model version used in the original submission is archived at <https://github.com/huangmy/fates-old/tree/logging-experiments>, which is obsolete and no longer available in the FATES github repository.

Since the responses will be published with the paper, we hope that this response can serve as a clarification for readers who have confusions.

In Table 1, the changes are an 0.001 increase in SLA for both PFTs, and significant increase in Vcmax for late successional PFT. Are these two increases the major reason for the better fitting in LAI and GPP? Or what is the major modification that leads to the improvement in model-data fitting?

Response: In the original manuscript, the values of SLA are 0.016 and 0.015, those of Vcmax are 68 and 60, for the early and late successional PFTs respectively. In the revised manuscript,

the values of SLA are reduced to 0.015 and 0.014, those of Vcmax are reduced to 65 and 50. Other parameter values remain unchanged. With such reductions in SLA and Vcmax, simulated GPP maintain at a similar level as that in the original manuscript, while LAI is significantly improved. Therefore, we believe that the model structural improvement in reducing for establishing leaf biomass was successful and is the key reason for the better model-data fitting.

Moreover, compared with the previous version, why do NPP and RH lose their seasonality?

Response: In the original manuscript, the comparison of NPP, HR, and AR were performed by comparing simulated monthly values against the annual estimates, which was not appropriate. In the revised version, we fixed this issue by comparing simulated annual values against estimated annual values from Miller et al., 2011. Such a difference is reflected in units of vertical axis in indicated in the units of the vertical axis in Figure 6 in the revised manuscript. We added a sentence in the caption of figure 6 of clarify it.

Table S1 and Figure S1 were used to show the uncertainty range due to different parameter combinations. However, it is not clear how did you determined the final set of parameter values in Table 1. Did you choose the set of parameter values, which gave you the lowest RMSE of NEE or something else?

Response: Thank you for asking this question. We selected the final set of parameter values using the following criteria:

1. Calculate the RMSEs of NEE, GPP, ER, AGB, CWD, and LAI of each simulation;
2. Select 10 simulations with the lowest sums of RMSEs of the selected variables;
3. Finalize the selection by choosing the simulations with the best ratio of early vs late successional PFTs as indicated in Figure 5.

We have added this procedure to the caption of Table S1 in the revised manuscript.

1 **Assessing impacts of selective logging on water,**
2 **energy, and carbon budgets and ecosystem dynamics**
3 **in Amazon forests using the Functionally Assembled**
4 **Terrestrial Ecosystem Simulator**

5
6 Maoyi Huang^{1*}, Yi Xu^{1,2}, Marcos Longo^{3,4}, Michael Keller^{3,4,5}, Ryan Knox⁶, Charles Koven⁶,
7 Rosie Fisher⁷
8

9 ¹Atmospheric Sciences and Global Change Division, Pacific Northwest National Laboratory, Richland, WA, USA

10 ²School of Geography, Nanjing Normal University, Nanjing, China

11 ³Embrapa Agricultural Informatics, Campinas, SP, Brazil

12 ⁴Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA

13 ⁵International Institute of Tropical Forestry, USDA Forest Service, Rio Piedras, Puerto Rico, USA

14 ⁶Earth & Environmental Sciences Division, Lawrence Berkeley National Laboratory, Berkeley, CA, USA

15 ⁷Climate and Global Dynamics Laboratory, National Center for Atmospheric Research, Boulder, CO, USA
16
17

18 *Correspondence to:* Maoyi Huang (Maoyi.Huang@pnnl.gov)

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20

21 **Abstract**

22 Tropical forest degradation from logging, fire, and fragmentation not only alters carbon stocks and
23 carbon fluxes, but also impacts physical land-surface properties such as albedo and roughness
24 length. Such impacts are poorly quantified to date due to difficulties in accessing and maintaining
25 observational infrastructures, and the lack of proper modeling tools for capturing the interactions
26 among biophysical properties, ecosystem demography, canopy structure, and biogeochemical
27 cycling in tropical forests. As a first step to address these limitations, we implemented a selective
28 logging module into the Functionally Assembled Terrestrial Ecosystem Simulator (FATES) by
29 mimicking the ecological, biophysical, and biogeochemical processes following a logging event.
30 The model can specify the timing and aerial extent of logging events, splitting the logged forest
31 patch into disturbed and intact patches, determine the survivorship of cohorts in the disturbed
32 patch, and modifying the biomass and necromass (total mass of coarse woody debris and litter)
33 pools following logging. We parameterized the logging module to reproduce a selective logging
34 experiment at the Tapajós National Forest in Brazil and benchmarked model outputs against
35 available field measurements. Our results suggest that the model permits the coexistence of early
36 and late successional functional types and realistically characterizes the seasonality of water and
37 carbon fluxes and stocks, the forest structure and composition, and the ecosystem succession
38 following disturbance. However, the current version of FATES overestimates water stress in the
39 dry season therefore fails to capture seasonal variation in latent and sensible heat fluxes.
40 Moreover, we observed a bias towards low stem density and leaf area when compared to
41 observations, suggesting that improvements are needed in both carbon allocation and
42 establishment of trees. The effects of logging were assessed by different logging scenarios to
43 represent reduced impact and conventional logging practices, both with high and low logging
44 intensities. The model simulations suggest that in comparison to old-growth forests the logged
45 forests rapidly recover water and energy fluxes in one to three years. In contrast, the recovery times
46 for carbon stocks, forest structure and composition are more than 30 years depending on logging
47 practices and intensity. This study lays the foundation to simulate land use change and forest
48 degradation in FATES, which will be an effective tool to directly represent forest management
49 practices and regeneration in the context of Earth System Models.

50 **1 Introduction**

51 Land cover and land use in tropical forest regions are highly dynamic, and nearly all tropical forests
52 are subject to significant human influence (*Martínez-Ramos et al.*, 2016;*Dirzo et al.*, 2014). While
53 old-growth tropical forests have been reported to be carbon sinks that remove carbon dioxide from
54 the atmosphere through photosynthesis, these forests could easily become carbon sources once
55 disturbed (*Luyssaert et al.*, 2008). Using data from forest inventory and long-term ecosystem
56 carbon studies from 1990 to 2007, *Pan et al.* (2011) suggested a net tropical forest can be a net
57 source of carbon source of $1.3 \pm 0.7 \text{ Pg C yr}^{-1}$ from land use change, consisting of a gross tropical
58 deforestation loss of $2.9 \pm 0.5 \text{ Pg C yr}^{-1}$ that is partially offset by a carbon uptake by tropical
59 secondary forest regrowth of $1.6 \pm 0.5 \text{ Pg C yr}^{-1}$. These estimates, however, do not account for
60 tropical forest that has been degraded through the combined effects of selective logging (cutting
61 and removal of merchantable timber), fuelwood harvest, understory fires, and fragmentation
62 (*Nepstad et al.*, 1999;*Bradshaw et al.*, 2009). To date, the effects of forest degradation remain
63 poorly quantified. Recent studies suggested that degradation may contribute to carbon loss 40% as
64 large as clear cut deforestation (*Berenguer et al.*, 2014), and the emission from selective logging
65 alone could be equivalent to ~10% to 50% of that from deforestation in the tropical countries
66 (*Pearson et al.*, 2014;*Huang and Asner*, 2010;*Asner et al.*, 2009). Selective logging of tropical
67 forests is an important contributor to many local and national economies, and correspond to
68 approximately one-eighth of global timber (*Blaser et al.*, 2011). The integrated impact of timber
69 production and other forest uses has been posited as the cause of up to ~30% of the difference
70 between potential and actual biomass stocks globally, comparable in magnitude to the effects of
71 deforestation (*Erb et al.* 2017). Selective logging includes cutting large trees and additional
72 degradation through widespread damage to remaining trees, sub-canopy vegetation, and soils
73 (*Asner et al.*, 2004;*Asner et al.*, 2005). Selective logging accelerates gap-phase regeneration
74 within the degraded forests (*Huang et al.*, 2008).

75 Over half of all tropical forests have been cleared or logged, and almost half of standing
76 old-growth tropical forests are designated by national forest services for timber production
77 (*Sist et al.*, 2015). Disturbances that result from logging are known to cause forest
78 degradation at the same magnitude as deforestation each year in terms of both geographic
79 extent and intensity, with widespread collateral damage to remaining trees, vegetation and

80 soils, leading to disturbance to water, energy, and carbon cycling, as well as ecosystem
81 integrity (*Keller et al., 2004b; Asner et al., 2004; Huang and Asner, 2010*).

82 In most Earth system models (ESMs) that couple terrestrial and atmospheric processes to
83 investigate global change (e.g., the Community Earth System Model or the Energy Exascale Earth
84 System Model), selective logging is typically represented as simple fractions of affected area or
85 an amount of carbon to be removed on a coarse grid (e.g., 0.5 degree). One exception is the
86 representation of wood harvest in the LM3V land model that explicitly accounts for post-
87 disturbance land age distribution, as part of the Geophysical Fluid Dynamics Laboratory (GFDL)
88 Earth system model (*Shevliakova et al., 2009*). In the ESMs, grid cell fractional areas are typically
89 based on timber production rates estimated from sawmill, sales, and export statistics (*Hurt et al.,*
90 *2011; Lawrence et al., 2012*). This approach, while practical, does not effectively differentiate
91 selective logging that retains forest cover from deforestation.

92 The realistic representation of wood harvest was absent in most ESMs because the models
93 generally did not represent the demographic structure of forests (tree size and stem number
94 distributions) (*Bonan, 2008*). But progress over the past two decades in ecological theory and
95 observations (*Bustamante et al., 2015; Strigul et al., 2008; Hurt et al., 1998; Moorcroft et al., 2001*)
96 has made it feasible to include vegetation demography more directly into Earth system models
97 through individual to cohort-based vegetation in land models (*Sato et al., 2007; Watanabe et al.,*
98 *2011; Smith et al., 2001; Smith et al., 2014; Weng et al., 2015; Roy et al., 2003; Hurt et al.,*
99 *1998; Fisher et al., 2015*). These vegetation demography modules are relatively new in land
100 models, so efforts are still under way to improve their parameterizations of resource competition
101 for light, water, and nutrients, recruitment, mortality, and disturbance including both natural and
102 anthropogenic components (*Fisher et al., 2017*).

103 In this study, we aim to (1) describe the development of a selective logging module
104 implemented into The Functionally Assembled Terrestrial Ecosystem Simulator (FATES), for
105 simulating anthropogenic disturbances of various intensities to forest ecosystems and their short-
106 term and long-term effects on water, energy, and carbon cycling, and ecosystem dynamics; (2)
107 assess the capability of FATES in simulating site-level water, energy, and carbon budgets, as well
108 as forest structure and composition; (3) benchmark the simulated variables against available
109 observations at the Tapajós National Forest in the Amazon, thus identifying potential directions
110 for model improvement; and (4) assess the simulated recovery trajectory of tropical forest

111 following disturbance under various logging scenarios. In section 2, we provide a brief summary
112 of FATES, introduce the new selective logging module, and describe numerical experiments
113 performed at two sites with data from field survey and flux towers. In section 3, FATES-simulated
114 water, energy, and carbon fluxes and stocks in intact and disturbed forests are compared to
115 available observations, and the effects of logging practice and intensity on simulated forest
116 recovery trajectory in terms of carbon budget, size structure and composition in plant functional
117 types are assessed. Conclusions and future work are discussed in section 4.

118 **2 Model description and study site**

119 **2.1 The Functionally Assembled Terrestrial Ecosystem Simulator**

120 The Functionally Assembled Terrestrial Ecosystem Simulator (FATES) has been developed as a
121 numerical terrestrial ecosystem model based on the ecosystem demography representation in the
122 community land model (CLM), formerly known as CLM (ED) (*Fisher et al.*, 2015). FATES is an
123 implementation of the cohort-based Ecosystem Demography (ED) concept (*Hurtt et al.*,
124 1998; *Moorcroft et al.*, 2001) that can be called as a library from an ESM land surface scheme,
125 currently including CLM (*Oleson et al.*, 2013) or Energy Exascale Earth system model (E3SM)
126 land model (ELM) ([https://climatemodeling.science.energy.gov/projects/energy-exascale-earth-](https://climatemodeling.science.energy.gov/projects/energy-exascale-earth-system-model)
127 [system-model](https://climatemodeling.science.energy.gov/projects/energy-exascale-earth-system-model)). In FATES, the landscape is discretized into spatially implicit *patches* each of
128 which represents land areas with a similar *age since last disturbance*. The discretization of
129 ecosystems along a disturbance/recovery axis allows the deterministic simulation of successional
130 dynamics within a typical forest ecosystem. Within each patch, individuals are grouped into
131 *cohorts* by plant functional types (PFTs) and size classes (SCs), so that cohorts can compete for
132 light based on their heights and canopy positions. Following disturbance, a patch fission process
133 splits the original patch into undisturbed and disturbed new patches. A patch fusion mechanism is
134 implemented to merge patches with similar structures, which helps prevent the number of patches
135 from growing too big. In addition to the ED concept, FATES also adopted a modified version of
136 the Perfect Plasticity Approximation (PPA) (*Strigul et al.*, 2008) concept by splitting growing
137 cohorts between canopy and understory layers as a continuous function of height designed for
138 increasing the probability of co-existence (*Fisher et al.*, 2010). An earlier version of FATES,

139 CLM(ED), has been applied regionally to explore the sensitivity of biome boundaries to plant trait
140 representation (*Fisher et al.*, 2015).

141 In this study, we specified two plant functional types (PFTs) in FATES corresponding to
142 early successional and late successional plants, representative of the primary axis of variability in
143 tropical forests (*Reich* 2014). The early successional PFT is light-demanding, and grows rapidly
144 under high light conditions common prior to canopy closure. This PFT has low density woody
145 tissues, shorter leaf and root lifetimes, and a higher background mortality compared to the late
146 successional PFT that has dense woody tissues, longer leaf and root lifetimes, and lower
147 background mortality (*Brokaw*, 1985; *Whitmore*, 1998) and thus can survive under deep shade and
148 grow slowly under closed canopy.

