

1 **Thinner bark increases sensitivity of wetter Amazonian tropical forests to fire**

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35 ABSTRACT

36 Understory fires represent an accelerating threat to Amazonian tropical forests and can,
37 during drought, affect larger areas than deforestation itself. These fires kill trees at rates varying
38 from < 10 to c. 90% depending on fire intensity, forest disturbance history, and tree functional
39 traits. Here, we examine variation in bark thickness across the Amazon. Bark can protect trees
40 from fires, but it is often assumed to be consistently thin across tropical forests. Here, we show
41 that investment in bark varies, with thicker bark in dry forests and thinner in wetter forests. We
42 also show that thinner bark translated into higher fire-driven tree mortality in wetter forests, with
43 between 0.67 to 5.86 gigatons CO₂ lost in Amazon understory fires between 2001-2010. Trait-
44 enabled global vegetation models that explicitly include variation in bark thickness are likely to
45 improve the predictions of fire effects on carbon cycling in tropical forests.

46

47 KEYWORDS: carbon cycle, Amazonia, tree mortality, tropical forest, functional traits

48

49 SPANISH LANGUAGE ABSTRACT

50 En los bosques tropicales de la Amazonia, los incendios de sotobosque representan una amenaza
51 que se está acelerando. Durante la sequía, pueden afectar un área mayor que la deforestación
52 misma. Estos incendios pueden matan árboles a tasas que varían desde <10 hasta cerca de 90%
53 dependiendo de la intensidad del fuego, la historia de perturbaciones forestales y los rasgos
54 funcionales de los árboles. En este estudio, examinamos la variación en el grosor de la corteza en
55 la Amazonía. La corteza puede proteger los árboles de los incendios, pero normalmente se supone
56 que es uniformemente delgada en los bosques tropicales. Aquí, mostramos que el grosor de la
57 corteza varía bastante, con una corteza más gruesa en los bosques secos y más delgada en los
58 bosques húmedos. También, mostramos que cortezas más delgadas resultan en tasas de
59 mortalidad más altas en bosques más húmedos. En total, estimamos que los incendios en el
60 sotobosque de la Amazonía han añadido entre 0,67 y 5,86 gigatoneladas de CO₂ atmosférico entre
61 2001-2010. Los modelos globales de vegetación que predicen los efectos de los incendios sobre
62 el reciclaje de carbono en los bosques tropicales deberían incluir explícitamente la variación en el
63 grosor de la corteza.

64

65 PORTUGUESE LANGUAGE ABSTRACT

66 Os incêndios rasteiros de sub-bosque representam uma ameaça cada vez maior às florestas
67 tropicais da Amazônia. Durante secas, eles podem afetar áreas maiores do que àquelas
68 desmatadas. Esses incêndios matam árvores a taxas que variam de <10 a c. 90%, dependendo da

69 intensidade do fogo, da história de distúrbios florestais e das características funcionais das
70 árvores. Neste estudo, examinamos a variação na espessura da casca na Amazônia. A casca pode
71 proteger árvores do fogo, mas geralmente é considerada uniformemente fina para diversas
72 florestas tropicais. Aqui, mostramos que a espessura da casca varia, com cascas mais espessas
73 ocorrendo em florestas secas e mais finas ocorrendo em florestas mais úmidas. Mostramos
74 também que a casca mais fina resulta em taxas de mortalidade mais altas em florestas úmidas. No
75 total, estimamos que os incêndios de sub-bosque adicionaram entre 0,67 e 5,86 gigatoneladas de
76 CO₂ atmosférico entre 2001-2010. Os modelos globais de vegetação devem incluir explicitamente
77 a variação na espessura da casca ao prever os efeitos do fogo no ciclo do carbono de florestas
78 tropicais.
79

80 INTRODUCTION

81 Fire has emerged as a primary threat to tropical forests in the Amazon over the past three
82 decades, in response to a combination of deforestation and increasing severity and frequency of
83 droughts (Cochrane 2003; Chen *et al.* 2014). Throughout the 20th century, fires were largely
84 restricted to areas experiencing deforestation or existing cleared areas for agricultural
85 maintenance (Alencar *et al.* 2011), but fires can now spread readily through forests that have not
86 been otherwise disturbed (Morton *et al.* 2013), dramatically increasing burned areas. Today,
87 during major droughts (including 2005, 2007, 2010, and 2015-2016), forest understory fires
88 affected larger areas in the Amazon basin than deforestation itself (Aragao *et al.* 2018) – in some
89 years as much as 5x larger (Morton *et al.* 2013). This trend is projected to continue in coming
90 decades, with a greater frequency of Amazon droughts in response to anthropogenic global
91 change (Le Page *et al.* 2017). Predicting forest responses to fires is increasingly imperative.

92 However, our understanding of the short- and long-term ecological impact of tropical forest
93 understory fires is poorly developed, which limits assessments of fire impacts on ecosystems and
94 the global carbon cycle (van der Werf *et al.* 2009; Rappaport *et al.* 2018). One major source of
95 uncertainty is the variability in rates of tree mortality across diverse forests in response to
96 understory fires, with estimates ranging from <10% to c. 90% (Barlow *et al.* 2012). Fire intensity
97 clearly impacts tree mortality (Barlow *et al.* 2012, Brando *et al.* 2014, Rappaport *et al.* 2018), but
98 even so, diverse forests can react differently to similar fire intensity (Hoffmann *et al.* 2009;
99 Barlow *et al.* 2012; Brando *et al.* 2019). Forest history likely explains some part of these
100 differences (Barlow & Peres 2008), but underlying fire-related traits may also vary
101 geographically – a contribution which has, to date, been overlooked in the humid tropical forest
102 context where fires are increasing in prevalence.

103 Among fire-related functional traits, bark is the most amenable to widespread sampling (e.g.,
104 Rosell 2016), and appears broadly to govern fire-driven mortality of tree stems (Harmon 1984).
105 The corky outer bark protects trees from fires by insulating tree cambium and xylem (Michaletz
106 *et al.* 2012; Rosell 2016; Pausas 2017), thereby reducing mortality from cambial necrosis or
107 cavitation due to excessive heating. Reductions in stem mortality among trees with thicker bark
108 have been extensively described in more flammable systems, like savannas (Trollope & Tainton
109 1986; Gignoux *et al.* 1997; Hoffmann *et al.* 2009; 2012), but variation in bark thickness can also
110 determine size- and species-specific differences among trees in their susceptibility to fires even
111 within tropical forests (Barlow *et al.* 2003; Hoffmann *et al.* 2009; Brando *et al.* 2011). However,
112 while bark in savanna and other flammable systems has been the subject of large-scale synthesis
113 (Dantas & Pausas 2013; Pellegrini *et al.* 2017), the extent and determinants of variation in bark

114 thickness within humid tropical forests are not known, complicating efforts to predict carbon
115 losses in the years following fires.

