

1 Quantifying immediate carbon emissions from El Niño-mediated wildfires in humid 2 tropical forests

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26 Summary

27 Wildfires produce substantial CO₂ emissions in the humid tropics during El Niño-mediated
28 extreme droughts, and these emissions are expected to increase in coming decades. Immediate
29 carbon emissions from uncontrolled wildfires in human-modified tropical forests can be
30 considerable owing to high necromass fuel loads. Yet, data on necromass combustion during
31 wildfires are severely lacking. Here, we evaluated necromass carbon stocks before and after the
32 2015–2016 El Niño in Amazonian forests distributed along a gradient of prior human disturbance.
33 We then used Landsat-derived burn scars to extrapolate regional immediate wildfire CO₂
34 emissions during the 2015–2016 El Niño. Before the El Niño, necromass stocks varied
35 significantly with respect to prior disturbance and were largest in undisturbed primary forests (30.2
36 ± 2.1 Mg ha⁻¹, mean ± s.e.) and smallest in secondary forests (15.6 ± 3.0 Mg ha⁻¹). However,
37 neither prior disturbance nor our proxy of fire intensity (median char height) explained necromass

38 losses due to wildfires. In our 6.5 million hectare (6.5 Mha) study region, almost 1 Mha of primary
39 (disturbed and undisturbed) and 20 000 ha of secondary forest burned during the 2015–2016 El
40 Niño. Covering less than 0.2% of Brazilian Amazonia, these wildfires resulted in expected
41 immediate CO₂ emissions of approximately 30 Tg, three to four times greater than comparable
42 estimates from global fire emissions databases. Uncontrolled understorey wildfires in humid
43 tropical forests during extreme droughts are a large and poorly quantified source of CO₂
44 emissions.

45

46 1. Introduction

47 Increased concentrations of atmospheric CO₂ during El Niño Southern Oscillation events [1,2]
48 have largely been attributed to emissions from the tropics [3,4], with wildfires playing an important
49 role [4,5]. In recent decades, despite a global reduction in burned vegetation area [6,7], relatively
50 low-intensity understorey wildfires that spread from agricultural lands have increased in the fire-
51 sensitive Amazon rainforest [8–11]. CO₂ emissions from such wildfires are expected to grow
52 further [10] as fire-conducive weather patterns increase across the humid tropics, particularly in
53 South America [12].

54 Large-scale understorey wildfires in Amazonia are unprecedented in recent millennia. During pre-
55 Columbian times, fires were limited to those occurring naturally from lightning strikes and
56 prescribed burns by indigenous peoples [13]. These fires were localized, and prescribed burns
57 were planned in accordance with environmental and ecological conditions [13]. However,
58 pervasive human modification of tropical forest landscapes, through, for example, road building,
59 cattle ranching and timber exploitation, combined with severe drought events and the widespread
60 use of fire as a land management tool, has fundamentally altered Amazonian fire regimes. Today,
61 uncontrolled large-scale understorey wildfires are being witnessed in the Amazon with sub-
62 decadal frequency [14]. Such wildfires result in high rates of tree mortality [15,16], shifts in forest
63 structure [17,18] and drier microclimatic conditions [19], ultimately leading to increased
64 susceptibility to future wildfires [19–21].

65 Carbon emissions from understorey wildfires can be split into committed and immediate
66 emissions. Committed emissions result from the complex interplay between delayed tree mortality
67 and decomposition, and are dependent on future climatic conditions and human influences.
68 Research indicates that long-term storage of carbon in wildfire-affected Amazonian forests can
69 be compromised for decades: even 31 years after a fire event, burned forests store approximately
70 25% less carbon than unburned control sites owing to high levels of tree mortality that are not
71 compensated by regrowth [22]. Immediate understorey emissions are those that occur during
72 wildfires and, in contrast to committed emissions, are relatively simple to estimate. Biome- and
73 continent-wide analyses that rely on satellite observations (known as top-down studies) suggest
74 that these immediate emissions from tropical forests can be substantial [23,24] and, for example,

75 can transform the Amazon basin from a carbon sink to a large carbon source during drought years
76 [25].

77 One potentially important source of immediate carbon emissions during wildfires is dead organic
78 matter found on forest floors. This necromass, which includes leaf litter and woody debris, is a
79 fundamental component of forest structure and dynamics and can account for up to 40% of the
80 carbon stored in humid tropical forests [26–28]. During long periods of drought, this large carbon
81 pool can become highly flammable [29]. However, studies quantifying necromass stocks have
82 overwhelmingly focused on undisturbed primary forests [27]; studies that estimate necromass in
83 human-modified tropical forests—forests that have been structurally altered by anthropogenic
84 disturbance, such as selective logging and fires, and those regenerating following deforestation
85 (commonly called secondary forests; table 1)—are rare (cf. [30,31]). This represents a key gap in
86 our understanding because human-modified tropical forests are increasingly prevalent [32] and
87 increasingly vulnerable to wildfires [33–35]. While many local-scale, bottom-up studies have
88 quantified combustion characteristics and carbon emissions following fires related to
89 deforestation and slash-and-burn practices (see Van Leeuwen et al. [36] for a recent review), we
90 know of no study that quantifies necromass before and after uncontrolled understorey wildfires in
91 human-modified Amazonian forests. These knowledge gaps and data shortfalls limit our
92 understanding of immediate carbon emissions from understorey wildfires. Improving such
93 estimates is essential for refining Earth Systems models and both national and global estimates
94 of greenhouse gas emissions.