149 The key parameters that differentiate the two PFTs in FATES are listed in Table 1, including
150 specific leaf area at the canopy top (SLA_0), the maximum rate of carboxylation at 25 °C (V_{cmax25}),
151 specific wood density, background mortality, leaf and fine root longevity, and leaf C:N ratio. The
152 parameter ranges were selected based on literature for tropical forests. Specifically, it has been
153 reported that SLA values ranges from 0.007-0.039 $m^2 gC^{-1}$ (*Wright et al.*, 2004) and V_{cmax25} ranges
154 between 10.1 and 105.7 $\mu mol m^{-2} s^{-1}$ (*Domingues et al.*, 2005). The specific wood densities were
155 set to be 0.5 and 0.9 $g cm^3$, and the background mortality rates were set to 0.035 and 0.014 yr^{-1}
156 for early and late succession PFTs respectively, consistent with those used in the Ecosystem
157 Demography Model version 2 for Amazon forests (*Longo et al.*, 2019). For simplicity, leaf
158 longevity and root longevity were set to be the same for each PFT (i.e., 0.9 yr and 2.6 yr for early
159 and late successional PFTs) following the range in *Trumbore and Barbosa De Camargo* (2009).

160 Given that both SLA_0 and V_{cmax25} span wide ranges, and have been identified as the most
161 sensitive parameters in FATES in a previous study (*Massoud et al.*, 2019), we performed one-at-
162 a-time sensitivity tests by perturbing them within the reported ranges. Based on these tests, it is
163 evident that these parameters not only affect water, energy, carbon budget simulations, but also
164 the coexistence of the two PFTs. In the version of FATES used in this study (Interested readers
165 are referred to the Code Availability section for details), coexistence of PFTs is not assured for all
166 parameter combinations, even if they are both within reasonable ranges, on account of competitive
167 exclusion feedback processes that prevent coexistence in the presence of large discrepancies in
168 plant growth and reproduction rates (*Fisher et al.* 2010; *Bohn et al.* 2011). In order to demonstrate
169 FATES' capability in simulating water, energy, carbon budgets as well as forest structure and

170 composition in a holistic way, we chose to report results based on a set of parameter values that
171 produces reasonable, stable fractions of two PFTs, as reported in Table 1. Nevertheless, we have
172 included a summary of all sensitivity tests performed in the supplementary material for
173 completeness. The sensitivity tests demonstrated that by tuning SLA_0 and $V_{\text{cmax}25}$ for the different
174 PFTs, FATES is not only capable of capturing coexistence of PFTs, but also capable of
175 reproducing observed water, energy, and carbon cycle fluxes in the tropics.

176

177 **2.2 The selective logging module**

178 The new selective logging module in FATES mimics the ecological, biophysical, and
179 biogeochemical processes following a logging event. The module (1) specifies the timing and
180 areal extent of a logging event; (2) calculates the fractions of trees that are damaged by direct
181 felling, collateral damage, and infrastructure damage, and adds these size-specific plant mortality
182 types to FATES; (3) splits the logged patch into disturbed and intact new patches; (4) applies the
183 calculated survivorship to cohorts in the disturbed patch; and (5) transports harvested logs off-site
184 by reducing site carbon pools, and adds remaining necromass to coarse woody debris and litter
185 pools.

186 The logging module structure and parameterization is based on detailed field and remote
187 sensing studies (*Putz et al., 2008; Asner et al., 2004; Pereira Jr et al., 2002; Asner et al.,*
188 *2005; Feldpausch et al., 2005*). Logging infrastructure including roads, skids, trails, and log decks
189 are conceptually represented (Figure 1). The construction of log decks used to store logs prior to
190 road transport leads to large canopy openings but their contribution to landscape-level gap
191 dynamics is small. In contrast, the canopy gaps caused by tree felling are small but their coverage
192 is spatially extensive at the landscape scale. Variations in logging practices significantly affect the
193 level of disturbance to tropical forest following logging (*Pereira Jr et al., 2002; Macpherson et al.,*
194 *2012; Dykstra, 2002; Putz et al., 2008*). Logging operations in the tropics are often carried out with
195 little planning, and typically use heavy machinery to access the forests accompanied by
196 construction of excessive roads and skid trails, leading to unnecessary tree fall and compaction of
197 the soil. We refer to these typical operations as conventional logging (CL). In contrast, reduced
198 impact logging (RIL) is a practice with extensive pre-harvest planning, where trees are inventoried
199 and mapped out for the most efficient and cost-effective harvest and *seed trees* are deliberately left

200 on site to facilitate faster recovery. Through planning, the construction of skid trails and roads, soil
201 compaction and disturbance can be minimized. Vines connecting trees are cut and tree-fall
202 directions are controlled to reduce damages to surrounding trees. Reduced impact logging results
203 in consistently less disturbance to forests than conventional logging (*Pereira Jr et al. 2002; Putz*
204 *et al. 2008*).

205 The FATES logging module was designed to represent a range of logging practices in field
206 operations at a landscape level. Both CL and RIL can be represented in FATES by specifying
207 mortality rates associated direct felling, collateral damages, and mechanical damages as follows:
208 once logging events are activated, we define three types of mortality associated with logging
209 practices: direct-felling mortality ($lmort_{direct}$), collateral mortality ($lmort_{collateral}$), and
210 mechanical mortality ($lmort_{mechanical}$). The direct felling mortality represents the fraction of trees
211 selected for harvesting that are greater or equal to a diameter threshold (this threshold is defined
212 by the diameter at breast height (DBH) = 1.3 m denoted as DBH_{min}); collateral mortality denotes
213 the fraction of adjacent trees that killed by felling of the harvested trees; and the mechanical
214 mortality represents the fraction of trees killed by construction of log decks, skid trails and roads
215 for accessing the harvested trees, as well as storing and transporting logs offsite (Figure 1a). In a
216 logging operation, the loggers typically avoid large trees when they build log decks, skids, and
217 trails by knocking down relatively small trees as it is not economical to knock down large trees.
218 Therefore, we implemented another DBH threshold, DBH_{max_infra} , so that only a fraction of trees \leq
219 DBH_{max_infra} (called mechanical damage fraction) are removed for building infrastructure
220 (*Feldpausch et al., 2005*).

221 To capture the disturbance mechanisms and degree of damage associated with logging
222 practices at the landscape level, we apply the mortality types following a workflow designed to
223 correspond to field operations. In FATES, as illustrated in Figure 2, individual trees of all plant
224 functional types (PFTs) in one patch are grouped into cohorts of similar-sized trees, whose size
225 and population sizes evolve in time through processes of recruitment, growth, and mortality. For
226 the purpose of reporting and visualizing the model state, these cohorts are binned into a set of 13
227 fixed size classes in terms of the diameter at the breast height (DBH) (i.e., 0 – 5, 5 – 10, 10 – 15,
228 15 – 20, 20 – 30, 30 – 40, 40 – 50, 50 – 60, 60 – 70, 70 – 80, 80 – 90, 90 – 100, and ≥ 100 cm).
229 Cohorts are further organized into canopy and understory layers, which are subject to different
230 light conditions (Figure 2a). When logging activities occur, the canopy trees and a portion of big

231 understory trees lose their crown coverage through direct felling for harvesting logs, or as a result
 232 of collateral and mechanical damages (Figure 2b). The fractions of the canopy trees affected by
 233 the three mortality mechanisms are then summed up to specify the areal percentages of an old
 234 (undisturbed) and a new (disturbed) patch caused by logging in the patch fission process as
 235 discussed section 2.1 (Figure 2c). After patch fission, the canopy layer over the disturbed patch
 236 is removed, while that over the undisturbed patch stays untouched (Figure 2d). In the undisturbed
 237 patch, the survivorship of understory trees is calculated using an understory death fraction
 238 consistent with the default value corresponds to that used for natural disturbance (i.e., 0.5598). To
 239 differentiate logging from natural disturbance, a slightly elevated, logging-specific understory
 240 death fraction is applied in the disturbed patch instead at the time of the logging event. Based on
 241 data from field surveys over logged forest plots in southern Amazon (*Feldpausch et al.*, 2005),
 242 understory death fraction corresponding to logging is now set to be 0.65 as the default, but can be
 243 modified via the FATES parameter file (Figure 2e). Therefore, the logging operations will change
 244 the forest from the undisturbed state shown in Figure 2a to a disturbed state in Figure 2f in the
 245 logging module. It is worth mentioning that the newly generated patches are tracked according to
 246 *age since disturbance* and will be merged with other patches of similar canopy structure following
 247 the patch fusion processes in FATES in later time steps of a simulation, pending the inclusion of
 248 separate land-use fractions for managed and unmanaged forest.

249 Logging operations affect forest structure and composition, and also carbon cycling (*Palace et*
 250 *al.*, 2008) by modifying the live biomass pools and flow of necromass (Figure 3). Following a
 251 logging event, the logged trunk products from the harvested trees are transported off-site (as an
 252 added carbon pool for resource management in the model), while their branches enter the coarse
 253 woody debris (CWD) pool, and their leaves and fine roots enter the litter pool. Similarly, trunks
 254 and branches of the dead trees caused by collateral and mechanical damages also become CWD,
 255 while their leaves and fine roots become litter. Specifically, the densities of dead trees as a result
 256 of direct felling, collateral, and mechanical damages in a cohort are calculated as follows:

$$\begin{aligned}
 D_{\text{direct}} &= \text{lmort}_{\text{direct}} \times \frac{n}{A} \\
 D_{\text{collateral}} &= \text{lmort}_{\text{collateral}} \times \frac{n}{A} \\
 D_{\text{mechanical}} &= \text{lmort}_{\text{mechanical}} \times \frac{n}{A}
 \end{aligned}
 \tag{1}$$

258 where A stands for the area of the patch being logged, and n is the number of individuals in the
 259 cohort where the mortality types apply (i.e., as specified by the size thresholds, DBH_{\min} and
 260 DBH_{\max_infra}). For each cohort, we denote $D_{\text{indirect}} = D_{\text{collateral}} + D_{\text{mechanical}}$ and $D_{\text{total}} =$
 261 $D_{\text{direct}} + D_{\text{indirect}}$.

262 Leaf litter ($\text{Litter}_{\text{leaf}}$, [kg C]) and root litter ($\text{Litter}_{\text{root}}$, [kg C]) at the cohort level are then
 263 calculated as:

$$264 \quad \text{Litter}_{\text{leaf}} = D_{\text{total}} \times B_{\text{leaf}} \times A \quad (2)$$

$$265 \quad \text{Litter}_{\text{root}} = D_{\text{total}} \times (B_{\text{root}} + B_{\text{store}}) \times A \quad (3)$$

266 where B_{leaf} , B_{root} , and B_{store} are live biomass in leaves and fine roots, and stored biomass in
 267 the labile carbon reserve in all individual trees in the cohort of interest.

268 Following the existing CWD structure in FATES (Fisher *et al.*, 2015), CWD in the logging
 269 module is first separated into two categories: above-ground CWD and below-ground CWD.
 270 Within each category, four size classes are tracked based on their source, following Thonicke *et*
 271 *al.* (2010): trunks, large branches, small branches and twigs. Above-ground CWD from trunks
 272 ($\text{CWD}_{\text{trunk_agb}}$, [kg C]) and large branches/small branches/twig ($\text{CWD}_{\text{branch_agb}}$, [kg C]) are
 273 calculated as follows:

$$274 \quad \text{CWD}_{\text{trunk_agb}} = D_{\text{indirect}} \times B_{\text{stem_agb}} \times f_{\text{trunk}} \times A \quad (4)$$

$$275 \quad \text{CWD}_{\text{branch_agb}} = D_{\text{total}} \times B_{\text{stem_agb}} \times f_{\text{branch}} \times A \quad (5)$$

276 where $B_{\text{stem_agb}}$ is the amount of above ground stem biomass in the cohort, f_{trunk} and f_{branch}
 277 represent the fraction of trunks and large branches/small branches/twig. Similarly, the below-
 278 ground CWD from trunks ($\text{CWD}_{\text{trunk_bg}}$, [kg C]) and branches/twig ($\text{CWD}_{\text{branch_bg}}$, [kg C]) are
 279 calculated as follows:

$$280 \quad \text{CWD}_{\text{trunk_bg}} = D_{\text{total}} \times B_{\text{root_bg}} \times f_{\text{trunk}} \times A \quad (6)$$

$$281 \quad \text{CWD}_{\text{branch_bg}} = D_{\text{total}} \times B_{\text{root_bg}} \times f_{\text{branch}} \times A \quad (7)$$

282 where B_{root} [kg C] is the amount of coarse root biomass in the cohort. Site-level total litter and
 283 CWD inputs can then be obtained by integrating the corresponding pools over all the cohorts in
 284 the site. To ensure mass conservation, the total loss of live biomass due to logging, ΔB (i.e.,

285 carbon in leaf, fine roots, storage, and structural pools), needs to be balanced with increases in
286 litter and CWD pools and the carbon stored in harvested logs shipped offsite as follows:

$$287 \quad \Delta B = \Delta Litter + \Delta CWD + trunk_product \quad (8)$$

288 where $\Delta litter$ and ΔCWD are the increments in litter and CWD pools, and *trunk_product*
289 represents harvested logs shipped offsite. The reduction in live biomass pools (e.g.,

290 Following the logging event, the forest structure and composition in terms of cohort
291 distributions, as well as the live biomass and necromass pools are updated. Following this logging
292 event update to forest structure, the native processes simulating physiology, growth and
293 competition for resources in and between cohorts resume. Since the canopy layer is removed in
294 the disturbed patch, the existing understory trees are promoted to the canopy layer, but, in general,
295 the canopy is incompletely filled in by these newly-promoted trees, and thus the canopy does not
296 fully close. Therefore, more light can penetrate and reach the understory layer in the disturbed
297 patch, leading to increases in light-demanding species in the early stage of regeneration, followed
298 by a succession process in which shade tolerant species dominate gradually.

299

300 **2.3 Study site and data**

301 In this study, we used data from two evergreen tropical forest sites located in the Tapajós National
302 Forest (TNF), Brazil (Figure 1b). These sites were established during the Large-Scale Biosphere-
303 Atmosphere Experiment in Amazonia (LBA), and are selected because of data availability
304 including those from forest plot surveys and two flux towers established during the LBA period
305 (*Keller et al.*, 2004a). These sites were named after distances along the BR-163 highway from
306 Santarém: km67 (54°58'W, 2°51'S) and km83 (54°56'W, 3°3'S). They are situated on a flat
307 plateau and were established as a control-treatment pair for a selective logging experiment. Tree
308 felling operations were initiated at km83 in September 2001 for a period of about two months.
309 Both sites are similar with mean annual precipitation of ~2000 mm, and mean annual temperature
310 of 25 °C, on nutrient-poor clay oxisols with low organic content (*Silver et al.*, 2000).