116 Known relationships of bark thickness variation to fire history (Pausas 2017) and abiotic
117 drivers (Richardson *et al.* 2015) allow us to generate informed expectations. The null expectation
118 is that bark is consistently thin and variation therefore minimal. After all, the contemporary
119 literature often assumes that today's fire return intervals in Amazonia are a historical anomaly
120 (Cochrane 2003), such that fire protection may be unnecessary for tropical forest trees. However,
121 the paleo-literature suggests that some Amazonian forests may historically have burned, at least
122 with relatively low frequency in the drier south and east (Bush *et al.* 2008; Power *et al.* 2008).
123 Moreover, within sites, bark thickness varies in tropical forests (Paine *et al.* 2010), and work in
124 temperate forests has documented patterns of variation linked to rainfall (Richardson *et al.* 2015)
125 and fire occurrence (Abatzoglou & Williams 2016). A more plausible alternative hypothesis
126 might therefore be that variation in bark thickness across the Amazon is substantial, reflecting
127 varying evolutionary pressures across the basin, especially from fire (Bond & Midgley 2001;
128 Pausas *et al.* 2006; Pausas 2017) but also from other processes (Rosell 2016). From a more
129 applied perspective, understanding the variability in bark thickness in humid tropical forests will
130 be a key step towards improving spatially-explicit predictions of fire-driven tree mortality and the
131 resulting carbon emissions.

132 Here, we evaluated the extent and degree of variation in bark thickness across Amazonian
133 tropical forests, combining data from a total of 6,280 trees in forests in 13 plots (~ 1 ha each), in
134 diverse regions across Amazonia (see Extended Data Figure 1, Extended Data Table 1), and
135 evaluate variations with respect to climate (annual rainfall and maximum cumulative water deficit
136 [MCWD]), yielding estimates of bark thickness across all Amazonian forests. We then combined
137 these maps of bark thickness with published relationships between bark thickness and tree
138 mortality (Hoffmann *et al.* 2009; Brando *et al.* 2011) to evaluate the potential contributions of
139 bark thickness variation to estimates of tree mortality and biomass loss from understory fires in
140 Amazon forests, evaluated against observed tree mortality and biomass loss synthesized from
141 published studies.

142

143 MATERIALS AND METHODS

144 *Functional Traits and Plot Level Size Class Distributions.* We measured bark thickness at 13
145 sites located throughout the Amazon between 2000 and 2013 (see Figure S1). At each site, we
146 sampled all trees in plots to total ~ 1 ha of area sampled at each site (see Table S1 for plot
147 dimensions). Trees were identified to species at 12 sites (leveraging existing data) or

148 morphospecies at one. At each tree, diameter was measured at breast height (1.3 m), bark was
149 sampled with a corer at 2-4 points around the trunk of a tree, $0.35 \text{ m} \pm 0.05 \text{ m}$ above the ground.

150 For comparison, where data were available, we also evaluated patterns of tree height and
151 wood density across sites. Because tree height and wood density both contribute by definition to
152 biomass (Chave *et al.* 2014), systematic variation in these traits can impact patterns of forest
153 biomass (Quesada *et al.* 2012; Álvarez-Dávila *et al.* 2017), with downstream effects on estimates
154 of biomass loss. Therefore, we examined these directly in order to control for their possible
155 contributions to biomass loss estimates; they also provide a useful point of comparison for
156 evaluating the magnitude of variation in bark thickness. Height was available at a subset of
157 RAINFOR-associated sites (with height observations at a total of 6 sites), with height
158 measurements following published RAINFOR protocols (Feldpausch *et al.* 2011). Wood density
159 was extracted via the ‘BIOMASS’ R package from a freely available dataset published by Chave
160 *et al.* (2014), with tree species, genus, or family as the lookup for extraction.

161 *Rainfall Climatology and Fire.* Annual rainfall and maximum climatological water deficit
162 (MCWD) was calculated from data from the Tropical Rainfall Measuring Mission (Nicholson *et al.*
163 *al.* 2003; Brando *et al.* 2014) from 1998 to 2012 at 0.25 degree resolution. Annual rainfall was
164 calculated by summing monthly rainfall products, and averaging across years to determine mean
165 annual rainfall.

166 MCWD was calculated starting from the first month of the year (south of the Equator =
167 January; north of the Equator = July), when climatological water deficit was defined as 0. Each
168 month, we subtract the theoretical water demand (evaporation plus transpiration) of a typical
169 tropical forest (100 mm monthly rainfall) from the incoming rainfall and add it to the existing
170 water deficit; if the result is > 0 (*i.e.*, there is excess rainfall), we reset the water deficit to 0. After
171 the last month of the year, this yields the CWD for the year. MCWD is defined as the maximum
172 of CWD across all years for each pixel (see also Aragão *et al.* 2007; Brando *et al.* 2010).

173 Fire occurrences were derived via two methods. First, we used the MODIS Active Fires
174 Product (Giglio *et al.* 2016) at the 1 km scale; we used the Active Fires instead of the Burned
175 Area product because the latter is considered somewhat more sensitive in detecting forest-
176 understory fires that do not generate a typical ash or char reflectance values needed for burned
177 area mapping. Pixels in which fires occurred were considered burned, but were then masked with
178 tree cover from Hansen’s Landsat-based tree cover estimates at a 1 km resolution (Hansen *et al.*
179 2013), to eliminate fires directly associated with deforestation from our predictions of fire-driven
180 losses (a known limitation of the Active Fires product for estimating understory fire extent;
181 (Morton *et al.* 2013). Each year, the burned area map was masked with all areas that experienced

182 deforestation of at least 2% (that year or any previous year). A deforestation threshold of 2% is
183 conservative, with the goal of eliminating direct deforestation fires and focusing instead on forest-
184 understory fires. Overall, we see that fire extent has declined in MODIS Active Fire detections as
185 deforestation has, suggesting some link, despite our efforts at masking. For this reason, we have
186 also used an independently calibrated estimate of understory fire extent (Morton *et al.* 2013) (also
187 using data from the MODIS satellite; referred to in figures as ‘Morton’), which is even more
188 conservative in removing deforestation-linked fires. Both fire distribution products detect
189 increases in fire activity during droughts associated with climate anomalies, suggesting that this is
190 a robust finding. However, given the moderate resolution of these satellite-based data products,
191 both likely underestimate the true spatial coverage of wildfires in closed canopy forests. For both
192 products, we re-aggregated burned area to yield an estimate at the resolution of rainfall and
193 MCWD calculations.