95 Here, we address these knowledge gaps using a hybrid bottom-up/top-down approach to study a
96 human-modified region of central-eastern Amazonia that experienced almost 1 million hectares
97 (1 Mha) of understorey wildfires during the 2015–2016 El Niño (figure 1). We combine data from
98 a previously published large-scale field assessment of carbon stocks [37] with on-the-ground
99 measures of woody debris before and after the 2015–2016 El Niño, proxies of fire intensity and
100 coverage within study plots, and remotely sensed analyses of fire extent across the region.
101 Specifically, we (a) quantify carbon stocks vulnerable to combustion across human-modified
102 tropical forests in central-eastern Amazonia, (b) use post-burn measures to investigate the factors
103 influencing the loss of necromass during wildfires, (c) estimate region-wide immediate carbon
104 emissions from wildfires and (d) compare these region-wide emission estimates with those
105 derived from widely used global fire emissions databases.

106 2. Methods

107 (a) Quantifying necromass stocks in human-modified Amazonian forests

108 We established 107 plots (0.25 ha) in human-modified forests in central-eastern Amazonia in
109 2010 (figure 1). Plots were located in the municipalities of Santarém, Belterra and Mojuí dos
110 Campos in the state of Pará, Brazil, and form part of the Sustainable Amazon Network (Rede
111 Amazônia Sustentável (RAS) in Portuguese [38]). Study plots covered a range of prior human
112 impacts (table 1) and included undisturbed primary forests ($n = 17$), primary forests selectively

113 logged prior to 2010 (n = 26), primary forests burned prior to 2010 (n = 7), primary forests logged
114 and burned prior to 2010 (n = 24) and secondary forests recovering after complete removal of
115 vegetation (n = 33; table 1).

116 Summary carbon estimates for these 107 plots can be found in Berenguer et al. [37]. Here, we
117 focused on carbon stored in their necromass pools. We estimated necromass stocks in dead-
118 standing tree and palm stems, coarse woody debris (CWD; ≥ 10 cm diameter at one extremity),
119 fine woody debris (FWD; ≥ 2 and < 10 cm diameter at both extremities) and leaf litter (including
120 twigs < 2 cm diameter at both extremities, leaves, and fruits and seeds). Full carbon estimation
121 methods can be found in Berenguer et al. [37]. In brief, in each plot, we measured the diameter
122 and height of all large (greater than or equal to 10 cm diameter at breast height (DBH)) dead tree
123 and palm stems. We measured the diameter and height of all small dead tree and palm stems
124 (≥ 2 and < 10 DBH) in five subplots (5 \times 20 m) in each plot. We used the allometric equations of
125 Hughes et al. [39] and Cummings et al. [40] to estimate, respectively, carbon stocks for dead-
126 standing trees and palms. Subplots were also used to estimate the diameters and lengths of all
127 pieces of fallen CWD. We estimated the volume of each piece of CWD using Smalian's formula
128 [27] after accounting for the extent of damage (i.e. void space). We multiplied the volume of each
129 CWD piece by its decomposition class to calculate CWD mass [30]. In all study plots, we
130 established five smaller subplots (2 \times 5 m) to assess FWD. This was sampled and weighed in the
131 field. A subsample (≤ 1 kg) was collected in each subplot and oven-dried to a constant weight.
132 The wet-to-dry ratios of the FWD samples were used to estimate the total FWD stocks per plot.
133 To estimate the biomass of leaf litter, ten 0.5 \times 0.5 m quadrats were established in each plot. We
134 oven-dried leaf litter samples to a constant weight to get an estimate of the leaf litter stocks in
135 each plot. Biomass estimates for each necromass component were then standardized to per
136 hectare values, and the carbon content was assumed to be 50% of biomass dry weight [41]. See
137 electronic supplementary materials (§1) for all equations we used to estimate necromass
138 biomass.

139 (b) Longitudinal monitoring of coarse woody debris

140 To estimate necromass change through time, we continued to monitor 18 of the 107 RAS plots
141 (figure 1). These 18 plots were chosen because they are spatially distributed across the region
142 and we were able to secure long-term authorization to monitor them. They included undisturbed
143 primary forests (n = 5), primary forests logged prior to 2010 (n = 5), primary forest logged and
144 burned prior to 2010 (n = 4), and secondary forests (n = 4; table 1). We conducted surveys of the
145 18 plots between November 2014 and September 2015, using a slightly altered sampling design
146 to align with the Global Ecosystem Monitoring protocol (see [42] for details). We established five
147 1 \times 20 m subplots in each of the 18 plots, measured all pieces of CWD, and estimated their
148 biomass and carbon content following the methods outlined above (see Methods (a)).