311 Prior to logging, both sites were old-growth forests with limited previous human disturbances
312 caused by hunting, gathering Brazil nuts, and similar activities. A comprehensive set of
313 meteorological variables, as well as land-atmosphere exchanges of water, energy, and carbon
314 fluxes have been measured by an eddy covariance tower at a hourly time step over the period of

315 2002 to 2011, including precipitation, air temperature, surface pressure, relative humidity,
316 incoming shortwave and longwave radiation, latent and sensible heat fluxes, and net ecosystem
317 exchange (NEE) (Hayek et al., 2018). Another flux tower was established at km83, the logged
318 site, with hourly meteorological and eddy covariance measurements in the period of 2000-2003
319 (Miller et al., 2004;Goulden et al., 2004;Saleska et al., 2003). The towers are listed as BR-Sa1
320 and BR-Sa3 in the AmeriFlux network (<https://ameriflux.lbl.gov>).

321 These tower and biometric based observations were summarized to quantify logging-induced
322 perturbations on old-growth Amazonian forests in Miller et al. (2011) and are used in this study to
323 benchmark the model simulated carbon budget. Over the period of 1999 to 2001, all trees ≥ 35 cm
324 in DBH in 20 ha of forest in four 1-km long transects within the km67 footprint were inventoried,
325 as well as trees ≥ 10 cm in DBH on subplots with an area of ~ 4 ha. At km83, inventory surveys on
326 trees ≥ 55 cm in DBH were conducted in 1984 and 2000, and another survey on trees > 10 cm in
327 DBH was conducted in 2000 (Miller et al., 2004). Estimates of above ground biomass (AGB) were
328 then derived using allometric equations for Amazon forests (Rice et al., 2004;Chambers et al.,
329 2004;Keller et al., 2001). Necromass (≥ 2 cm diameter) production was also measured
330 approximately every six months in a 4.5-year period from November 2001 through February 2006
331 in logged and undisturbed forest at km83 (Palace et al., 2008). Field measurements of ground
332 disturbance in terms of number of felled trees, areas disturbed by collateral and mechanical
333 damages were also conducted at a similar site in Pará state along multitemporal sequences of post-
334 harvest regrowth of 0.5–3.5 yr (Asner et al., 2004;Pereira Jr et al., 2002).

335 Table 2 provides a summary of stem density and basal area distribution across size classes at
336 km83 based on the biomass survey data (Menton et al. 2011; de Sousa et al., 2011). To facilitate
337 comparisons with simulations from FATES, we divided the inventory into early and late
338 succession PFTs using threshold of 0.7 g cm^{-3} for specific wood density, consistent with the
339 definition of these PFTs in Table 1. As shown in Table 2, prior to the logging event in year 2000,
340 this forest was composed of 399, 30 & 30 trees per hectare in size classes of 10-30 cm, 30-50 cm,
341 and ≥ 50 cm respectively; Following logging, the numbers were reduced to 396, 29, and 18 trees
342 per hectare, losing $\sim 1.3\%$ of trees ≥ 10 cm in size. The changes in stem density (SD) were caused
343 by different mechanisms for different size classes. The reduction in stem density of 2 ha^{-1} in the
344 ≥ 50 cm size class was caused by timber harvest directly, while the reductions of 3 ha^{-1} and 1 ha^{-1}
345 in the 10-30 cm and 30-50 cm size classes were caused by collateral and mechanical damages.

346 Corresponding to the loss of trees in logging operations, basal area (BA) decreased from 3.9, 4.0,
347 and 12.9 m² ha⁻¹ to 3.8, 3.9, and 10.8 m² ha⁻¹, and above ground biomass (AGB) decreased from
348 3.8, 2.3, and 10.4 kg C m⁻² to 3.8, 2.2, 8.7 kg C m⁻² in the 10-30 cm, 30-50 cm, and ≥50 cm size
349 class, respectively.

350 **2.4 Numerical Experiments**

351 In this study, the gap-filled meteorological forcing data for Tapajós National Forest processed by
352 *Longo (2014)* are used to drive the CLM(FATES) model. Characteristics of the sites, including
353 soil texture, vegetation cover fraction, and canopy height, were obtained from the LBA-Data
354 Model Intercomparison Project (*de Gonçalves et al., 2013*). Specifically, soil at km 67 contains
355 90% clay and 2% sand, while soil at km 83 contains 80% clay and 18% sand. Both sites are covered
356 by tropical evergreen forest at ~ 98% within their footprints, with the remaining 2% assumed to
357 be covered by bare soil. As discussed in *Longo et al. (2018)*, who deployed the Ecosystem
358 Demography model version 2 at this site, soil texture and hence soil hydraulic parameters are
359 highly variable even with the footprint of the same eddy covariance tower, and could have
360 significant impacts on not only water and energy simulations, but also simulated forest
361 composition and carbon stocks and fluxes. Further, generic pedo-transfer functions designed to
362 capture temperate soils typically perform poorly in clay-rich Amazonian soils (*Fisher et al. 2008*,
363 *Tomasella and Hodnett, 1998*). Because we focus on introducing the FATES-logging, we leave
364 for forthcoming studies the exploration of the sensitivity of the simulations to soil texture and other
365 critical environmental factors.

366 CLM(FATES) was initialized using soil texture at km83 (i.e., 80% clay and 18% sand) from
367 bare ground and spun up for 800 years until the carbon pools and forest structure (i.e., size
368 distribution) and composition of PFTs reached equilibrium, by recycling the meteorological
369 forcing at km67 (2001-2011) as the sites are close enough. The final states from spin-up were
370 saved as the initial condition for follow-up simulations. An *intact* experiment was conducted by
371 running the model over a period of 2001 to 2100 without logging by recycling the 2001-2011
372 forcing using the parameter set in Table 1. The atmospheric CO₂ concentration was assumed to be
373 a constant of 367 ppm over the entire simulation period, consistent with the CO₂ levels during the
374 logging treatment (*Dlugokencky et al., 2017*).

375 We specified an experimental logging event in FATES on 1 September 2001 (Table 3). It
376 was reported by *Figueira et al.* (2008) that following the reduced impact logging event in
377 September 2001, 9% of the trees greater or equal to $DBH_{min} = 50$ cm were harvested, with an
378 associated collateral damage fraction of 0.009 for trees $\geq DBH_{min}$. DBH_{max_infra} is set to be 30 cm,
379 so that only a fraction of trees ≤ 30 cm are removed for building infrastructure (*Feldpausch et al.*,
380 2005). This experiment is denoted as the RIL_{low} experiment in Table 2 and is the one that matches
381 the actual logging practice at km83.

382 We recognize that the harvest intensity in September 2001 at km83 was extremely low.
383 Therefore, in order to study the impacts of different logging practices and harvest intensities, three
384 additional logging experiments were conducted as listed in Table 3: conventional logging with
385 high intensity (CL_{high}), conventional logging with low intensity (CL_{low}), and reduced impact
386 logging with high intensity (RIL_{high}). The high intensity logging doubled the direct felling fraction
387 in RIL_{low} and CL_{low} , as shown in the RIL_{high} and CL_{high} experiments. Compared to the RIL
388 experiments, the CL experiments feature elevated collateral and mechanical damages as one would
389 observe in such operations. All logging experiments were initialized from the spun-up state using
390 site characteristics at km83 previously discussed and were conducted over the period of 2001-2100
391 by recycling meteorological forcing from 2001- 2011.

392 **3 Results and discussions**

393 **3.1 Simulated energy and water fluxes**

394 Simulated monthly mean energy and water fluxes at the two sites are shown and compared to
395 available observations in Figure 4. The performances of the simulations closest to site conditions
396 were compared to observations and summarized in Table 4 (i.e., intact for km67 and RIL_{low} for
397 km83). The observed fluxes as well as their uncertainty ranges noted as Obs67 and Obs83 from
398 the towers were obtained from *Saleska et al.* (2013), consistent with those in *Miller et al.* (2011).
399 As shown in Table 4, the simulated mean (\pm standard deviation) latent heat (LH), sensible heat
400 (SH), and net radiation (Rn) fluxes at km83 in RIL_{low} over the period of 2001-2003 are $90.2 \pm$
401 10.1 , 39.6 ± 21.2 and 112.9 ± 12.4 $W m^{-2}$, compared to tower-based observations of 101.6 ± 8.0 ,
402 25.6 ± 5.2 and 129.3 ± 18.5 $W m^{-2}$. Therefore, the simulated and observed Bowen ratios are 0.35
403 and 0.20 at km83, respectively. This result suggests that at an annual time step, the observed

404 partitioning between LH and SH are reasonable, while the net radiation simulated by the model
405 can be improved. At seasonal scales, even though net radiation is captured by CLM (FATES), the
406 model does not adequately partition sensible and latent heat fluxes. This is particularly true for
407 sensible heat fluxes as the model simulates large seasonal variabilities in SH when compared to
408 observations at the site (i.e., standard deviations of monthly-mean simulated SH are $\sim 21.2 \text{ W m}^{-2}$,
409 while observations are $\sim 5.2 \text{ W m}^{-2}$). As illustrated in figures 4(c) and 4(d), the model
410 significantly overestimates SH in the dry season (June-December), while it slightly underestimates
411 SH in the wet season. It is worth mentioning that incomplete closure of the energy budget is
412 common at eddy covariance towers (*Wilson et al., 2002; Foken, 2008*) and has been reported to be
413 $\sim 87\%$ at the two sites (*Saleska et al., 2003*).

414 Figure 4(j) shows the comparison between simulated and observed (*Goulden et al., 2010*)
415 volumetric soil moisture content (m^3m^{-3}) at top 10 cm. This comparison reveals another model
416 structural deficiency, that is, even though the model simulates higher soil moisture contents
417 compared to observations (a feature generally attributable to the soil moisture retention curve), the
418 transpiration beta factor, the down-regulating factor of transpiration from plants, fluctuates
419 significantly over a wide range, and can be as low as 0.3 in the dry season. In reality flux towers
420 in the Amazon generally do not show severe moisture limitations in the dry season (*Fisher et al.*
421 *2007*). The lack of limitation is typically attributed to the plant's ability to extract soil moisture
422 from deep soil layers, a phenomenon that is difficult to simulate using a classical beta function
423 (*Baker et al. 2008*), and potentially is reconcilable using hydrodynamic representation of plant
424 water uptake (*Powell et al. 2014; Christoffersen et al. 2016*) as are in the final stages of
425 incorporation into the FATES model. Consequently, the model simulates consistently low ET
426 during dry seasons (figures 4(e) and 4(f)), while observations indicate that canopies are highly
427 productive owing to adequate water supply to support transpiration and photosynthesis, which
428 could further stimulate coordinated leaf growth with senescence during the dry season (*Wu et al.*
429 *2016; 2017*).

430

431 **3.2 Carbon budget, and forest structure and composition in the intact forest**

432 Figures 5, 6, and 7 show simulated carbon pools and fluxes, which are tabulated in Table 5 as well.
433 As shown in Figure 5, prior to logging, the simulated above ground biomass and necromass (CWD
434 + litter) are 174 Mg C ha^{-1} and 50 Mg C ha^{-1} , compared to 165 Mg C ha^{-1} and $58.4 \text{ Mg C ha}^{-1}$ based

435 on permanent plot measurements. The simulated carbon pools are generally lower than
436 observations reported in *Miller et al.* (2011) but are within reasonable ranges, as errors associated
437 with these estimates could be as high as 50% due to issues related to sampling and allometric
438 equations, as discussed in *Keller et al.* (2001). The lower biomass estimates are consistent with the
439 finding of excessive soil moisture stress during the dry season, and low LAI in the model.

440 Combining forest inventory and eddy covariance measurements, *Miller et al.* (2011) also
441 provides estimates for net ecosystem exchange (NEE), gross primary production (GPP), net
442 primary production (NPP), ecosystem respiration (ER), heterotrophic respiration (HR), and
443 autotrophic respiration (AR). As shown in Table 5, the model simulates reasonable values in GPP
444 ($30.4 \text{ Mg C ha}^{-2} \text{ yr}^{-1}$) and ER ($29.7 \text{ Mg C ha}^{-2} \text{ yr}^{-1}$), when compared to values estimated from the
445 observations ($32.6 \text{ Mg C ha}^{-2} \text{ yr}^{-1}$ for GPP and $31.9 \text{ Mg C ha}^{-2} \text{ yr}^{-1}$ for ER) in the intact forest.
446 However, the model appears to overestimate NPP ($13.5 \text{ Mg C ha}^{-2} \text{ yr}^{-1}$ as compared to the
447 observation-based estimate of $9.5 \text{ Mg C ha}^{-2} \text{ yr}^{-1}$) and HR ($12.8 \text{ Mg C ha}^{-2} \text{ yr}^{-1}$ as compared to the
448 estimated value of $8.9 \text{ Mg C ha}^{-2} \text{ yr}^{-1}$), while underestimate AR ($16.8 \text{ Mg C ha}^{-2} \text{ yr}^{-1}$ as compared
449 to observation-based estimate of $23.1 \text{ Mg C ha}^{-2} \text{ yr}^{-1}$). Nevertheless, it is worth mentioning that
450 we selected the specific parameter set to illustrate the capability of the model in capturing species
451 composition and size structure, while the performance in capturing carbon balance is slightly
452 compromised given the limited number of sensitivity tests performed.

453 Consistent with the carbon budget terms, Table 5 lists the simulated and observed values of
454 stem density (ha^{-1}) in different size classes in term of DBH. The model simulates 471 trees per
455 hectare with DBHs greater than or equal to 10 cm in the intact forest, compared to 459 trees per
456 hectare from observed inventory. In terms of distribution across the DBH classes of 10-30 cm, 30-
457 50 cm, and ≥ 50 cm, 339, 73, and 59 N ha^{-1} of trees were simulated, while 399, 30, and 30 N ha^{-1}
458 were observed in the intact forest. In general, this version of FATES is able to reproduce the size
459 structure and tree density in the tropics reasonably well. In addition to size distribution, by
460 parametrizing early and late successional PFTs (Table 1), FATES is capable of simulating the co-
461 existence of the two PFTs, therefore the PFT-specific trajectories of stem density, basal area,
462 canopy and understory mortality rates. We will discuss these in section 3.4.