194 Climatological data were produced, extracted at each site, and modeled to produce basin-
195 wide estimates of bark thickness using the packages *sp*, *ncdf4*, and *raster* in R 3.2.2. Fire and tree
196 cover data were managed in the same way.

197 *Above-Ground Biomass.* At each site for which we collected tree size and bark thickness, we
198 calculated biomass using the *BIOMASS* package (Chave *et al.* 2014) in R 3.2.2, based on species-,
199 genus-, or (where necessary) family-level wood density and on plot location (as a proxy for tree
200 height). To scale to basin-wide fire-driven biomass losses, we used a recently-published biomass
201 map for forests that integrates remote-sensing with field-based biomass estimates from Avitabile
202 and colleagues (2016). Biomass was also resampled to match the scale of the climatological data
203 in R 3.2.2.

204 *Effects of Bark Thickness on Mortality in Fires.* Rates of mortality in fires were derived from
205 two major studies examining forest tree mortality in fires (Hoffmann *et al.* 2009; Brando *et al.*
206 2011). The first considered the effects of bark thickness on stem mortality of forest trees in fires
207 at the IBGE Reserve outside Brasilia by Hoffmann *et al.* (Hoffmann *et al.* 2009). We constructed
208 a linear model of tree mortality probability with respect to bark thickness (see Figure 2b) to
209 model mortality of trees. As the model more representative of the range of forest understory fires
210 (Figure 2a), we used this for most calculations in the main body of the paper. Second, we also
211 used stem mortality from a fire experiment in the southern Amazon (at Tanguro) for a more
212 detailed data source (see Brando *et al.* for a formal analysis of these data [2011]). Here, we
213 considered mortality in the three years following a fire as fire-driven mortality, so this should be
214 considered an estimate of short-term committed losses and not an estimate of instantaneous
215 responses to a fire. Probability of mortality was modeled using a general linear model assuming

216 an underlying binomial distribution (each tree survives or dies in/after a fire). Fires at Tanguro
217 were mild during normal years and more intense during drought years (see Figure 2a), with major
218 effects on tree mortality (see Figure 2b).

219 We modeled fire-driven mortality at each site using four different scenarios: 1) real trees,
220 with measured diameters and bark thickness, 2) trees with measured diameters, with bark
221 modelled according to the real community-wide bark allometric constant calculated at each site,
222 3) tree diameters drawn from an idealized diameter distribution calculated across all sites, and
223 bark modelled according to the real bark allometric constant at each site, and 4) an idealized
224 diameter distribution and bark modeled according to a bark allometric relationship modeled from
225 climate at each site. In each scenario, we modeled the probability of mortality of each tree, from
226 which we calculated proportional mortality and biomass losses.

227 Because mortality is a stochastic event (described by a deterministic rate), and because we
228 propagated errors in bark allometry and diameter distribution estimates, we bootstrapped each
229 scenario 100 times to calculate average probability of mortality and average biomass losses
230 across sites. Scenarios reproduced qualitatively similar variation in tree mortality with respect to
231 rainfall (see Figure S6). We followed the same method (scenario 4) to calculate mortality rates
232 and biomass losses across the entire Amazon.

233 *Comparisons with Observed Mortality and Biomass.* Predictions were compared qualitatively
234 and quantitatively with data from two meta-analyses of tree mortality in fires from across tropical
235 forests by Hoffmann *et al* (2009) and Barlow *et al* (2012). The former included rainfall estimates
236 but no locations, while the latter provided a map of study locations included in the synthesis
237 (enabling comparison of rainfall vs. MCWD as drivers of forest tree stem mortality). Biomass
238 loss estimates from Barlow *et al* (2012) were also used to directly estimate biomass losses (via a
239 relationship between rainfall vs. biomass loss; see Figure 3B) for comparison with estimates
240 generated via bark-mortality relationships.

241

242 RESULTS

243 Stem and region-level bark thickness varied substantially across the Amazon, constrained by
244 a combination of tree size and climate. On individual stems, bark thickness varied from fractions
245 of a millimeter to more than 4 cm of bark, and average bark thickness ranged from 0.5 mm to > 1
246 cm across plots. At each site, bark thickness increased with diameter at breast height (DBH;
247 Figure S2), as expected (Hoffmann *et al.* 2003). This allometric relationship yields a constant for
248 examining bark accumulation, controlling for tree size (α , where $bark = DBH^\alpha$). Bark
249 accumulation varied with respect to climate (Figure 1a-b, S3), decreasing most predictably with

250 rainfall ($R^2 = 0.62$, $df = 11$, $p = 0.0015$; Table S2), providing the first spatial estimate of bark
251 investment across the Amazon (Figure 1c).

252 We next aimed to translate this variation in bark as a functional trait into predictions of tree
253 mortality using published estimates linking bark thickness with tree stem mortality following
254 tropical forest understory fires. These estimates are sparse in the literature, with forest work at
255 only two sites, Amazon forests at Tanguro (Brando *et al.* 2011) and dense woodlands and riparian
256 forests in the *cerrado* biome at the IBGE Reserve (Hoffmann *et al.* 2009). Stem mortality
257 decreased with bark thickness and increased with increasing fire intensity (Barlow *et al.* 2012)
258 (consistent with results from better-studied savanna systems [Williams *et al.* 1999]; Figure 2b).
259 However, tropical forests where fires have been studied in detail (Tanguro and IBGE) have
260 experienced relatively low-intensity fires compared to the documented range of fire intensities
261 possible across the Amazon (Figure 2a).

262 In reality, stem mortality depends on actual bark thickness, not an allometric constant.
263 Therefore, we also evaluated variations in realized tree bark thickness across sites that arose from
264 variation in tree size across Amazonian forests. Whereas tree density increased markedly with
265 rainfall (Figure S4), diameter class distributions showed no consistent trends (Figure S5). We also
266 examined whether mortality estimates at each field site were sensitive to how we estimated bark
267 thickness. Results were robust to all forms of bark thickness estimation (Figure S6), with no
268 systematic biases introduced by general assumptions about size class distributions, although we
269 note that local variations in tree size distributions might nonetheless change fire susceptibility
270 depending on site history (Barlow & Peres 2008).

271 Thinner bark at high rainfall translated into consistently higher predicted mortality from
272 understory fires (Figure 3a), which in turn translated into increasing biomass loss with rainfall
273 (Figure 3b). We compared these predictions to observations of stem mortality rates from field
274 observations across Amazonian forest fires (Hoffmann *et al.* 2009; Barlow *et al.* 2012), showing
275 that stem mortality and biomass loss rates do actually increase with rainfall (Figure 3), even more
276 strongly than our modeled estimates. Taken together, these patterns suggest that bark variability
277 may indeed contribute to variability in the effects of fires on forests. Drier forests near the
278 biogeographic limit of Amazonian forests – where, incidentally, most research on the relationship
279 between bark and fire-driven mortality has focused – are substantially more resistant to fires than
280 forests in the wetter core of the Amazon.