149 (c) Impacts of El Niño-mediated wildfires on necromass stocks

150 Extensive understory wildfires burned seven of our 18 study plots during the 2015–2016 El Niño,
151 including two previously undisturbed primary forests, four primary forests logged prior to 2010,
152 and one primary forest that was logged and burned prior to 2010. To investigate necromass
153 carbon stock losses due to these wildfires, we resurveyed all 18 plots in June 2017. We re-
154 measured each individual piece of CWD and estimated biomass using the methods described
155 above (Methods (a)). By comparing CWD stocks before and after the El Niño in the 11 plots that
156 did not experience wildfires, we were able to estimate CWD background decomposition rates. By
157 comparing CWD stocks before and after the El Niño in the seven plots that burned, we were able
158 to measure CWD combustion completeness.

159 We used values from the 2010 surveys to provide estimates of the pre-El Niño carbon stocks in
160 leaf litter and FWD. Based on visual inspection of the sites (electronic supplementary material,
161 figure S1), we assumed 100% combustion completeness of these necromass components in the
162 fire-affected proportion of burned plots. Recognizing that this is a strong assumption, we consider
163 the validity of it in our Discussion. We did not consider wildfire-mediated changes in necromass
164 carbon stocks in dead-standing trees and palms, owing to a lack of data on combustion
165 completeness.

166 In the seven plots that burned, we calculated average char height for each stem, defined as the
167 sum of the maximum and minimum char heights divided by two. We then used these average
168 stem char heights to calculate the plot-level median char height, which we used as our proxy for
169 fire intensity. In addition, we used the proportion of sampled stems with burn scars as an estimate
170 of the area of each plot that burned (electronic supplementary materials). To increase our sample
171 of fire-affected plots (to 16), we also measured the area burned in an additional nine of the original
172 RAS plots that were sampled during the 2010 censuses and burned during 2015–2016 (table 1).
173 Prior to the wildfires, these additional plots included undisturbed primary forests ($n = 3$), primary
174 forests logged prior to 2010 ($n = 1$), primary forests logged and burned prior to 2010 ($n = 4$), and
175 secondary forests ($n = 1$).

176 We used these data to estimate the per hectare necromass loss (NL) attributable to wildfires using
177 the following equation:

$$178 \quad NL = FL_{CWD} \times (CC_{CWD} - D_{CWD}) + FL_{LLFWD} \times BA \quad (1)$$

179 where FL_{CWD} is the per hectare fuel load of CWD estimated from the 107 RAS plots surveyed in
180 2010, CC_{CWD} is the combustion completeness of CWD estimated from seven of the 18 CWD
181 monitoring plots that burned during the 2015–2016 El Niño, D_{CWD} is the background CWD
182 decomposition rate estimated from the 11 CWD monitoring plots that did not burn during the
183 2015–2016 El Niño, FL_{LLFWD} is the per hectare fuel load of leaf litter and FWD estimated from the
184 107 plots surveyed in 2010, and BA is the proportion of the plot that burned estimated from the
185 16 RAS plots that burned (seven necromass monitoring sites and nine additional sites in which
186 burned area was estimated) during the 2015–2016 El Niño (table 1).

187 (d) Data analysis

188 We used the Kruskal–Wallis test to investigate variation across forest classes of prior human
189 disturbance (table 1) and used the Conover–Iman test with Bonferroni adjustments to perform
190 multiple pairwise comparisons of forest class medians. We assessed differences across forest
191 classes in: carbon stocks stored in each necromass component (i.e. dead-standing stems, CWD,
192 FWD and leaf litter) from the 2010 survey; total and percentage necromass carbon stock losses
193 in the 18 plots surveyed between 2014 and 2017; and the proportion/area of plots burned during
194 the 2015–2016 El Niño. We used linear regression to investigate the relationship between:
195 necromass carbon stocks before and after the 2015–2016 El Niño; fire intensity and stock losses;
196 and the burned area in each plot and stock losses.

197

198 (e) Quantification of burned area and estimation of region-wide emissions from forest fires

199 To estimate wildfire-mediated carbon emissions from necromass across our study region, we first
200 calculated the cumulative area of primary and secondary forest that experienced understory
201 wildfires during 2015–2016 in the central-eastern region of the Amazon, an area of approximately
202 6.5 Mha (figure 1). We built a time-series of Landsat (5, 7 and 8) imagery from 2010 to 2017 for
203 the RAS study region and the surrounding area from the EROS Science Processing Architecture
204 (ESPA)/U.S. Geological Survey (USGS) website (<https://espa.cr.usgs.gov>). We performed an
205 unsupervised classification of raw imagery, followed by manual correction of classification errors,
206 to identify several land-uses throughout the time-series (see electronic supplementary material,
207 table S2 for all land-use classes and §2 for a detailed description of burned area detection). We
208 then used the burned area of primary and secondary forests and estimates of per hectare
209 necromass stock losses from wildfires (equation (1)) to determine region-wide necromass carbon
210 emissions, using a conversion factor of 3.286 kg of CO₂ per kg of C [43]. This conversion factor
211 does not include other forms of emitted C (such as CO), in keeping with global fire emissions
212 databases.