463
464

465 **3.3 Effects of logging on water, energy, and carbon budgets**

466 The response of energy and water budgets to different levels of logging disturbances are illustrated
467 in Table 4 and Figure 4. Following the logging event, the LAI is reduced proportionally to the
468 logging intensities (-9%, -17%, -14% and -24% for RL_{low} , RL_{high} , CL_{low} , and CL_{high} respectively
469 in September 2001, see figure 4h). Leaf area index recovers within three years to its pre-logging
470 level, or even to slightly higher levels as a result of the improved light environment following
471 logging leading to changes in forest structure and composition (to be discussed in section 3.4). In
472 response to the changes in stem density and LAI, discernible differences are found in all energy
473 budget terms. For example, less leaf area leads to reductions in LH (-0.4%, -0.7%, -0.6%, -1.0%)
474 and increases in SH (0.6%, 1.0%, 0.8%, and 2.0%) proportional to the damage levels (i.e., RL_{low} ,
475 RL_{high} , CL_{low} , and CL_{high}) in the first three years following the logging event when compared to
476 the control simulation. Energy budget responses scale with the level of damage, so that the biggest
477 differences are detected in the CL_{high} scenario, followed by RIL_{high} , CL_{low} and RIL_{low} . The
478 difference in simulated water and energy fluxes between the RIL_{low} (i.e., the scenario that is the
479 closest to the experimental logging event) and intact cases is the smallest, as the level of damage
480 is the lowest among all scenarios.

481 As with LAI, the water and energy fluxes recover rapidly in 3-4 years following logging.
482 *Miller et al.* (2011) compared observed sensible and latent heat fluxes between the control (km67)
483 and logged sites (km83). They found that in the first three years following logging, the between-
484 sites difference (i.e., logged – control) in LH reduced from 19.7 ± 2.4 to 15.7 ± 1.0 W m², and that
485 in SH increased from 3.6 ± 1.1 to 5.4 ± 0.4 W m². When normalized by observed fluxes during the
486 same periods at km83, these changes correspond to a -4% reduction in LH and a 7% increase in
487 SH, compared to the -0.5% and 4% differences in LH and SH between RL_{low} and the control
488 simulations. In general, both observations and our modelling results suggest that the impacts of
489 reduced impact logging on energy fluxes are modest and that the energy and water fluxes can
490 quickly recover to their pre-logging conditions at the site.

491 Figures 6 and 7 show the impact of logging on carbon fluxes and pools at a monthly time
492 step, and the corresponding annual fluxes and changes in carbon pools are summarized in Table 5.
493 The logging disturbance leads to reductions in GPP, NPP, AR, and AGB, and increases in ER,
494 NEE, HR, and CWD. The impacts of logging on the carbon budgets are also proportional to
495 logging damage levels. Specifically, logging reduces the simulated AGB from 174 Mg C ha⁻¹

496 (intact) to 156 Mg C ha⁻¹ (RIL_{low}), 137 Mg C ha⁻¹ (RIL_{high}), 154 Mg C ha⁻¹ (CL_{low}) and 134 (CL_{high}),
497 while increases the simulated necromass pool (CWD + litter) from 50.0 Mg C ha⁻¹ in the intact
498 case to 73 Mg C ha⁻¹ (RIL_{low}), 97 Mg C ha⁻¹ (RIL_{high}), 76 Mg C ha⁻¹ (CL_{low}) and 101 (CL_{high}). For
499 the case closest to the experimental logging event (RIL_{low}), the changes in AGB and necromass
500 from the intact case are -18 Mg C ha⁻¹ (10%) and 23.0 Mg C ha⁻¹ (46%), in comparison to observed
501 changes of -22 Mg C ha⁻¹ in AGB (12%) and 16 Mg C ha⁻¹ (27%) in necromass from *Miller et al.*
502 (2011), respectively. The magnitudes and directions of these changes are reasonable when
503 compared to observations (i.e., decreases in GPP, ER, and AR following logging). On the other
504 hand, the simulations indicate that the forest could be turned from a carbon sink (-0.69 Mg C ha⁻¹
505 yr⁻¹) to a larger carbon source in 1-5 years following logging, consistent with observations from
506 the tower suggested that the forest was a carbon sink or a modest carbon source (-0.6 ± 0.8 Mg C
507 ha⁻¹ yr⁻¹) prior to logging.

508 The recovery trajectories following logging are also shown in figures 6, 7, and Table 5. It
509 takes more than 70 years for AGB to return to its pre-logging levels, but the recovery of carbon
510 fluxes such as GPP, NPP, and AR is much faster (i.e., within five years following logging). The
511 initial recovery rates of AGB following logging are faster for high-intensity logging because
512 increased light reaching the forest floor, as indicated by the steeper slopes corresponding to the
513 CL_{high} and RIL_{high} scenarios compared to those of CL_{low} and RIL_{low} (figure 9h). This finding is
514 consistent with previous observational and modelling studies (*Mazzei et al.*, 2010; *Huang and*
515 *Asner*, 2010) in that the damage level determines the number of years required to recover the
516 original AGB, and the AGB accumulation rates in recently logged forests are higher than that in
517 intact forest. For example, by synthesizing data from 79 permanent plots at 10 sites across the
518 Amazon basin, *Ruttishauser et al.* (2016) and *Piponiot et al.* (2018) show that it requires 12, 43,
519 and 75 years for the forest to recover with initial losses of 10, 25, or 50% in AGB. Corresponding
520 to the changes in AGB, logging introduces a large amount of necromass to the forest floor, with
521 the highest increases in the CL_{high} and RIL_{high} scenarios. As shown in Figure 7(d) and Table 5,
522 necromass and CWD pools return to the pre-logging level in ~15 years. Meanwhile, HR in RIL_{low}
523 stays elevated in five years following logging but converges to that from the intact simulation in
524 ~10 years, which is consistent with observation (*Miller et al. 2011*; Table 5).

525

526 **3.4 Effects of logging on forest structure and composition**

527 The capability of the CLM(FATES) model to simulate vegetation demographics, forest structure
528 and composition, while simulating the water, energy, and carbon budgets simultaneously (Fisher
529 et al. 2017) allows interrogation of the modelled impacts of alternative logging practices on forest
530 size structure. Table 6 shows forest structure in terms of stem density distribution across size
531 classes from the simulations compared to observations from the site, while figures 8 and 9 further
532 break it down into early and late successional PFTs and size classes in terms of stem density and
533 basal areas. As discussed in section 2.2 and summarized in Table 3, the logging practices, reduced
534 impact logging and conventional logging, differ in terms of pre-harvest planning and actual field
535 operation to minimize collateral and mechanical damages, while the logging intensities (i.e., high
536 and low) indicate the target direct felling fractions. The corresponding outcomes of changes in
537 forest structure in comparison to the intact forest, as simulated by FATES, are summarized in
538 tables 6 and 7. The conventional logging scenarios (i.e., CL_{high} and CL_{low}), feature more losses in
539 small trees less than 30 cm in DBH, when compared to the smaller reduction in stem density in
540 size classes less than 30 cm in DBH in the reduced impact logging scenarios (i.e., RIL_{high} and
541 RIL_{low}). Scenarios with different logging intensities (i.e., high and low) result in different direct
542 felling intensity. That is, the numbers of surviving large trees (DBH \geq 30 cm) in RIL_{low} and CL_{low}
543 is 117 ha⁻¹ and 115 ha⁻¹ but those in RIL_{high} and CL_{high} are 106 ha⁻¹ and 103 ha⁻¹.

544 In response to the improved light environment after removal of large trees, early successional
545 trees quickly establish and populate the tree fall gaps following logging in 2-3 years as shown
546 Figure 8a). Stem density in the <10 cm size classes is proportional to the damage levels (i.e.,
547 ranked as CL_{high} > RIL_{high} > CL_{low} > RIL_{low}), followed by a transition to late successional trees in
548 later years when the canopy is closed again (Figure 8b). Such a successional process is also evident
549 in figures 9(a) and 9(b) in terms of basal areas. The number of early successional trees in the <10
550 cm size classes then slowly declines afterwards but is sustained throughout the simulation as a
551 result of natural disturbances. Such a shift in the plant community towards light-demanding species
552 following disturbances is consistent with observations reported in literature (*Baraloto et al.*, 2012;
553 *Both et al.*, 2018). Following regeneration in logging gaps, a fraction of trees wins the competition
554 within the 0-10 cm size classes and is promoted to the 10-30 cm size classes in about 10 years
555 following the disturbances (figures 8d and 9d). Then a fraction of those trees subsequently enter
556 the 30-50 cm size classes in 20-40 years following the disturbance (figures 8f and 9f) and so on

557 through larger size classes afterwards (figures 8h and 9h). We note that despite the goal of
558 achieving a deterministic and smooth averaging across discrete stochastic disturbance events using
559 the ecosystem demography approach (*Moorcroft et al.*, 2001) in FATES, the successional process
560 described above, as well as the total numbers of stems in each size bin, shows evidence of episodic
561 and discrete waves of population change. These arise due to the required discretization of the
562 continuous time-since-disturbance heterogeneity into patches, combined with the current
563 maximum cap on the number of patches in FATES (10 per site).

564 As discussed in section 2.4, the early successional trees have a high mortality (figure
565 10a,c,e,g) compared to the mortality (figure 10b,d,f,h) of late successional trees as expected given
566 their higher background mortality rate. Their mortality also fluctuates at an equilibrium level
567 because of the periodic gap dynamics due to natural disturbances, while the mortality of late
568 successional trees remains stable. The mortality rates of canopy trees (figures 11a,c,e,g) remain
569 low and stable over the years for all size classes, indicating that canopy trees are not light-limited
570 or water-stressed. In comparison, the mortality rate small understory trees (figure 11b) shows a
571 declining trend following logging, consistent with the decline in mortality of the small early
572 successional tree (Figure 10a). As the understory trees are promoted to larger size classes (figure
573 11d,f), their mortality rates stays high. It is evident that it is hard for the understory trees to be
574 promoted to the largest size class (figure 11h), therefore the mortality cannot be calculated due to
575 the lack in population.

576 **4 Conclusion and Discussions**

577 In this study, we developed a selective logging module in FATES and parameterized the model to
578 simulate different logging practices (conventional and reduced impact) with various intensities.
579 This newly developed selective logging module is capable of mimicking the ecological,
580 biophysical, and biogeochemical processes at a landscape level following a logging event in a
581 lumped way by (1) specifying the timing and areal extent of a logging event; (2) calculating the
582 fractions of trees that are damaged by direct felling, collateral damage, and infrastructure damage,
583 and adding these size-specific plant mortality types to FATES ; (3) splitting the logged patch into
584 disturbed and intact new patches; (4) applying the calculated survivorship to cohorts in the
585 disturbed patch; and (5) transporting harvested logs off-site and adding the remaining necromass
586 from damaged trees into coarse woody debris and litter pools.

587 We then applied FATES coupled to CLM to the Tapajós National Forest by conducting
588 numerical experiments driven by observed meteorological forcing, and benchmarked the
589 simulations against long-term ecological and eddy covariance measurements. We demonstrated
590 that the model is capable of simulating site-level water, energy, and carbon budgets, as well as
591 forest structure and composition holistically, with responses consistent with those documented in
592 the existing literature as follows:

- 593 1. The model captures perturbations on energy and water budget terms in response to different
594 levels of logging disturbances. Our modelling results suggest that logging leads to reductions
595 in canopy interception, canopy evaporation and transpiration, as well as elevated soil
596 temperature and soil heat fluxes in magnitudes proportional to the damage levels.
- 597 2. The logging disturbance leads to reductions in GPP, NPP, AR, and AGB, and increases in ER,
598 NEE, HR, and CWD. The initial impacts of logging on the carbon budget are also proportional
599 to damage levels as results of different logging practices.
- 600 3. Following the logging event, simulated carbon fluxes such as GPP, NPP, and AR recover
601 within five years, but it takes decades for AGB to return to its pre-logging levels. Consistent
602 with existing observational based literature, initial recovery of AGB is faster when the logging
603 intensity is higher in response to improved light environment in the forest but the time to full
604 AGB recovery in higher intensity logging is longer.
- 605 4. Consistent with observations at Tapajós, the prescribed logging event introduces a large
606 amount of necromass to the forest floor proportional to the damage level of the logging event,
607 which returns to pre-logging level in ~15 years. Simulated HR in low-damage reduced impact
608 logging scenario stays elevated in five years following logging and declines to be the same as
609 the intact forest in ~10 years.
- 610 5. The impacts of alternative logging practices on forest structure and composition were assessed
611 by parameterizing cohort-specific mortality corresponding to direct felling, collateral damage,
612 mechanical damage in the logging module to represent different logging practices (i.e.,
613 conventional logging and reduced impact logging) and intensity (i.e., high and low). In all
614 scenarios, the improved light environment after removal of large trees facilitates establishment
615 and growth of early successional trees in the 0-10 cm DBH size class proportional to the
616 damage levels in the first 2-3 year. Thereafter there is a transition to late successional trees in

617 later years when the canopy is closed. The number of early successional trees then slowly
618 declines but is sustained throughout the simulation as a result of natural disturbances.

619 Given that the representation of gas exchange processes is related to, but also somewhat
620 independent of the representation of ecosystem demography, FATES shows great potential in its
621 capability to capturing ecosystem successional processes in terms of gap-phase regeneration,
622 competition among light-demanding and shade-tolerant species following disturbance, as well as
623 responses of energy, water, and carbon budget components to disturbances. The model projections
624 suggest that while most degraded forests rapidly recover energy fluxes, the recovery times for
625 carbon stocks, forest size structure and forest composition are much longer. The recovery
626 trajectories are highly dependent on logging intensity and practices, the difference between which
627 can be directly simulated by the model. Consistent with field studies, we find through numerical
628 experiments that reduced impact logging leads to more rapid recovery of the water, energy, and
629 carbon cycles, allowing forest structure and composition to recover to their pre-logging levels in a
630 shorter time frame.