281 We next calculated committed biomass-C fluxes across all Amazonian forests across years.
282 The net result of incorporating variable bark into our predictions (from Figure 1) was a 57.6%
283 increase over constant-bark estimates in the basin-wide understory fire-driven biomass loss, with

284 estimates that more closely match biomass losses estimated directly from plot-level mortality
285 observations (Fig. 4; plot-level estimates in Fig. 3a). Trends and variation are evident through
286 time, with overall decreases in fire extent based on MODIS active fires, likely reflecting
287 decreases in deforestation-associated fires during the study period, and dramatic increases in fire
288 extent during drought years (*e.g.*, 2007 and 2010). Summing potential losses across years (see
289 Fig. 4) yielded a total fire-driven aboveground biomass loss estimate ranging from 0.67 to 5.86
290 gigatons of CO₂ (0.18 to 1.60 gT C) to the atmosphere between 2001-2010.

291

292 DISCUSSION

293 Here, we find that tree investment in bark varies across Amazonian tropical forests, with
294 thicker bark in dry forests and thinner in wetter forests. Combining these patterns with published
295 relationships between bark thickness and tree mortality (Hoffmann *et al.* 2009; Brando *et al.*
296 2011) suggests that fire-driven tree mortality and biomass loss is greater in wet forests than in dry
297 ones, which is also supported by our synthesis of observed post-fire tree mortality across the
298 Amazon. Overall, thinner bark in wetter tropical forests may make these forests more sensitive to
299 fire, which substantially changes estimates of fire impacts on the Amazon-wide carbon cycle.
300 This fuller understanding of bark variability is likely to improve estimates of the fire-driven
301 carbon cycle in tropical forests.

302 Variation in bark investment across tropical forests raises an intriguing question: Why are
303 there thick-barked species in forests at all (Paine *et al.* 2010)? One possibility is that fire may
304 have been historically widespread (if infrequent) in drier tropical forests, making thick bark
305 advantageous. Certainly, the paleo-fire literature suggests that fires probably did occur in the
306 Amazon before the modern era in drier Amazonian forests (Bush *et al.* 2008; Power *et al.* 2008)
307 and much less so wetter ones (McMichael *et al.* 2012). Patterns of bark investment observed here
308 are roughly consistent with this, suggesting that fire may have had some ecological and
309 evolutionary importance at the margins of Amazonia. Another possibility is that the functionality
310 of bark is not limited to withstanding fires, and that bark plays a role in drought tolerance (Rosell
311 *et al.* 2013; Rosell 2016), nutrient and water storage (Richardson *et al.* 2015), and herbivore and
312 disease defense (Richardson *et al.* 2015). Drought and water storage hypotheses are weakly
313 supported by the current evidence. First, past work has shown that bark has limited function in
314 mitigating drought susceptibility (Paine *et al.* 2010). Second, resource storage by bark is usually
315 associated with inner bark (Pausas 2017), not the more insulating corky outer bark (Brando *et al.*
316 2011; Michaletz *et al.* 2012), such that future work should clearly differentiate between these two
317 features. Anecdotally, most of the thick bark in this study was corky, although we did observe a

318 few instances of extremely thick inner bark (see also Roth 1981); that bark was mostly corky is
319 consistent with observations at Tanguro (included in this study) that bark thickness overall was
320 more predictive of fire-protection than bark traits than bark moisture or density (Brando *et al.*
321 2011). However, the defense hypothesis argues that thin bark has evolved to resist pathogens at
322 high rainfall (Richardson *et al.* 2015) where pathogen loads are heavy (Swinfield *et al.* 2012),
323 consistent with and potentially contributing to patterns observed here. Mechanisms that lead to
324 bark differences, particularly within forest system, merit further direct consideration.

325 Of course, important caveats apply, especially relating to the time scales of these patterns and
326 processes. First of all, we have documented decreases in bark thickness only with respect to
327 modern rainfall patterns, without considering any historical or paleo-rainfall distributions.
328 Secondly, humans have been an important influence on the ecology of the Amazon basin for the
329 past 16,000 years at least, perhaps filtering the composition of marginal Amazonian forests
330 towards the species most tolerant of disturbances from fire (*e.g.*, Heckenberger *et al.* 2003).
331 Although anthropogenic filtering cannot account for the existence of species with thick bark to
332 begin with (*i.e.*, for standing variation in bark thickness), it may have strengthened existing
333 patterns.

334 Whatever its evolutionary or ecological origins, patterns of bark investment across the
335 Amazon suggest that fire-driven tree mortality should occur at higher rates in wet forests than in
336 dry ones. These predictions are borne out in real mortality and biomass-loss estimates from
337 understory fires (see Fig. 4), although, curiously, the observed response of mortality and biomass
338 loss to rainfall was even stronger than our models predicted (Figure 3). There are a number of
339 possible reasons that our models may underestimate high stem mortality rates in wet forests (see
340 also Cochrane 1999; Barlow *et al.* 2012; Rappaport *et al.* 2018). One probable contributor is that
341 we have only poorly represented the effects of fires that are intense (at least by tropical forest
342 standards; Figure 2; Cochrane & Schulze 1999). This highlights a well-appreciated need for ways
343 to quantify fire intensity, especially after fires have already occurred (see, *e.g.*, Rappaport *et al.*,
344 2018), and for work across a broader range of forests and forest types.

345 Another possibility is that bark alone does not determine how trees respond to fire (Ryan &
346 Williams 2011). For instance, hydraulic vulnerability may contribute to making the combination
347 of drought and fire potent in killing tropical forest trees (Brando *et al.* 2014), if drought-induced
348 water stress makes cavitation during fires more likely (Michaletz *et al.* 2012). Vulnerable
349 hydraulic architecture – common in trees that have not experienced a history of drought or fire
350 and perhaps also in taller forests – and root susceptibility to fires may both merit further

351 examination as a contributor to fire-driven mortality of forest trees. Nonetheless, bark thickness
352 clearly had major impacts on mortality and thus on biomass losses in understory fires.

353 An increased emphasis on plant functional responses to fire – via bark but also other traits –
354 could further contribute to improving predictions of fire effects on tropical forests. For one,
355 although fires often cause the mortality of the tree stem, they do not always kill the whole
356 individual. Resprouting following fires (Hoffmann *et al.* 2009) can be widespread, and may
357 dramatically speed forest community and biomass recovery following fires. Resprouting traits are
358 understudied in tropical forests (Clarke *et al.* 2012), a critical gap if we are to understand the
359 long-term implications of tropical understory fires for the carbon cycle. Conversely, repeated fires
360 may slow post-fire forest succession. Changes in forest structure following an initial burn may
361 predispose forests to additional fires (Barlow & Peres 2008), which in extreme cases can lead to
362 grass invasion and eventual forest savannization (Silvério *et al.* 2013), although the generality of
363 this runaway feedback is an issue of some debate (Cochrane 1999). Bark traits may make this
364 more likely, since many of the smaller trees that grow back after fires have thinner bark, and
365 these pioneers are often highly susceptible to subsequent fires (Barlow & Peres 2008).