213 We took two approaches to account for uncertainty in expected regional necromass emissions.
214 First, we considered four land-use scenarios using two sets of primary and secondary forests
215 (electronic supplementary material, table S1). To account for potential variation in fire
216 susceptibility across primary forest disturbance classes, we estimated the five variables in
217 equation (1) using all undisturbed and disturbed primary forest classes (prim1) and then only
218 disturbed primary forests (prim2). For secondary forests, we used CC_{CWD} and FL_{LLFWD} from all
219 secondary forests, used D_{CWD} and BA from all forest classes combined, and used CC_{CWD} from all
220 primary forest classes because none of the secondary forest plots we were monitoring for
221 changes in CWD burned during 2015–2016 (sec1). Our other scenario for secondary forests
222 (sec2) was more restrictive: we used the fuel load (FL_{CWD}, FL_{LLFWD}), decomposition (D_{CWD}), and
223 BA values from secondary forests only and combined these with all CCCWD values we had from
224 disturbed and undisturbed primary forests.

225 Second, to account for uncertainty in the distribution of the variables in equation (1), we ran 1000
226 bootstrap with replacement simulations to determine each variable's mean value and standard
227 error. We calculated the standard error of equation (1) using the variable standard errors,

228 accounting for error propagation, and we constructed 95% confidence intervals for equation (1)
229 as its mean value ± 1.96 times the standard error of the mean.

230 (f) Quantitative comparisons with GFED and GFAS

231 We compared our region-wide CO₂ emission estimates with two fire emissions databases
232 frequently used in Earth Systems models and carbon budgets: the Global Fire Emissions
233 Database (GFED) version 4.1s [44] and the Global Fire Assimilation System (GFAS) version 1.1
234 [45]. For both datasets, we obtained data for our study period (August 2015–July 2016) and
235 cropped them to our approximately 6.5 Mha study region, shown in figure 1. We first calculated
236 cumulative emissions from GFED and GFAS (electronic supplementary material) and compared
237 these with our emissions estimates. Second, to investigate potential sources of discrepancy
238 between estimates, we spatially mapped GFED, GFAS and our CO₂ emissions estimates. At both
239 GFED and GFAS resolutions (0.25° and 0.1°, respectively), we mapped our mean (across land-
240 use scenarios; electronic supplementary material, table S1) expected emissions assuming that
241 emissions were constant in a burned area (i.e. if a cell contained x% of the burned area, we
242 assumed it accounted for x% of the total emissions). Finally, because GFED also provides
243 estimates of the area burned at 0.25°, we used our land-use map to estimate burned area at that
244 resolution.

245 3. Results

246 (a) Necromass carbon stocks across human-modified Amazonian forests

247 Total necromass and its components varied significantly with respect to forest class ($p < 0.05$ in
248 all cases; figure 2). Primary forests contained significantly higher total necromass than secondary
249 forests ($p < 0.01$ for all pairwise comparisons), with the highest total found in undisturbed primary
250 forests ($30.2 \pm 2.1 \text{ Mg ha}^{-1}$, mean \pm s.e.). By contrast, secondary forests contained only half as
251 much necromass as undisturbed primary forests ($15.6 \pm 3.0 \text{ Mg ha}^{-1}$). Variation in total necromass
252 was driven in large part by variation in CWD, which accounted for $61.3 \pm 2.7\%$ of the total
253 necromass stocks across forest classes. Leaf litter was the next most important component of
254 total necromass, with $19.8 \pm 2.7\%$ residing in this component. Dead-standing stems accounted
255 for $14.4 \pm 1.8\%$ of total necromass. Finally, FWD was by far the smallest necromass component,
256 harbouring just $4.6 \pm 0.2\%$ of the total.

257 (b) Impacts of El Niño mediated wildfires on necromass stocks

258 On average, $87.1 \pm 2.7\%$ of the ground area of our fire-affected study plots burned, and there was
259 no significant difference in the total unburned area of fire-affected plots across forest classes (χ^2_3
260 = 2.1; $p = 0.56$). For CWD, all but two pieces had burned from a total of 34, and CWD carbon
261 stocks losses from combustion varied from 38% to 94% (mean = 65.4%, SE = 7.1%).

262 Necromass carbon stock losses in the seven burned plots were unrelated to median char height
263 ($R^2 = 0.09$; $p = 0.51$; figure 3a) and area of plot burned ($R^2 = 0.10$; $p = 0.49$; figure 3b). Forest

264 class did not predict necromass carbon stock losses in burned sites when expressed as either
265 percentage ($\chi^2_2 = 2.25$; $p = 0.32$) or total ($\chi^2_2 = 1.12$; $p = 0.57$) loss. Similarly, forest class did not
266 predict necromass losses in unburned sites when expressed as either percentage ($\chi^2_3 = 1.58$; $p =$
267 0.66) or total ($\chi^2_3 = 2.18$; $p = 0.54$) loss.

268 On average, burned sites lost $73.0 \pm 4.9\%$ of their pre-El Niño necromass stocks (figure 4),
269 compared to a $26.1 \pm 4.8\%$ reduction in unburned sites (from decomposition). As expected, pre-
270 El Niño necromass stocks strongly predicted post-El Niño necromass in our unburned sites ($R^2 =$
271 0.95 ; $p < 0.001$; figure 4a). This relationship disappeared in fire-affected plots ($R^2 = 0.08$; $p = 0.54$;
272 figure 4b), indicating that combustion completeness was insensitive to initial necromass stocks.
273 Despite our small sample size, visual inspection suggests that these findings were unaffected by
274 forest class.