631 **5 Future work**

632 Currently, the selective logging module can only simulate single logging events. We also assumed
633 that for a site such as km83, once logging is activated, trees will be harvested from all patches. For
634 regional-scale applications, it will be crucial to represent forest degradation as a result of logging,
635 fire, and fragmentation and their combinations that could repeat over a period. Therefore, structural
636 changes in FATES has been made by adding prognostic variables to track disturbance histories
637 associated with fire, logging, and transitions among land use types. The model also needs to
638 include the dead tree pool (snags and standing dead wood) as harvest operations (especially
639 thinning) can lead to live tree death from machine damage and windthrow. This will be more
640 important for using FATES in temperate, coniferous systems and the varied biogeochemical legacy
641 of standing versus downed wood is important (*Edburg et al. 2011; 2012*). To better understand
642 how nutrient limitation or enhancement (e.g., via deposition or fertilization) can affect the
643 ecosystem dynamics, a nutrient-enabled version of FATES is also under testing and will shed more
644 lights on how biogeochemical cycling could impact vegetation dynamics once available.
645 Nevertheless, this study lays the foundation to simulate land use change and forest degradation in

646 FATES, leading the way to direct representation of forest management practices and regeneration
647 in Earth System Models.

648 We also acknowledge that as a model development study, we applied the model to a site using
649 a single set of parameter values and therefore we ignored the uncertainty associated with model
650 parameters. Nevertheless, the sensitivity study in the supplement material shows that the model
651 parameters can be calibrated with a good benchmarking dataset with various aspects of ecosystem
652 observations. For example, *Koven et al. (2019)* demonstrated a joint team effort of modelers and
653 field observationist toward building field-based benchmarks from Barro Colorado Island, Panama
654 and a parameter sensitivity test platform for physiological and ecosystem dynamics using FATES.
655 We expect to see more of such efforts to better constrain the model in future studies.

656

657

658 **Author contribution**

659 M.H., M.K., and M. L. conceived the study, conceptualized the design of the logging module, and
660 designed the numerical experiments and analysis. Y. X., M. H., and R. K. coded the module. Y.
661 X., R. K., C. K., R. F., M. H. integrated the module into FATES. M. H. performed the numerical
662 experiments and wrote the manuscript with inputs from all coauthors.

663

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672 **Code and data availability**

673 FATES-CLM has two separate repositories for FATES and CLM at:

674 https://github.com/NGEET/fates/releases/tag/sci.1.27.2_api.7.3.0

675 <https://github.com/NGEET/fates-clm/releases>.

676 Site information and data at km67 and km83 can be found at <http://sites.fluxdata.org/BR-Sa1> and
677 <http://sites.fluxdata.org/BR-Sa13>.

678 A README guide to run the model and formatted datasets used to drive model in this study will
679 be made available from the open-source repository

680 https://github.com/huangmy/FATES_Logging_Manuscript.git.

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961 **Tables and Figures**

962

963 Table 1. FATES Parameters that define early and late successional PFTs

Parameter names	Units	Early successional PFT	Late successional PFT
Specific leaf area	$\text{m}^2 \text{gC}^{-1}$	0.015	0.014
V_{cmax} at 25°C	$\mu\text{mol m}^{-2} \text{s}^{-1}$	65	50
Specific wood density	g cm^{-3}	0.5	0.9
Leaf longevity	yr	0.9	2.6
Background mortality rate	yr^{-1}	0.035	0.014
Leaf C:N	gC gN^{-1}	20	40
root longevity	yr	0.9	2.6

964

965 Table 2. Distributions of stem density ($N\ ha^{-1}$), basal area ($m^2\ ha^{-1}$) and above ground biomass ($Kg\ C\ m^{-2}$)
 966 before and after logging at km83, separated by diameter of breast height (normal text) and aggregated across
 967 all sizes (bold text).

Time	Before logging			After Logging		
Variables	Early	Late	Total	Early	Late	Total
Stem Density ($N\ ha^{-1}$)	264	195	459	260	191	443
Stem Density (10-30 cm, $N\ ha^{-1}$)	230	169	399	229	167	396
Stem Density (30-50 cm, $N\ ha^{-1}$)	18	12	30	17	12	29
Stem Density (≥ 50 cm, $N\ ha^{-1}$)	16	14	30	14	12	18
Basal Area ($m^2\ ha^{-1}$)	11.6	9.2	21.0	10.3	8.3	18.5
Basal Area (10-30 cm, $m^2\ ha^{-1}$)	2.2	1.7	4.2	2.2	1.7	3.8
Basal Area (30-50 cm, $m^2\ ha^{-1}$)	2.4	1.6	4.2	2.4	1.6	3.9
Basal Area (≥ 50 cm, $m^2\ ha^{-1}$)	7.0	5.9	12.6	5.8	5.1	10.8
AGB ($Kg\ C\ m^{-2}$)	7.6	8.9	16.5	6.8	7.9	14.7
AGB (10-30 cm, $Kg\ C\ m^{-2}$)	1.8	2.0	3.8	1.8	2.0	3.8
AGB (30-50 cm, $Kg\ C\ m^{-2}$)	1.1	1.1	2.3	1.1	1.1	2.2
AGB (≥ 50 cm, $Kg\ C\ m^{-2}$)	4.6	5.8	10.4	3.8	4.9	8.7

968 * based on inventory during the LBA period (Menton *et al.*, 2011; de Sousa *et al.*, 2011)

969

970 Table 3. Cohort-level fractional damage fractions in different logging scenarios

Scenarios	Conventional Logging		Reduced Impact Logging	
	High	Low	High (KM83×2)	Low (KM83)
Experiments	CL _{high}	CL _{low}	RIL _{high}	RIL _{low}
Direct felling fraction (DBH ≥ DBH _{min} ¹)	0.18	0.09	0.24	0.12
Collateral damage fraction (DBH ≥ DBH _{min})	0.036	0.018	0.024	0.012
mechanical damage fraction (DBH < DBH _{max_infra} ²)	0.113	0.073	0.033	0.024
Understory death fraction ³	0.65	0.65	0.65	0.65

971 ¹DBH_{min} = 50 cm

972 ²DBH_{max_infra} = 30 cm

973 ³Applied to the new patch generated by direct felling and collateral damage

974 Table 4. Comparison of energy fluxes (Mean \pm Standard Deviation) between eddy covariance
 975 tower measurements and FATES simulations.

Variables	LH (W m⁻²)	SH (W m⁻²)	Rn (W m⁻²)
Observed (km83)	101.6 \pm 8.0	25.6 \pm 5.2	129.3 \pm 18.5
Simulated (Intact)	87.6 \pm 13.2	39.4 \pm 21.2	112.8 \pm 12.3
Simulated (RIL_{low})	87.3\pm13.3	39.6\pm21.2	112.9\pm12.4
Simulated (RIL _{high})	87.0 \pm 13.3	39.8 \pm 21.3	112.9 \pm 12.4
Simulated (CL _{low})	87.1 \pm 13.3	39.7 \pm 21.3	112.8 \pm 12.4
Simulated (CL _{high})	86.8 \pm 13.3	39.7 \pm 21.2	112.9 \pm 12.4

976

978 Table 5. Comparison of carbon budget terms between observation-based estimates* and
 979 simulations at km83

Variable	Obs.		Simulated								
	Pre-logging	3-yr Post-logging	Intact	Disturb level	0 yr	1 yr	3 yr	15 yr	30 yr	50 yr	70 yr
AGB (MgC ha ⁻¹)	165	147	174	RIL _{low}	156	157	159	163	167	169	173
				RIL _{high}	137	138	142	152	158	163	168
				CL _{low}	154	155	157	163	167	168	164
				CL _{high}	134	135	139	150	156	163	162
Necromass (MgC ha ⁻¹)	58.4	74.4	50	RIL _{low}	73	67	58	50	50	53	51
				RIL _{high}	97	84	67	48	49	52	51
				CL _{low}	76	69	59	50	50	54	54
				CL _{high}	101	87	68	48	49	51	54
NEE (MgC ha ⁻¹ yr ⁻¹)	-0.6±0.8	-1.0±0.7	-0.69	RIL _{low}	-0.50	1.65	1.83	-0.24	0.27	-0.23	-0.16
				RIL _{high}	-0.43	3.91	3.84	-0.33	0.13	-0.35	-0.27
				CL _{low}	-0.47	2.02	2.04	-0.27	0.27	0.04	0.3
				CL _{high}	-0.39	4.53	4.17	-0.37	0.14	-0.55	0.23
GPP (MgC ha ⁻¹ yr ⁻¹)	32.6±1.3	32.0±1.3	30.4	RIL _{low}	30.0	29.5	30.5	30.0	30.4	30.1	29.9
				RIL _{high}	29.5	28.5	30.0	30.0	30.3	30.1	30.0
				CL _{low}	29.7	29.2	30.3	30.0	30.4	29.8	30.0
				CL _{high}	29.5	27.8	29.7	30.0	30.5	30.4	30.0
NPP (MgC ha ⁻¹ yr ⁻¹)	9.5	9.8	13.5	RIL _{low}	13.5	13.5	14.0	13.3	13.6	13.4	13.2
				RIL _{high}	13.5	13.3	13.8	13.2	13.6	13.4	13.2
				CL _{low}	13.5	13.5	13.9	13.2	13.6	13.2	13.1
				CL _{high}	13.6	13.2	13.8	13.2	13.6	13.5	13.1
ER (MgC ha ⁻¹ yr ⁻¹)	31.9±1.7	31.0±1.6	29.7	RIL _{low}	29.5	31.2	32.3	29.8	30.7	29.8	29.8
				RIL _{high}	29.2	32.4	33.9	29.7	30.4	29.7	29.7
				CL _{low}	29.4	31.2	32.3	29.7	30.7	29.8	30.2
				CL _{high}	29.1	32.4	33.8	29.7	30.6	29.9	30.1
HR (MgC ha ⁻¹ yr ⁻¹)	8.9	10.4	12.8	RIL _{low}	13.0	15.2	15.8	13	13.9	13.2	13.0
				RIL _{high}	13.1	17.2	17.7	12.9	13.7	13.1	12.9
				CL _{low}	13.0	15.5	16.0	13.0	13.9	13.2	13.4
				CL _{high}	13.2	17.7	17.9	12.9	13.77	12.9	13.4
AR (MgC ha ⁻¹ yr ⁻¹)	23.1	20.1	16.8	RIL _{low}	16.5	16.0	16.6	16.8	16.8	16.7	16.7
				RIL _{high}	16.2	15.2	16.2	16.8	16.8	16.7	16.8
				CL _{low}	16.3	15.7	16.4	16.8	16.8	16.6	16.7
				CL _{high}	15.9	14.6	15.9	16.8	16.8	17.0	16.7

980 *Source of observation-based estimates: Miller et al. (2011), Uncertainty in carbon fluxes (GPP, ER, NEE) are based
 981 on u*-filter cutoff analyses described in the same paper.

982

983 Table 6. Simulated Stem Density ($N\ ha^{-1}$) Distribution at km83.

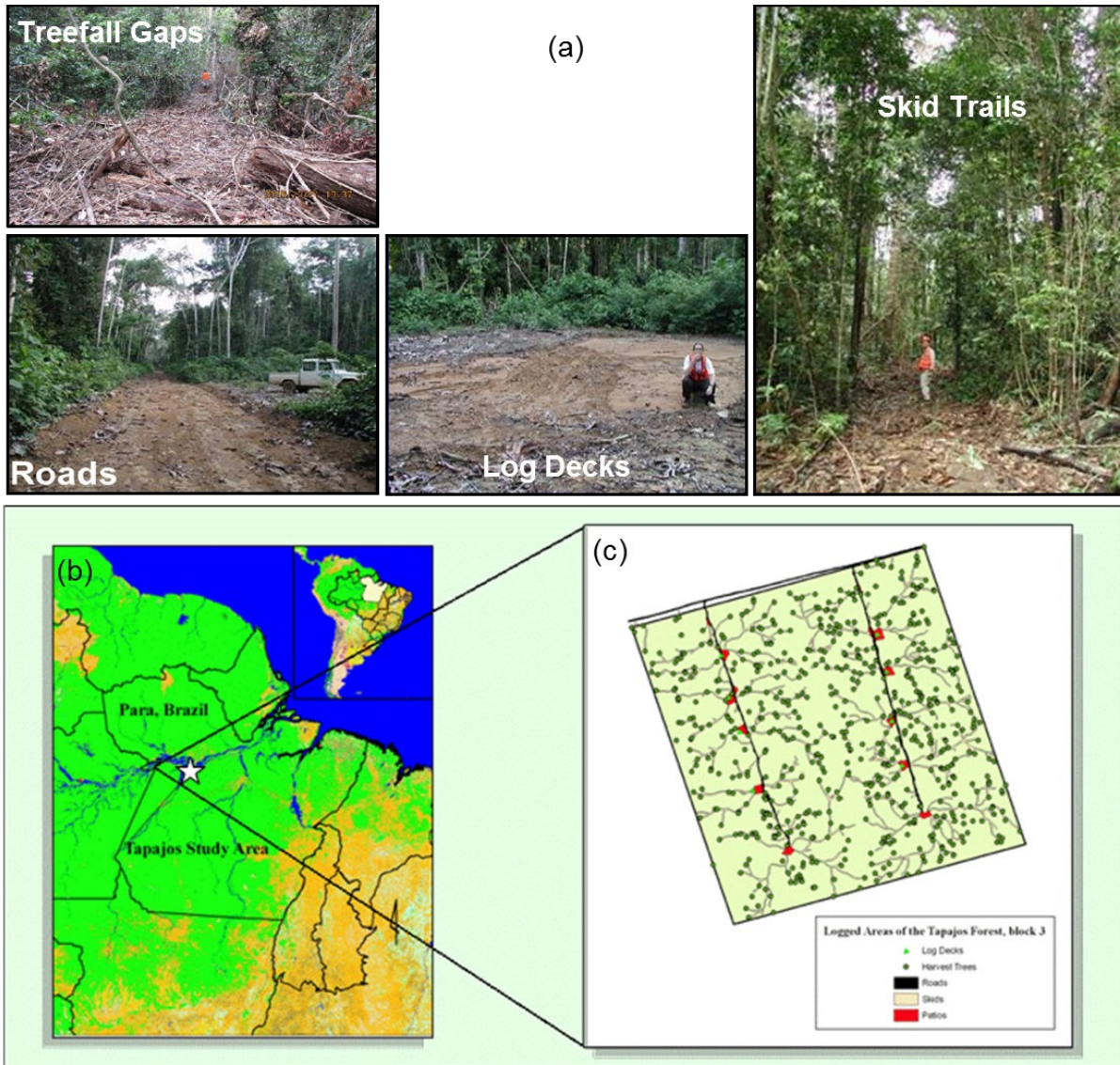
Years following logging	Disturbance level	Size classes (DBH, cm)			
		< 10 cm	10-30 cm	30-50 cm	≥ 50 cm
Pre-logging	Intact	21799	339	73	59
0-yr	RIL _{low}	19101	316	68	49
	RIL _{high}	17628	306	65	41
	CL _{low}	18031	299	66	49
	CL _{high}	15996	280	62	41
1-yr	RIL _{low}	22518	316	67	54
	RIL _{high}	22450	306	66	46
	CL _{low}	23673	303	66	54
	CL _{high}	23505	279	63	46
3-yr	RIL _{low}	23699	364	68	50
	RIL _{high}	25960	368	66	43
	CL _{low}	25048	346	68	51
	CL _{high}	28323	337	64	43
15-yr	RIL _{low}	21105	389	63	56
	RIL _{high}	20618	389	67	53
	CL _{low}	22886	323	61	57
	CL _{high}	22975	348	66	55
30-yr	RIL _{low}	22979	291	82	62
	RIL _{high}	21332	288	87	59
	CL _{low}	23140	317	66	66
	CL _{high}	23273	351	77	53
50-yr	RIL _{low}	22119	258	84	62
	RIL _{high}	23369	335	61	66
	CL _{low}	24806	213	60	76
	CL _{high}	26205	320	72	58
70-yr	RIL _{low}	20594	356	58	64
	RIL _{high}	22143	326	63	61
	CL _{low}	19705	326	55	63
	CL _{high}	19784	337	56	62