366 Here, we provide the first evidence of substantial variation in bark investment across
367 Amazonian forests. Thinner bark in wetter forests provides a convincing explanation for
368 extremely high local tree mortality in understory fires, which improves our understanding of both
369 carbon emissions and biodiversity losses. Together with improved models for fire behavior, a
370 more comprehensive perspective on how plant functional traits (including bark thickness and
371 resprouting) mediate ecosystem responses to global change will be critical to predicting the future
372 of Amazonian forests and associated climate-carbon feedbacks, including fires (Cochrane 2003).
373 In this study, aboveground biomass loss estimates based on varying bark thickness suggest that
374 Amazon understory fires have added between 0.67 to 5.86 gigatons of CO₂ to the atmosphere
375 between 2001-2010 (Fig. 4), without accounting for regrowth. Ignoring fire-related functional
376 traits thus risks missing a major ecological influence on forest responses to fire, with
377 consequences for predictions of tropical forest impacts on global carbon cycles.

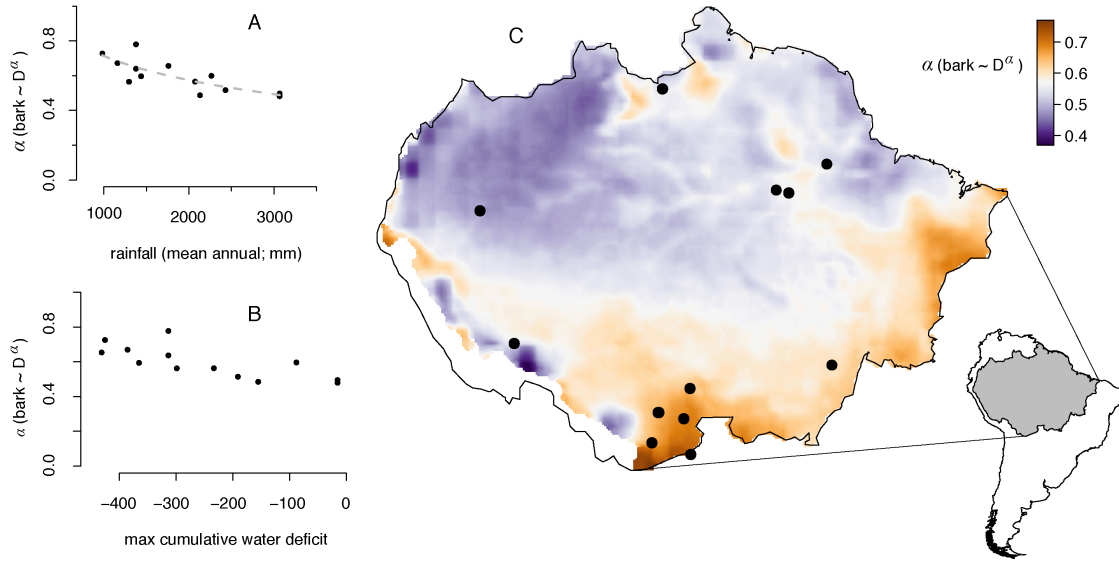
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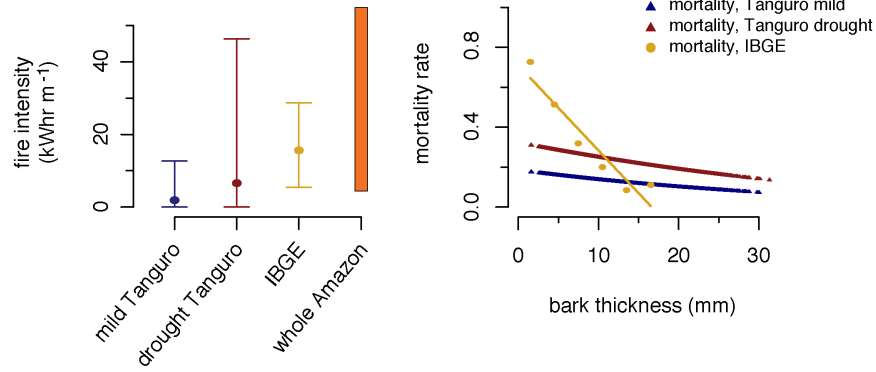
385 FIGURES
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389 **Figure 1.** Response of community-wide bark thickness to rainfall (A) and maximum cumulative
 390 water deficit (B), and modeled bark thickness across the Amazon (C). Log-rainfall was the
 391 preferred explanatory variable (Table S2; $R^2 = 0.616$, $df = 11$, $p = 0.0015$). Higher values of α
 392 indicate that bark accumulates more quickly as tree diameter increases (*i.e.*, that bark is thicker).
 393 Thus, bark is thicker in lower-rainfall forests.

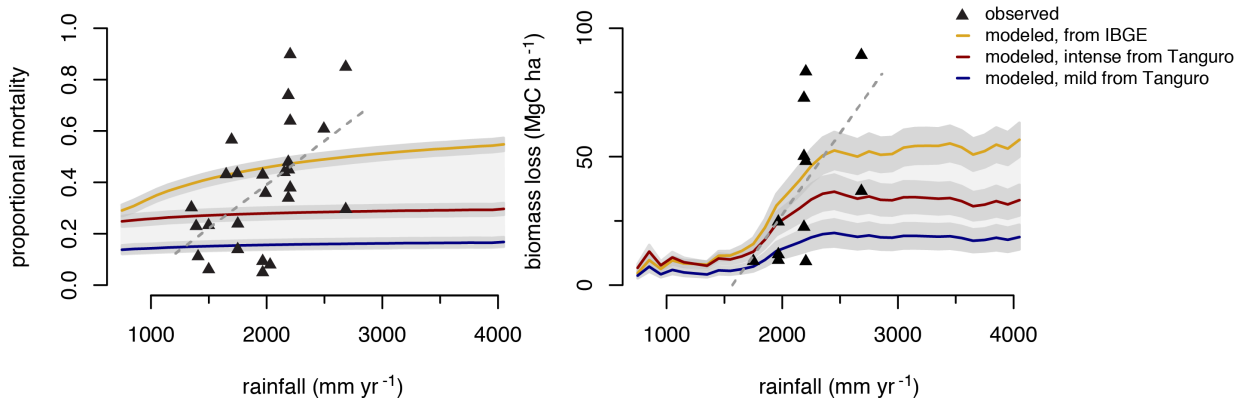
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396 **Figure 2.** Fire intensity at Tanguro, the IBGE Reserve, and across the Amazon (A), and predicted
 397 mortality response to bark thickness from Tanguro and the IBGE Reserve (B). Fire intensities at
 398 Tanguro and IBGE were calculated from char height observations using equations given in
 399 [(Williams *et al.* 1998)]. At IBGE, the probability of tree mortality decreased with bark thickness
 400 ($R^2 = 0.909$, $df = 4$, $p = 0.0032$). At Tanguro, a model including bark thickness, year (as a proxy
 401 for fire intensity and drought stress), and the interaction between them was used to predict tree
 402 mortality (see Brando *et al.* (2014) for a formal analysis) and explained 16.2 % of variation in
 403 tree mortality. Tanguro data are drawn from Brando *et al.* (2011; 2014), IBGE data from
 404 Hoffmann *et al.* (2009), and whole-Amazon syntheses from Cochrane *et al.* (1999).