275 (c) Region-wide burned area and estimates of carbon stock losses

276 During the 2015–2016 El Niño, 15.2% of our study region and 982, 276 ha of forest experienced
277 understory wildfires. These wildfires were overwhelmingly concentrated in primary forests: less
278 than 2% of the burned area was in secondary forests, despite these accounting for 9% of the
279 forest cover in our study region. When considering all primary and secondary forest plots (prim1
280 + sec1), resultant necromass carbon stock losses amounted to 10.06 Tg (95% confidence
281 interval, 5.85–14.27 Tg). Converting to CO₂, this is equivalent to expected emissions of 33.05 Tg
282 (95% confidence interval, 19.22–46.87 Tg; figure 5). Our mean CO₂ emission estimates were
283 relatively insensitive to the land-use scenarios (figure 5). However, the 95% confidence interval
284 was substantially wider with land-use scenario prim2 (scenarios b and d; figure 5) owing to greater
285 uncertainty in decomposition rates when restricted to disturbed primary forest only compared with
286 all primary forests—undisturbed and disturbed—combined.

287 (d) Comparing our results with global fire emission databases

288 Both GFED and GFAS vastly underestimated expected wildfire CO₂ emissions for our study
289 region and period. Respectively, these databases suggest cumulative emissions that are 77%
290 and 68% lower than the expected value we found with land-use scenario a (prim1 + sec1; figure
291 5). These discrepancies can be explained by the underdetection of understory wildfires by both
292 GFED and GFAS algorithms. This can be seen across our whole study region but is particularly
293 evident in areas free from historic deforestation (figure 6). GFED and GFAS appeared to be more
294 successful at detecting fires in agricultural areas with lower levels of forest cover (figure 6).
295 Highlighting the insensitivity of GFED to understory wildfires, this database suggests that, at most,
296 6% of any given 0.25° cell across our study region, and approximately 90,000 ha in total, burned
297 during the 2015–2016 El Niño (figure 6e). By contrast, we show that as much as 74% of a cell
298 (figure 6f) and almost 1 Mha of forest was affected by understory wildfires.

299 4. Discussion

300 (a) Region-wide carbon emissions from El Niño-mediated wildfires

301 We investigated necromass carbon stocks in human-modified forests before and after large-scale
302 understory wildfires in central-eastern Amazonia that occurred during the 2015–2016 El Niño.
303 Our novel assessment revealed that expected immediate necromass CO₂ emissions from these
304 wildfires are around 30 Tg (figure 5). This is equivalent to total CO₂ emissions from fossil fuel
305 combustion and the production of cement in Denmark, or 6% of such emissions from Brazil, in
306 2014 [46]. Consequently, wildfire-mediated immediate carbon emissions, which are not currently
307 considered under national greenhouse gas inventories [47], represent a large source of CO₂
308 emissions. Moreover, these immediate emissions will be greatly exacerbated by further
309 committed emissions resulting from tree mortality, which can be as high as 50% [16] and may not
310 be balanced by post-fire regrowth on decadal time scales [22].

311 Our results add to work on prescribed burns associated with deforestation [36], contributing
312 important information about the role of El Niño-mediated wildfires. The scale of the immediate
313 emissions we estimated, coupled with future committed emissions, make wildfires particularly
314 relevant to climate change mitigation programmes such as REDD+ [9,48]. For REDD+ to succeed
315 in Amazonia, we demonstrate that forests must be protected from wildfires, as even the immediate
316 emissions from large-scale wildfires can equal those from whole countries. Future climate change
317 will make this only more imperative, with extreme droughts, higher temperatures, and reduced
318 rainfall all predicted for the Amazon basin in the near future [49–51]. Wildfires may also undermine
319 the important role that protected areas have historically served as carbon stores [52], as illustrated
320 by the large areas burned in the Tapajós National Forest and the Tapajós-Arapiuns Extractive
321 Reserve (figure 1).

322 (b) Fuel loads in humid tropical forests

323 Total necromass carbon stocks in the 107 RAS plots surveyed in 2010 did not vary significantly
324 between disturbed and undisturbed primary forests (figure 2e). The mean value we found for total
325 necromass carbon stocks in undisturbed forests was 30.2±2.1 Mg ha⁻¹. This value is broadly
326 consistent with previous estimates for the eastern Amazon. For example, Keller et al. [30] and
327 Palace et al. [31] found necromass carbon stocks of, respectively, 25.4 and 29.2 Mg ha⁻¹ in
328 undisturbed primary forests in the Tapajós region of Pará. In primary forests disturbed by reduced-
329 impact logging, these studies found, respectively, 36.4 and 42.75 Mg ha⁻¹ of necromass carbon.
330 However, our estimates for necromass stocks in disturbed primary forests are markedly lower
331 (figure 2e). This discrepancy is likely a function of time since disturbance. Keller et al. [30] and
332 Palace et al. [31] assessed necromass carbon stocks soon after disturbance, when necromass
333 stocks are likely to be higher. By contrast, disturbance of RAS sites occurred between 1.5 and 25
334 years before the 2010 surveys. Necromass stocks can be highly dynamic, with residence times
335 for most CWD estimated at less than a decade [28], especially in the case of small diameter and
336 low wood density tree species [53]. Thus, necromass stocks in many of our disturbed primary
337 forest sites may have had time to decrease to an equilibrium level, similar to that of undisturbed
338 forests, where input and decomposition are largely balanced.