984

985 Table 7. Simulated Basal Area ($m^2 ha^{-1}$) Distribution at km83.

Years following logging	Disturbance level	Size classes (DBH, cm)			
		< 10 cm	10-30 cm	30-50 cm	≥ 50 cm
Pre-logging	Intact	3.2	8.1	8.5	44.0
0-yr	RIL _{low}	3.1	8.0	8.3	38.3
	RIL _{high}	3.0	7.7	8.0	31.8
	CL _{low}	2.9	7.6	8.1	37.9
	CL _{high}	2.7	7.1	7.8	31.7
1-yr	RIL _{low}	3.3	7.7	7.7	38.8
	RIL _{high}	3.3	7.5	7.6	32.8
	CL _{low}	3.1	7.4	7.6	38.8
	CL _{high}	3.0	6.8	7.4	32.7
3-yr	RIL _{low}	3.3	8.4	8.4	38.4
	RIL _{high}	3.4	8.5	8.2	32.4
	CL _{low}	3.2	8.0	8.3	38.3
	CL _{high}	3.2	7.9	8.0	32.5
15-yr	RIL _{low}	3.1	9.4	7.6	40.1
	RIL _{high}	3.4	9.5	8.1	35.3
	CL _{low}	3.4	8.9	7.4	40.2
	CL _{high}	3.5	9.1	7.8	35.4
30-yr	RIL _{low}	3.3	7.0	9.0	42.0
	RIL _{high}	3.4	7.2	9.8	37.9
	CL _{low}	3.2	7.7	7.7	42.5
	CL _{high}	3.1	8.7	7.8	38.1
50-yr	RIL _{low}	3.2	6.6	9.1	42.9
	RIL _{high}	3.2	7.6	7.0	41.8
	CL _{low}	3.4	5.3	6.8	45.4
	CL _{high}	3.3	7.1	9.8	38.4
70-yr	RIL _{low}	3.2	8.4	7.3	44.9
	RIL _{high}	3.3	7.9	7.8	42.7
	CL _{low}	3.8	7.6	5.8	42.8
	CL _{high}	3.7	7.0	7.0	41.6

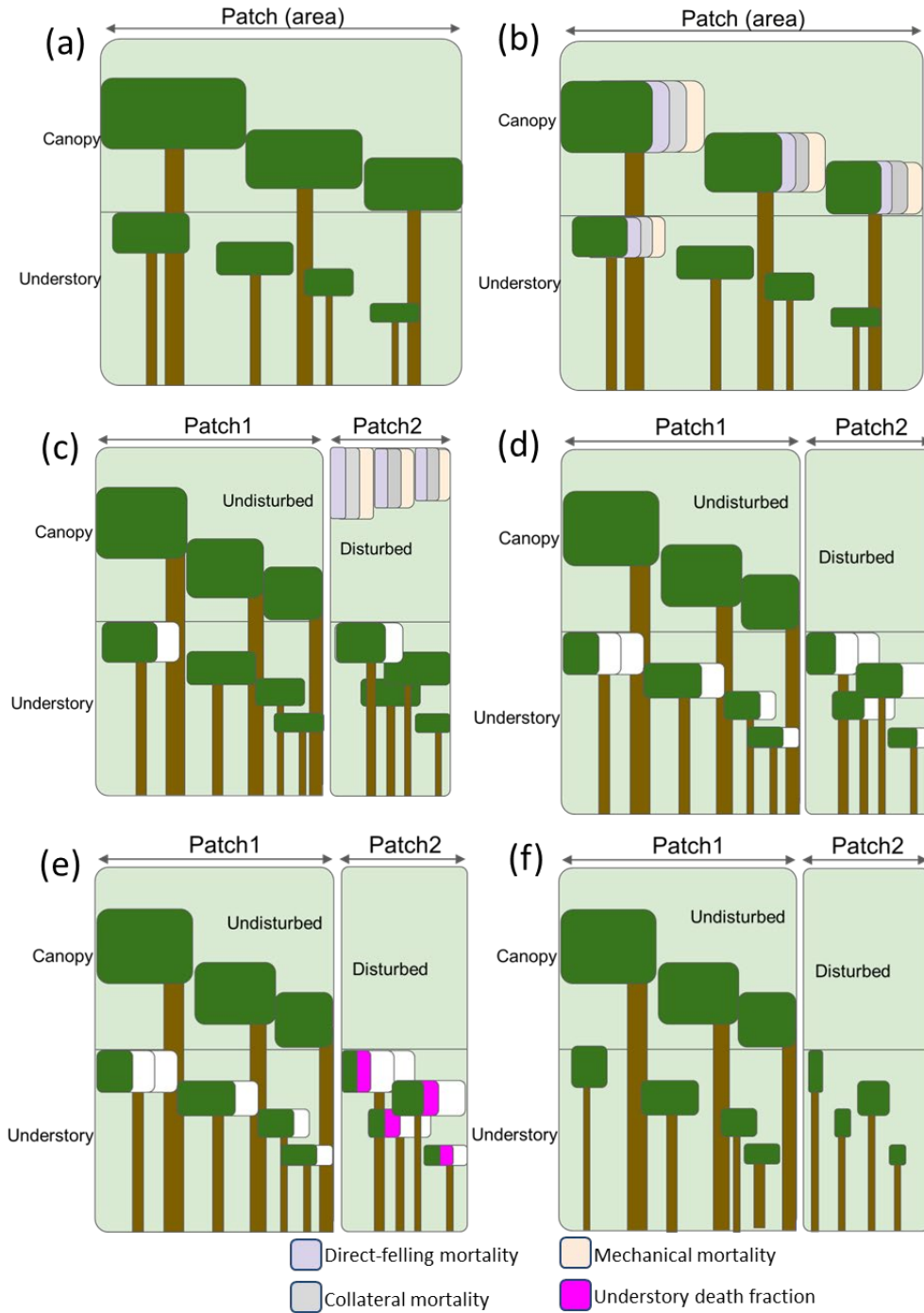
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989 Figure 1. (a) Landscape components of selective logging; (b) location of the Tapajos National Forest in the
 990 Amazon; and (c) a typical logging block showing tree-fall location, skid trail, road, and log deck coverages.
 991 Panels (b) and (c) are from *Asner et al.* (2008).

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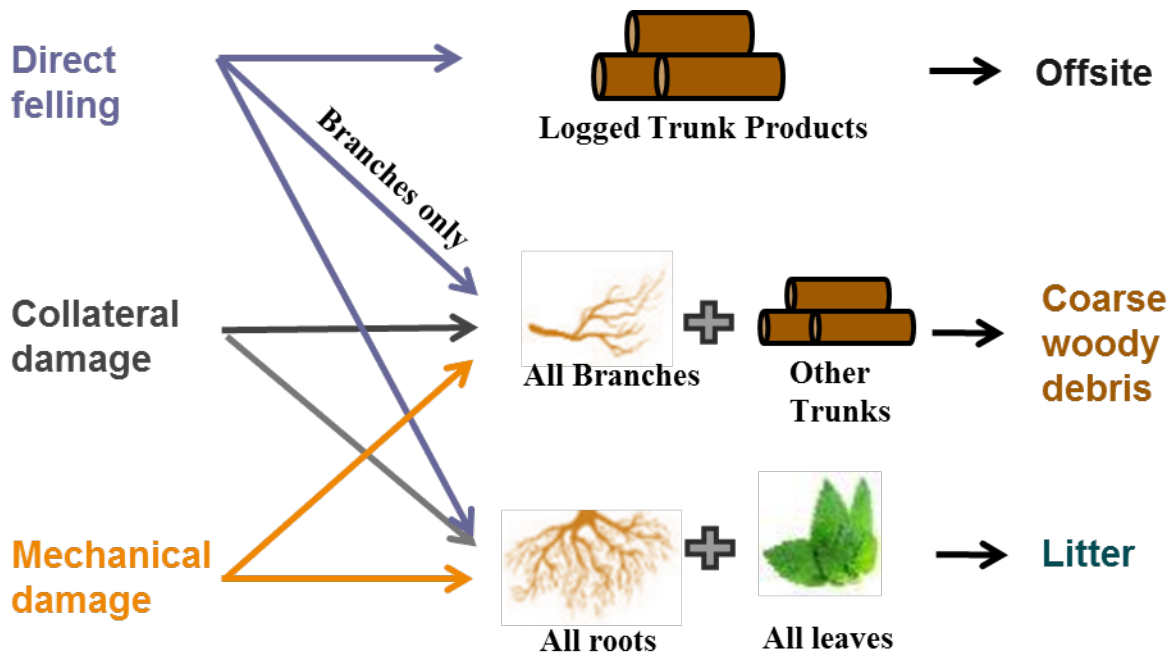


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994 Figure 2. The mortality types (direct-felling, mechanical, and collateral) and patch generating process in
 995 the FATES logging module. The white fraction in (c), (d), (f) indicates mortality associated with other
 996 disturbances in FATES. (a) Canopy and understory layers in each cohort in FATES; (b) Mortality applied
 997 at the time of a logging event; (c) the patch fission process following a given logging event; (d) canopy
 998 removal in the disturbed patch following the logging event; (e) calculate the understory survivorship based
 999 on the understory death fraction in each patch; (d) the final states of the intact and disturbed patches.

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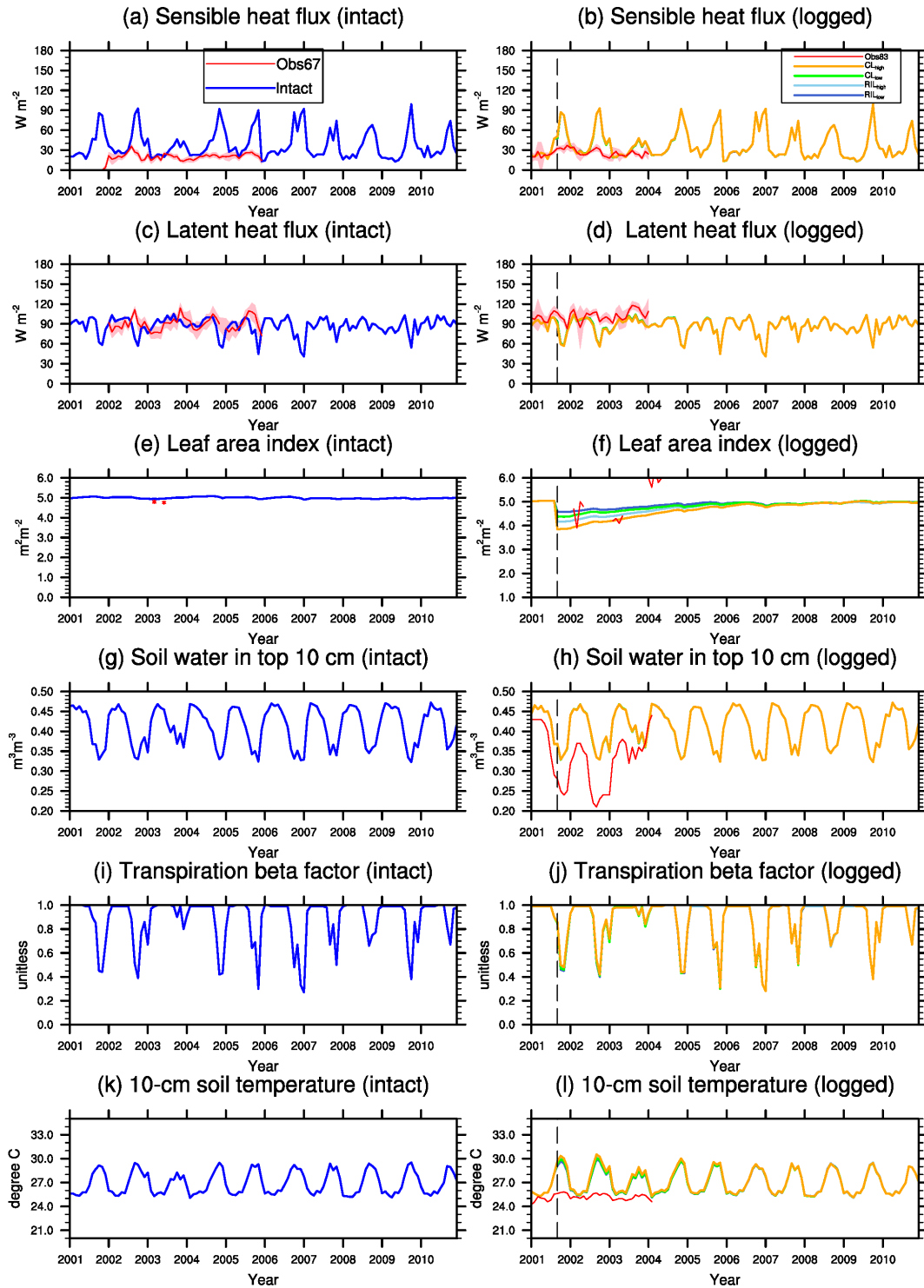
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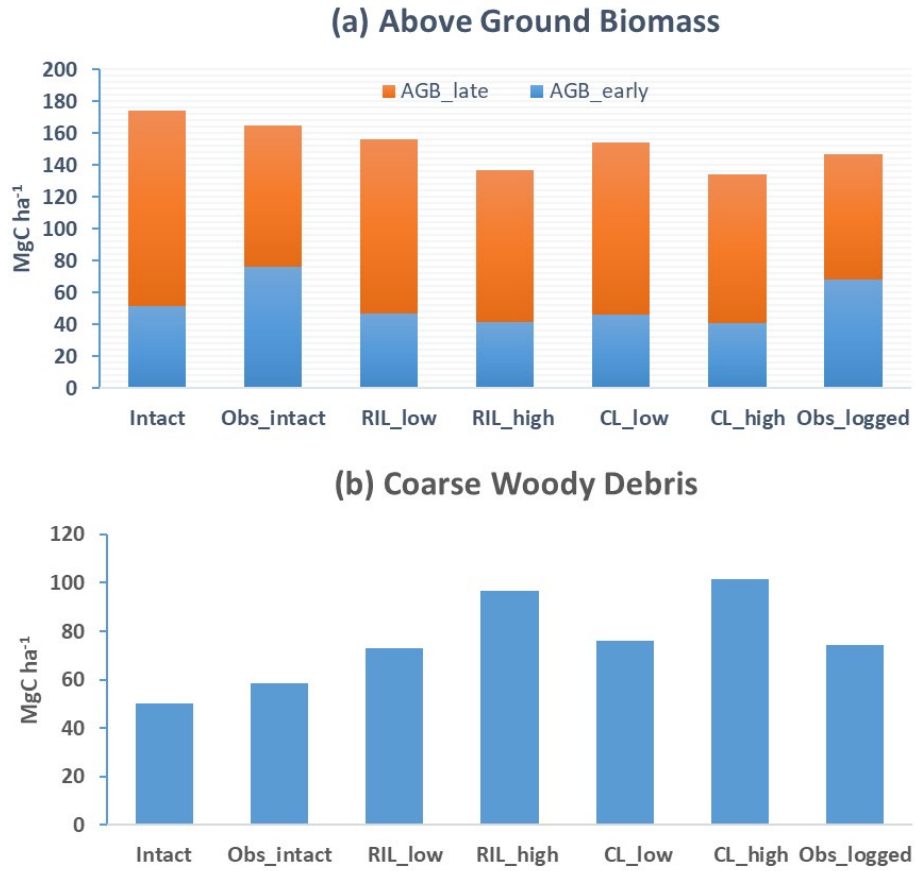
1003 Figure 3. The flow of necromass following logging.