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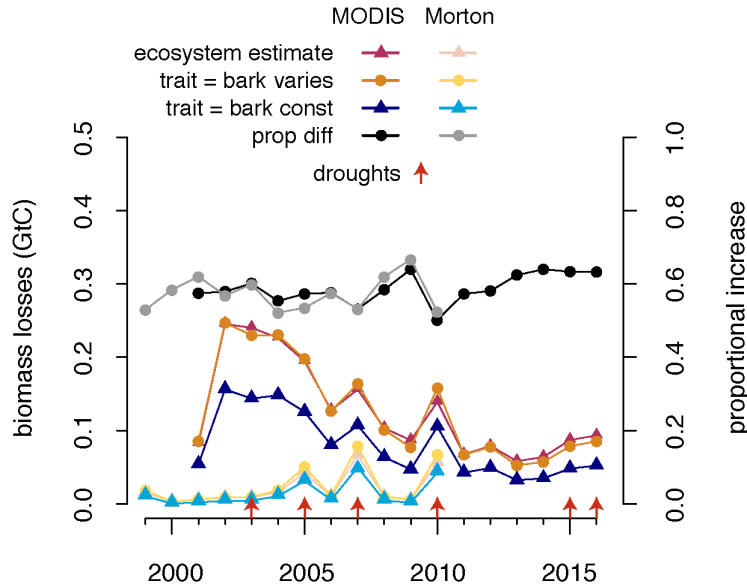


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408 **Figure 3.** Modeled and observed fire-driven tree mortality (A) and biomass loss (B) in response
 409 to rainfall. Mortality (Hoffmann *et al.* 2009; Barlow *et al.* 2012) and biomass loss (Barlow *et al.*
 410 2012) observations are drawn from published meta-analyses of field studies across the Amazon,
 411 and modeled fire-driven mortality is based on published relationships between tree bark and
 412 mortality at Tanguro in mild and intense fires (Brando *et al.* 2011) and at the IBGE reserve
 413 (Hoffmann *et al.* 2009). Observed fire-driven mortality rates increased with rainfall ($R^2 = 0.290$,
 414 $df = 24$, $p = 0.0045$) more strongly than modeled mortality did. So too did biomass losses ($R^2 =$

415 0.347, $df = 10$, $p = 0.044$). Note that in both cases, rainfall was a better predictor of observed
 416 mortality and biomass loss than MCWD ($R^2 = 0.121$, $df = 15$, $p = 0.17$ and $R^2 = 0.331$, $df = 10$, p
 417 = 0.05, respectively).

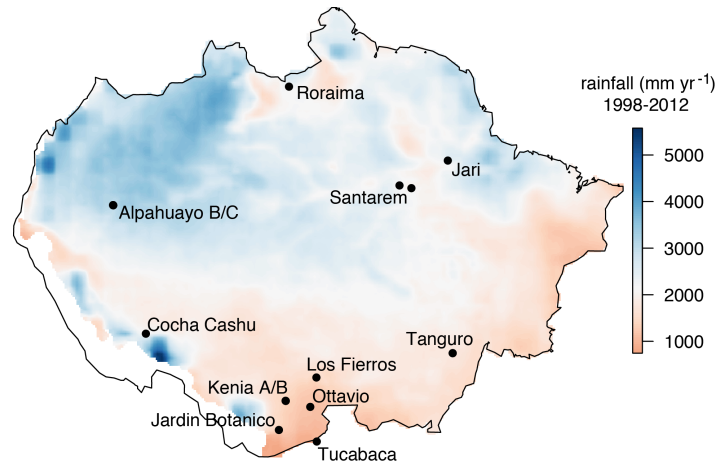


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420 **Figure 4.** Predicted fire-driven losses of above-ground biomass (GtC) across all Amazonian
 421 forests, calculated from published estimates of biomass loss (Barlow *et al.* 2012) (magenta, pink)
 422 and modeled assuming constant bark thickness (navy, blue) vs. variable bark (orange, yellow) and
 423 a bark-mortality relationship from [(Hoffmann *et al.* 2009)]. For constant bark calculations, we
 424 assume bark equivalent to our four driest sites, near the southern edge of the Amazon. Fire extent
 425 was estimated directly from MODIS Active Fires data (‘MODIS’) (Giglio *et al.* 2016) and via
 426 independent MODIS-derived understory fire distributions (‘Morton’) (Morton *et al.* 2013). This
 427 reveals the effects of extrapolating current and future fire-driven losses from historical fire-driven
 428 losses in comparatively fire-tolerant forests. See Methods for detail. Including variations in bark
 429 thickness across the Amazon increases predicted fire-driven carbon losses by $57.6 \pm 3.9\%$ (see
 430 Table S2).