339 We did, however, find significantly larger necromass stocks in primary forests compared with
340 secondary forests. This may be explained by (a) pre-abandonment secondary forest land-uses
341 removing all fallen biomass with machinery or intensive fires; (b) the smaller necromass input pool
342 in secondary forests owing to lower levels of aboveground live biomass [37]; and (c) the lower
343 wood density of stems in secondary forests [54], resulting in more rapid CWD decomposition.

344 (c) Impacts of El Niño-mediated wildfires on necromass stocks

345 On average, we estimate that wildfires burned $87.1 \pm 2.7\%$ of our fire-affected necromass
346 monitoring plots (figure 3b). This figure is substantially higher than the 62–75% burn coverage
347 measured during experimental fires in previously undisturbed transitional Amazonian forests [18].
348 The areal extent of these wildfires reduced necromass (in CWD, FWD and leaf litter) carbon
349 stocks by $46.9 \pm 6.9\%$, when gross necromass loss ($73.0 \pm 4.9\%$) was corrected for
350 decomposition ($26.1 \pm 4.8\%$). The understory wildfires that affected our burned plots were
351 relatively low intensity, with maximum median char height of 20.5 cm. Nonetheless, our findings
352 demonstrate that these low-intensity wildfires can dramatically diminish necromass stocks in
353 human-modified tropical forests. Further, both area of plot burned and necromass carbon stock
354 losses showed little variation across disturbance classes. This may indicate that the 2015–2016
355 El Niño, which was one of the strongest in recorded history, produced drought conditions so
356 severe that necromass moisture content was reduced across all forest classes to a level that
357 permitted combustion and sustained fires, overriding any pre-existing microclimatic differences
358 that may have existed owing to the initial disturbance. This is further corroborated by the fact that
359 wildfires did not distinguish between largely undisturbed forests (mostly inside protected areas)
360 and those that have been modified by humans (mostly outside protected areas), burning vast
361 areas of both types of forest (figure 1).

362 (d) Caveats

363 Though our dataset is the first to our knowledge that allows for quantification of necromass carbon
364 stocks pre- and post-uncontrolled understory wildfires in human-modified Amazonian forests,
365 our sample size was limited, with just 18 necromass monitoring plots, of which seven burned
366 during the 2015–2016 El Niño. Consequently, results that follow from these samples should be
367 treated with a degree of caution. In particular, we found that necromass stock losses were not
368 significantly related to our plot-level estimate of burned area and that fire susceptibility did not
369 appear to vary across disturbance classes. In both cases, the lack of significance may reflect the
370 small sample sizes rather than a genuine lack of relationship.

371 Moreover, owing to the limitations of our data, we assumed 100% combustion of leaf litter and
372 FWD in the fraction of plots that burned when calculating necromass carbon losses (equation (1)).
373 In a recent review, Van Leeuwen et al. [36] found that mean combustion completeness of leaves,
374 litter and smaller classes of woody debris was 73–94%. However, as they acknowledge,
375 combustion completeness can be significantly higher during El Niño years. Thus, given the

376 strength of the 2015–2016 El Niño, and our personal observations (electronic supplementary
377 material, figure S1), our combustion completeness assumption is likely to be reasonable.

378 Because of our small sample size, the 95% confidence intervals for our region-wide CO₂
379 immediate emissions were wide, ranging from around 8 Tg to almost 48 Tg. Future research
380 efforts should prioritize necromass monitoring in a larger number of sites, across a range of
381 tropical forests, to better constrain these values; as we show, such emissions have the potential
382 to significantly exacerbate global climate change.

383 Despite the above limitations, there are reasons to suspect that our necromass stock loss and
384 carbon emission estimates are highly conservative. First, we did not measure wildfire induced
385 carbon changes in the soil organic layer, yet research from the same region suggests that wildfires
386 significantly reduce soil carbon pools [55]; nor could we estimate combustion of dead-standing
387 stems, which accounted for approximately 15% of total necromass (figure 2). Second, none of
388 the disturbed primary forest plots in which we monitored necromass changes was recently
389 disturbed prior to the 2015–2016 wildfires, allowing time for decomposition to reduce high levels
390 of post-disturbance necromass. Had our sample included recently disturbed sites, necromass
391 losses would have been greater. Third, detection of low-intensity understory wildfires continues
392 to present a remote sensing challenge. Although manual correction of our unsupervised land-use
393 classifications revealed only a small number of misclassifications, it is possible that some wildfire-
394 affected sites were missed, leading to an underestimation of regional emissions.

395 In addition to showing that wildfire carbon emissions can be substantial, we also showed that
396 such emissions remain poorly quantified. GFED and GFAS, CO₂ emission databases that are
397 widely used in Earth Systems models and carbon budgets, returned considerably lower emission
398 estimates for our study region and period than our expected values (figure 5). Nevertheless, the
399 scale of this discrepancy is underestimated for several reasons. First, we focused solely on
400 necromass carbon losses from understory wildfires, whereas GFED and GFAS include emissions
401 from all land-use classes combined. Both databases therefore account for grassland and
402 agricultural fires, which can affect large areas of human-modified tropical landscapes. Second,
403 GFED includes both committed and immediate CO₂ emissions. Third, and again with respect to
404 GFED, fuel loads are much high than those present in our post-disturbance plots, because they
405 are primarily derived from slash-and-burn and deforestation studies.