1004

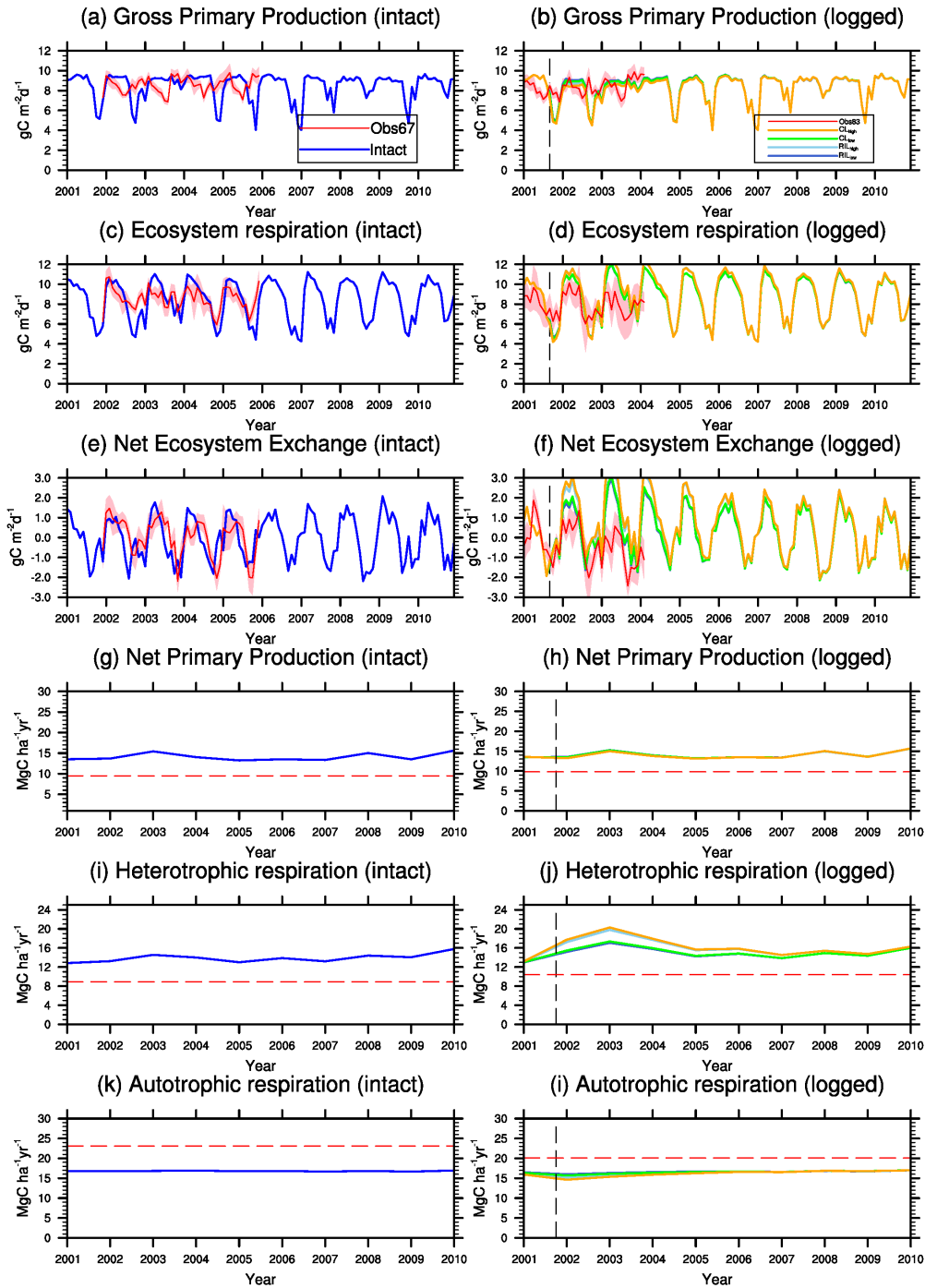


1005

1006 Figure 4. Simulated energy budget terms and leaf area indices in intact and logged forests compared to
 1007 observations from km67 (left) and km83 (right) (Miller *et al.*, 2011). The dashed vertical line indicates the
 1008 timing of the logging event. The shaded area in panel (a)-(f) are uncertainty estimates based on based on
 1009 u^* -filter cutoff analyses in Miller *et al.* (2011).
 1010



1011
 1012 Figure 5. Simulated (a) Above Ground Biomass; and (b) Coarse Woody Debris in intact and logged forests
 1013 in a one-year period before or after the logging event in the four logging scenarios listed in Table 3. The
 1014 observations (Obs_{intact} and Obs_{logged}) were derived from inventory (*Menton et al.*, 2011; *de Sousa et al.*,
 1015 2011).
 1016

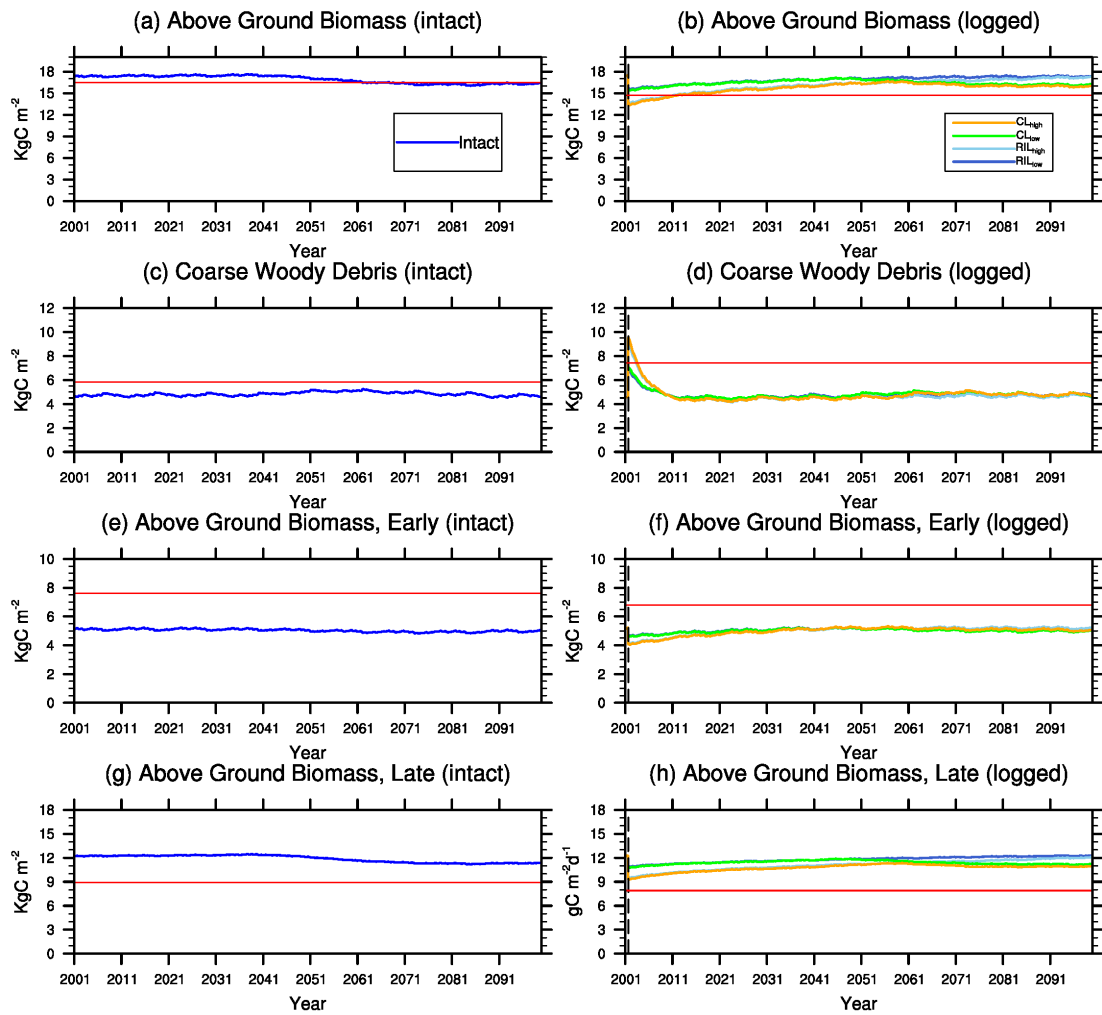


1017

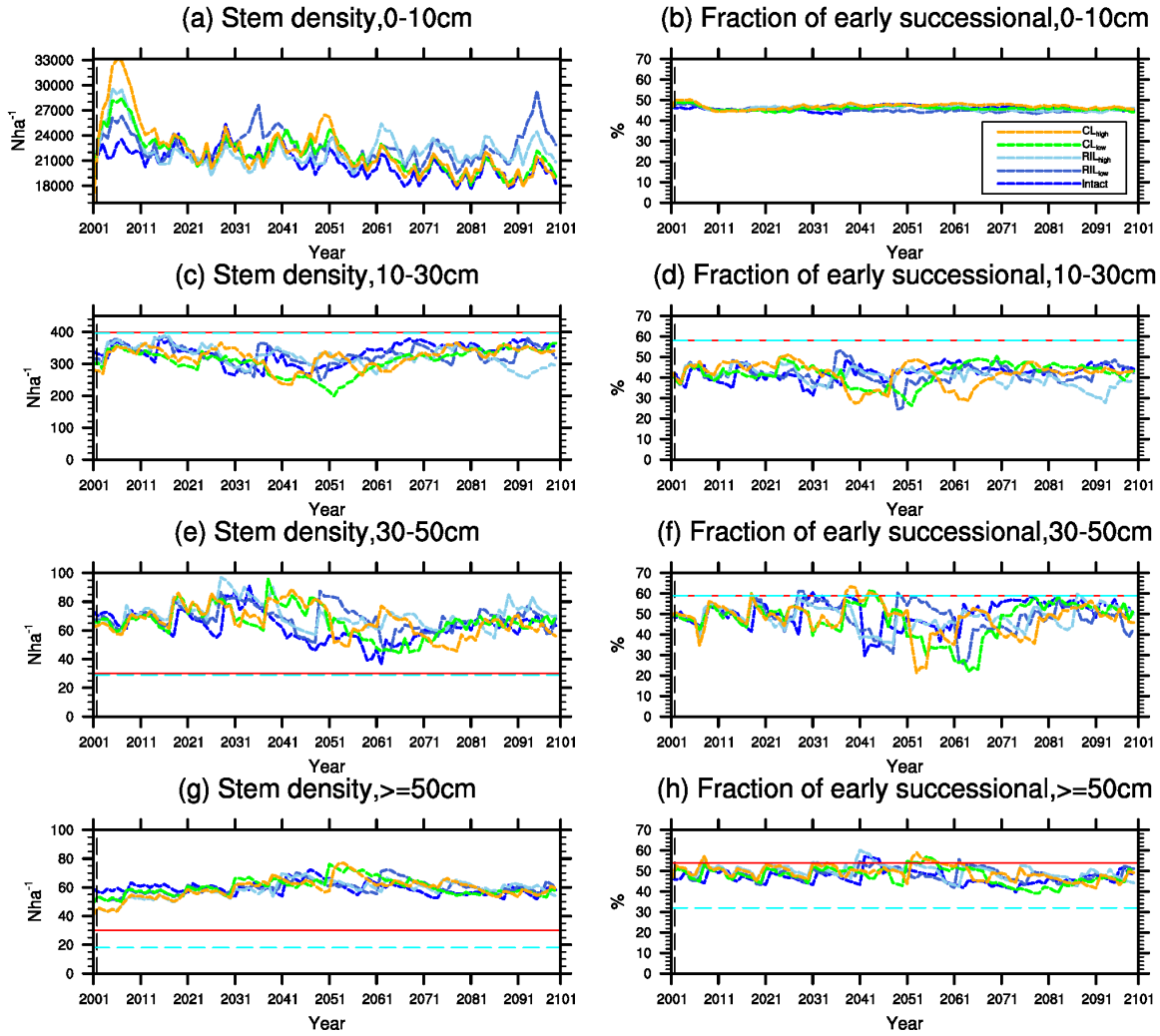
1018 Figure 6. Simulated carbon fluxes in intact and logged forests compared to observed fluxes from km67
 1019 (left) and km83 (right). The dashed black vertical line indicates the timing of the logging event, while the
 1020 red dashed horizontal line indicates estimated fluxes derived based on eddy covariance measurements and
 1021 inventory (Miller *et al.*, 2011). The shaded area in panels (a)-(f) are uncertainty estimates based on
 1022 on u^* -filter cutoff analyses in Miller *et al.* (2011). Panels (g)-(i) show comparisons between annual fluxes
 1023 as only annual estimates of these fluxes are available from Miller *et al.* (2011).