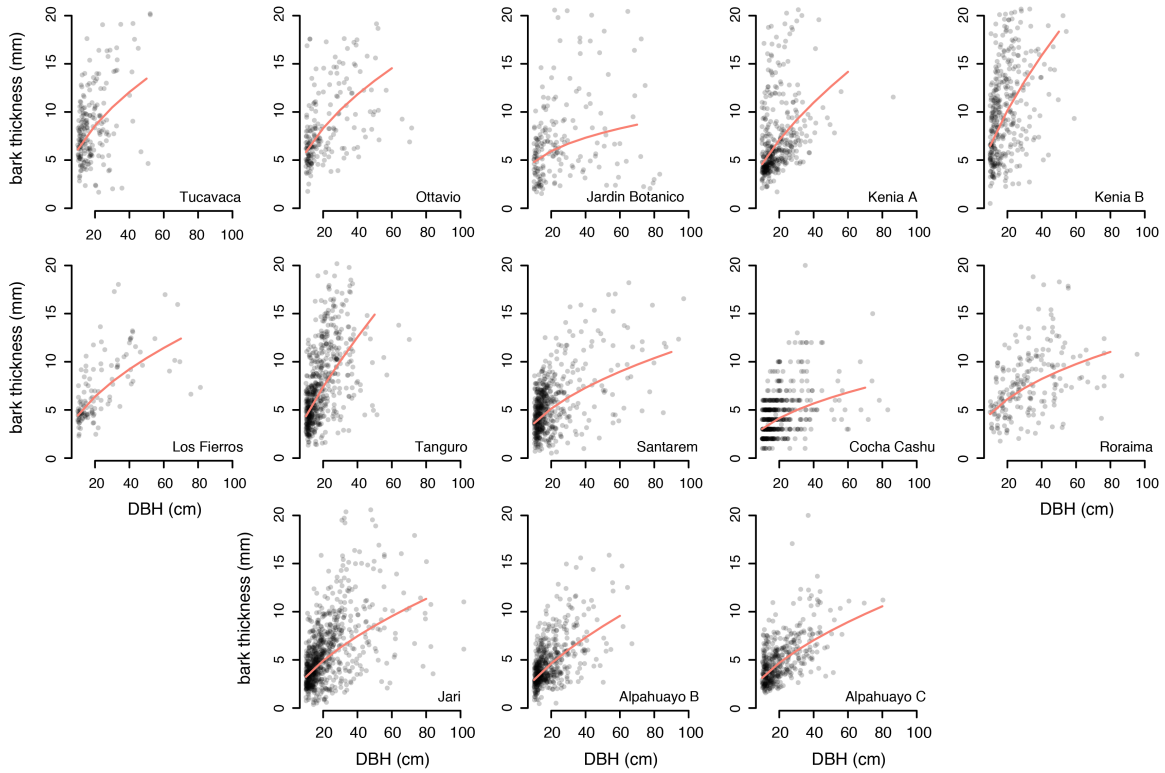
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433 SUPPLEMENTARY FIGURES AND TABLES
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437 **Figure S1.** Mean annual rainfall and site locations and names across the Amazon.
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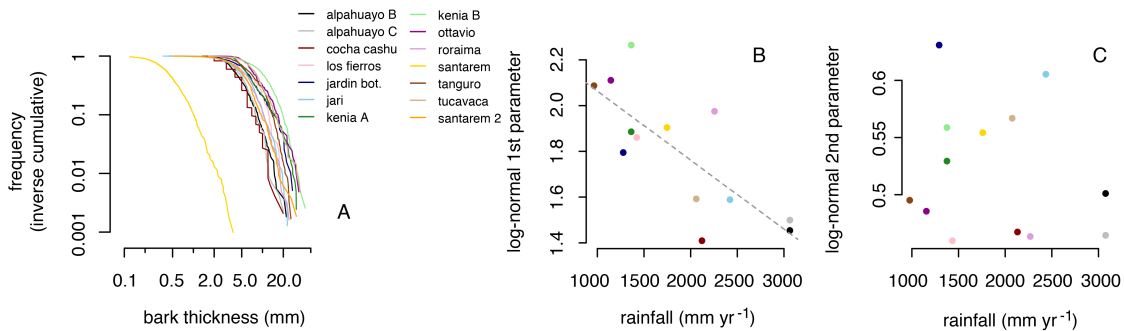
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442 **Figure S2.** Bark allometries by site. Lines represent the best-fit relationship between diameter
 443 (DBH; cm) and bark thickness (mm) with a form given by $bark = DBH^\alpha$. Here, fits are shown to
 444 all trees at a site, but for formal analysis, allometric constants were calculated by species, and
 445 averaged weighted by species abundance at a site. Note that all plots have been truncated at 20
 446 mm bark thickness and 100 cm DBH, focusing on the majority of data (89.4%) and avoiding
 447 sparse regions of morphological space.

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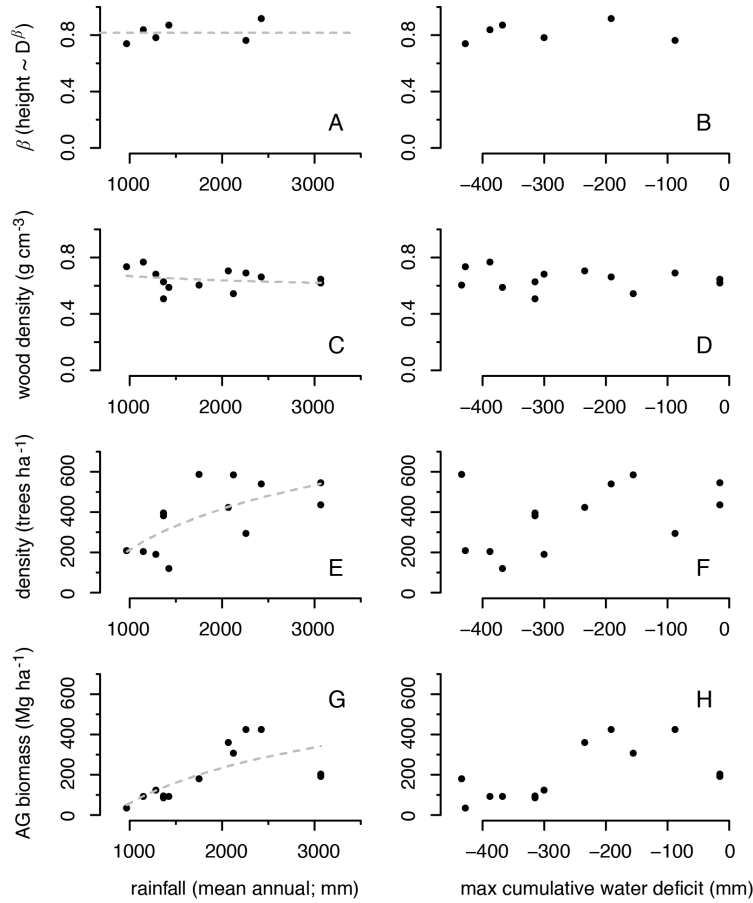
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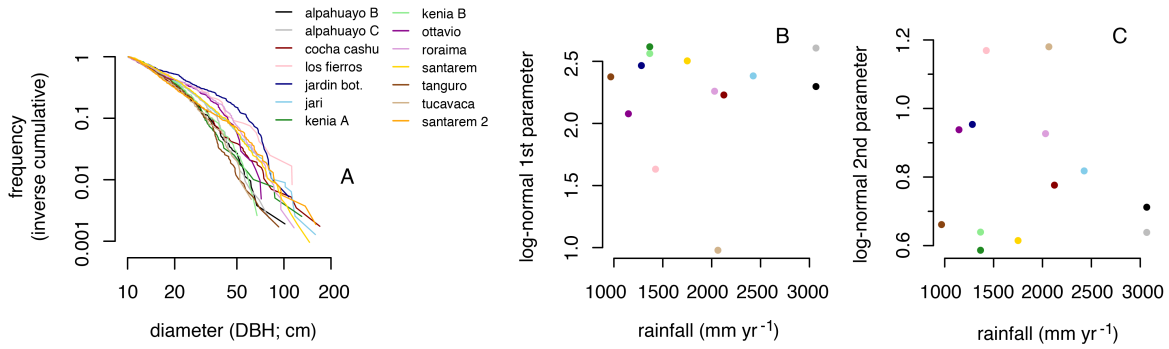
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452 **Figure S3.** Inverse cumulative bark thickness distribution at each site (A), and response of the
 453 best-fit log-normal parameters at each site to rainfall (B-C). The first parameter of the log-normal
 454 distribution varied predictably with rainfall across sites ($R^2 = 0.592$, $df = 11$, $p = 0.0021$).
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 459 **Figure S4.** Response of height allometry (A-B), wood density (C-D), tree density (E-F), and
 460 above-ground biomass (G-H) at each site to rainfall and MCWD.
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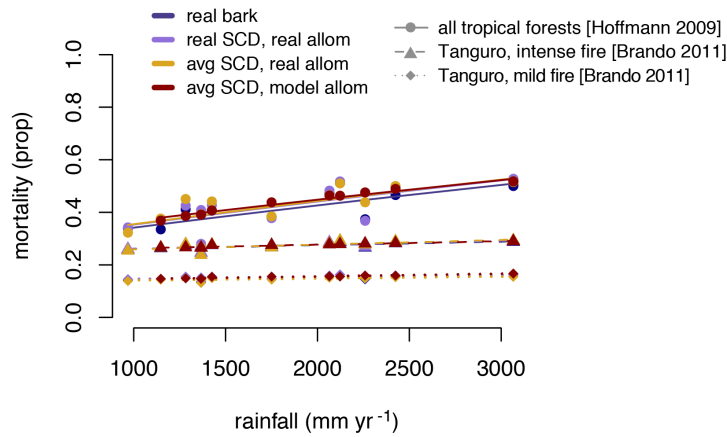
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467 **Figure S5.** Inverse cumulative diameter distribution at each site (A), and response of the best-fit