406 (e) Conclusions

407 We demonstrate that there was a substantial loss of necromass following El Niño-mediated
408 wildfires in the central-eastern Amazon. We conservatively estimate that wildfires in this region
409 burned 982,276 ha (15.2% of our study region) of primary and secondary forest, resulting in
410 expected immediate CO₂ emissions of approximately 30 Tg. Better understanding this large and
411 poorly quantified source of atmospheric carbon is crucial for climate change mitigation efforts.

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427 Author contributions

428 JB, FE-S and EB designed the study. EB and JF were responsible for plot selection and
429 subsequent authorizations from landowners. EB, JB, JF, LEOCA and YM designed the field
430 protocols. EB, AP, FF, LCR, and KW performed data collection. KW, GDL, AP, EB and CVJS
431 performed data analyses. KW, GDL, EB, and JB wrote the paper with input from all co-authors.

432 Data accessibility

433 The field data and code used in this paper have been deposited at
434 <https://doi.org/10.6084/m9.figshare.7059494>. The satellite imagery is available from USGS
435 (see <https://landsat.usgs.gov/landsat-data-access>). The GFED and GFAS dataset are available
436 from <https://www.globalfiredata.org/data.html> and [http://apps.ecmwf.int/datasets/data/cams-](http://apps.ecmwf.int/datasets/data/cams-gfas/)
437 [gfas/](http://apps.ecmwf.int/datasets/data/cams-gfas/), respectively.

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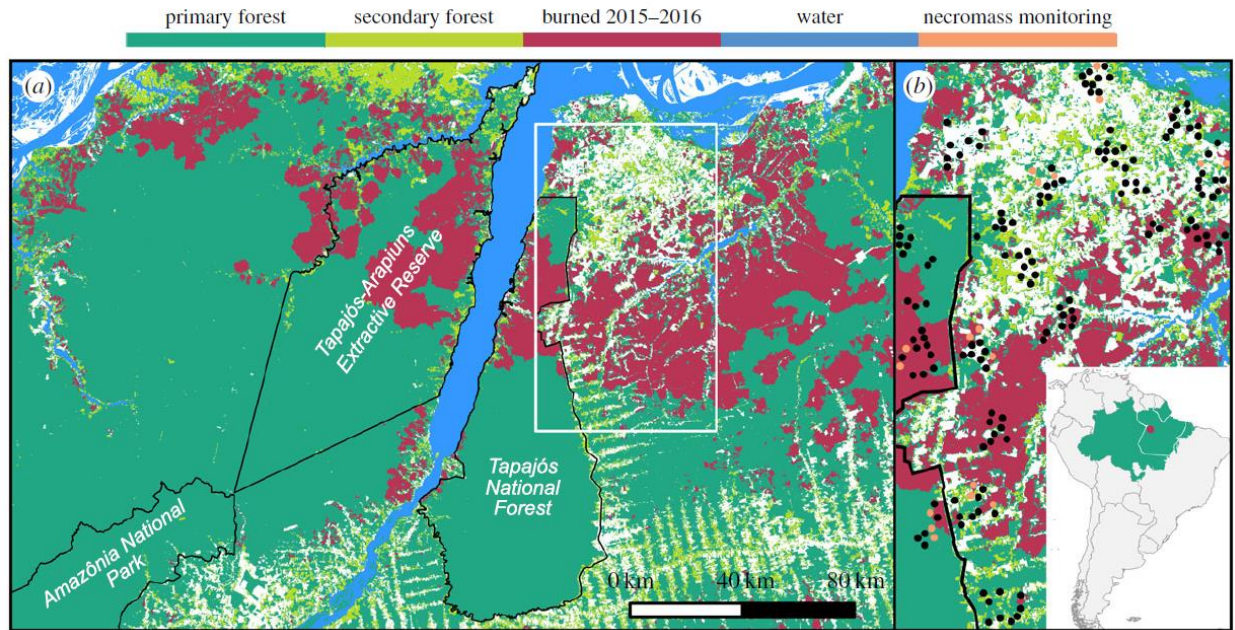
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597 **Figures & Tables**