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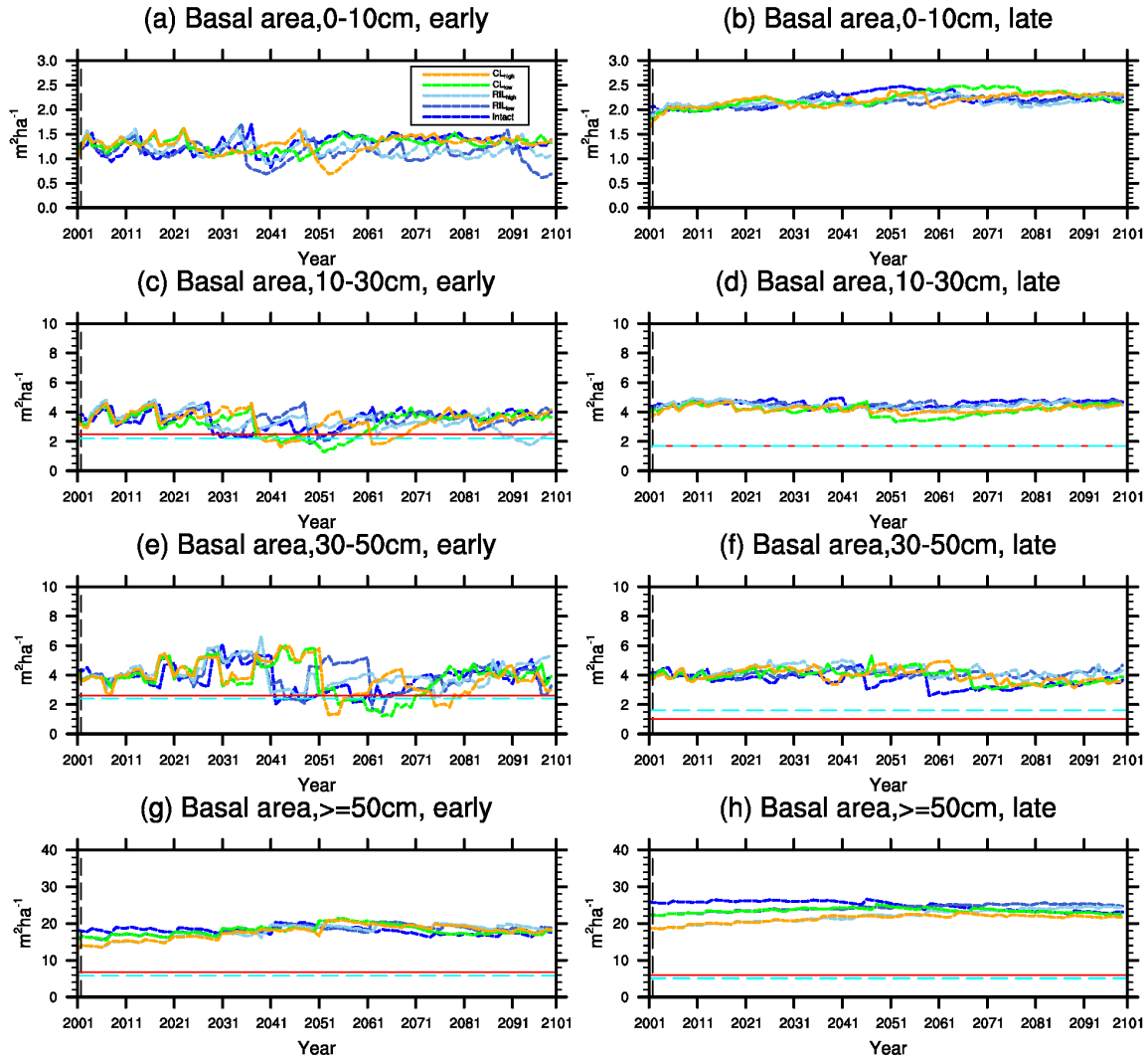


1028 Figure 7. Trajectories of carbon pools in intact (left) and logged (right) forests. The dashed black vertical
 1029 line indicates the timing of the logging event. The red dashed horizontal line indicates observed pre- (left)
 1030 and post-logging (right) inventories respectively (*Menton et al.*, 2011; *de Sousa et al.*, 2011).
 1031



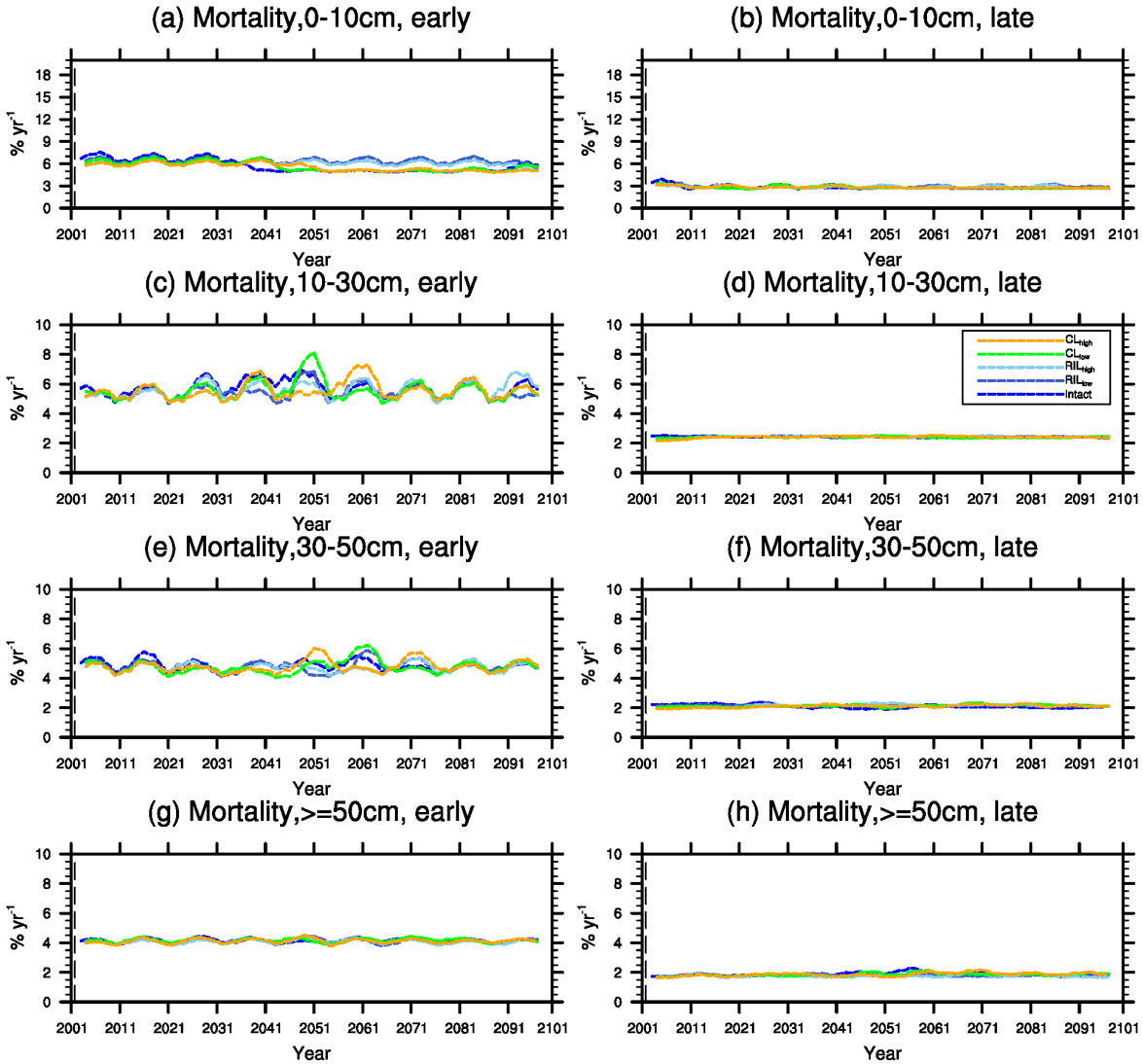
1032

1033 Figure 8. Changes in total stem densities and the fractions of the early successional PFT in different size
 1034 classes following a single logging event on 1 September 2001 at km83. The black dashed vertical line
 1035 indicates the timing of the logging event, while the red solid line and the cyan dashed horizontal line indicate
 1036 observed pre- and post-logging inventories respectively (Menton *et al.*, 2011; de Sousa *et al.*, 2011).
 1037

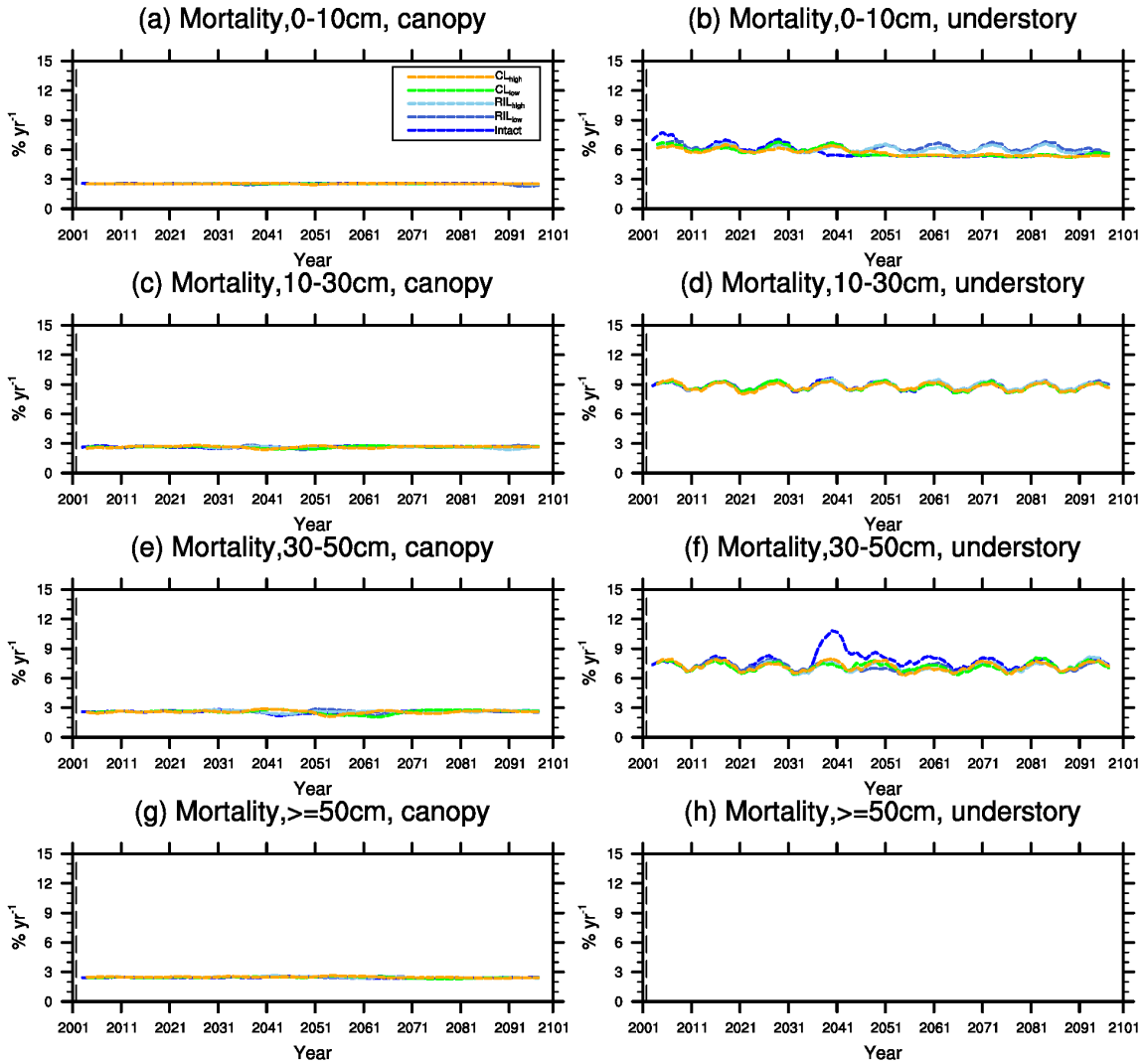


1038

1039 Figure 9. Changes in basal area of the two PFTs in different size classes following a single logging event
 1040 on 1 September 2001 at km83. The black dashed vertical line indicates the timing of the logging event,
 1041 while the red solid line and the cyan dashed horizontal line indicates observed pre- and post-logging
 1042 inventories respectively (Menton *et al.*, 2011; de Sousa *et al.*, 2011). Note that for the size class 0-10 cm,
 1043 observations are not available from the inventory.



1044
 1045 Figure 10. Changes in mortality (5-yr running average) of the (a) early and (b) late successional trees in
 1046 different size classes following a single logging event on 1 September 2001. The black dashed vertical
 1047 line indicates the timing of the logging event.
 1048



1049

1050 Figure 11. Changes in mortality (5-yr running average) of the (a) canopy and (b) understory trees in different
 1051 size classes following a single logging event on 1 September 2001. The black dashed vertical line indicates
 1052 the timing of the logging event.

1053

1054