468 log-normal parameters at each site to rainfall (B-C).

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472 **Figure S6.** Fire-driven tree mortality response to rainfall, modeled using real bark measurements

473 (blue), bark modeled on real diameter measurements and real bark allometric constants by site

474 (purple), bark modeled on a stylized diameter distribution (see Figure S4) and real bark allometric

475 constants by site (yellow), and bark modeled on a stylized diameter distribution and modelled

476 bark allometric constants (see Figure 1) (red). Mortality was estimated using published

477 relationships between bark and mortality from Tanguro (Brando *et al.* 2011) (triangle and

478 diamonds for intense and mild fires, respectively) and from all tropical forests (Hoffmann *et al.*

479 2009) (circles).

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484 **Table S1.** Sites and plot details.

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Site	Plot dimensions	Total area sampled
Tucabaca	100 m × 100 m	1 ha
Ottavio	100 m × 100 m	1 ha
Jardin Botanico	100 m × 100 m	1 ha
Kenia A	100 m × 100 m	1 ha
Kenia B	100 m × 100 m	1 ha
Los Fierros	500 m × 20 m	1 ha
Tanguro	50 m × 50 m × 4	1 ha
Santarem†	50 m × 50 m × 5	1.25 ha
Cocha Cashu	100 m × 100 m	1 ha
Roraima	50 m × 50 m × 3	0.75 ha
Jari	10 m × 250 m × 6	1.5 ha
Alpahuayo B	100 m × 100 m	1 ha
Alpahuayo C	100 m × 100 m	1 ha

486

487 † At Santarem, species were identified only to morphospecies, so site-specific biomass
 488 was calculated for another nearby site, where taxonomic information was available, for
 489 use in analyses.

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492 **Table S2.** Akaike information criterion model selection for bark allometry (α : bark = DBH $^\alpha$),
 493 height (β : height = DBH $^\beta$), and wood density (ρ) functional traits, and plot-level stem density (ha $^{-1}$)
 494 and above ground biomass (Mg ha $^{-1}$). The simplest model with Δ AIC < 2 was selected as the
 495 best, indicated in bold.

predictors	Δ AIC				
	bark (α)	height (β)	wood (ρ)	stem density (ha $^{-1}$)	AG biomass (Mg ha $^{-1}$)
~ log (mar) * mcwd	9.31	> 10	11.05	6.21	4.78
~ log (mar) + mcwd	3.92	> 10	6.85	1.18	6.04
~ mar * mcwd	9.11	> 10	11.84	5.60	0
~ mar + mcwd	4.39	> 10	7.44	2.73	8.40
~ log (mar)	*0*	8.65	2.83	*0*	*1.81*
~ mar	0.37	8.81	3.13	1.22	4.15
~ mcwd	1.83	9.96	3.26	5.14	4.92
~ 1	8.96	*0*	*0*	4.35	6.96

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500 **Table S3.** Fire-driven carbon losses from Amazonian forests, calculated assuming constant bark
 501 thickness vs. variable bark. For constant bark calculations, we assume bark equivalent to our four
 502 driest sites, near the southern edge of the Amazon, where fires may have been historically
 503 frequent. This reveals the effects of extrapolating from comparatively fire-tolerant forests to the
 504 entire Amazon basin. Errors represent standard deviations.

fire extent estimate	mortality model	Total fire-driven biomass loss (GtC), constant bark	Total fire-driven biomass loss (GtC), variable bark	Percent change (%)
MODIS Active Fires	All forests [†]	0.16 ± 0.09	0.26 ± 0.14	57.6 ± 3.9
	Mild Tanguro [‡]	0 ± 0	0.11 ± 0.06	∞
	Intense Tanguro [‡]	0.097 ± 0.053	0.20 ± 0.11	1927.3 ± 14.3
MODIS-derived 'Morton'	All forests [†]	0.015 ± 0.017	0.024 ± 0.026	57.2 ± 0.047
	Mild Tanguro [‡]	0 ± 0	0.019 ± 0.021	∞
	Intense Tanguro [‡]	0.0010 ± 0.0011	0.010 ± 0.012	18.2 ± 0.16

505 [°]Morton *et al.* 2013

506 [†](Hoffmann *et al.* 2009)

507 [‡](Brando *et al.* 2011)

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