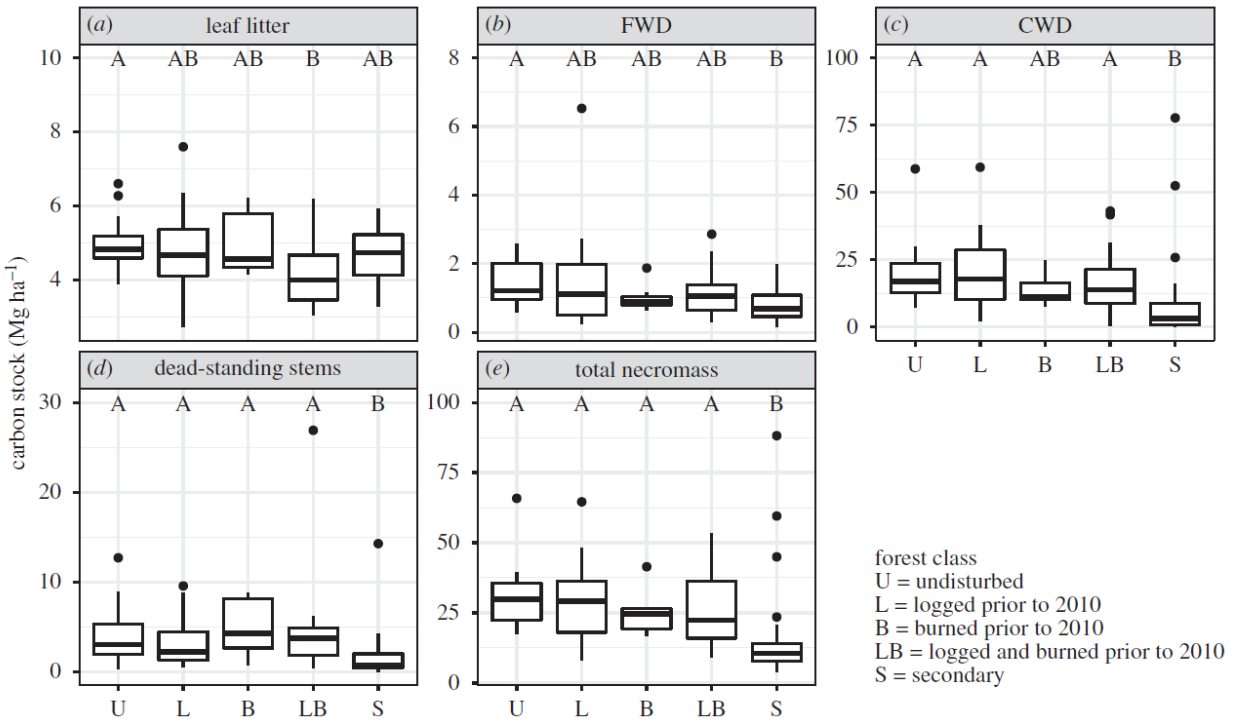
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600 Figure 1. (a) The 2017 land-use map across the ~6.5 million ha study region. (b) The land-use
 601 map within the RAS study area (shown by the white border in (a)). Also shown in this panel are
 602 the locations of the 107 study plots (black circles). The 18 of these that were used for necromass
 603 monitoring are shown as orange circles. The inset shows the Santarém study region (red circle)
 604 within South America, the Brazilian Amazon (green), and Pará (white border).

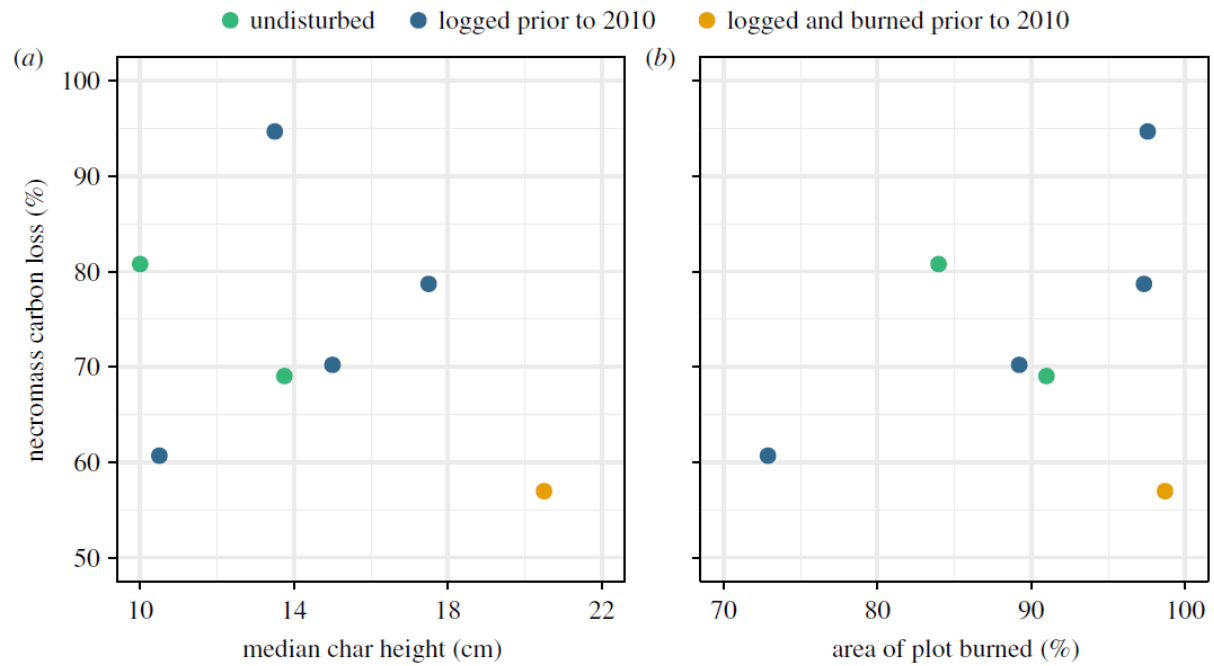
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607 Figure 2. Necromass carbon stocks in leaf litter (a), fine woody debris (FWD; b), coarse woody
 608 debris (CWD; c), dead standing stems (d), and the total across all components (e) in human-
 609 modified Amazonian forests. Boxplots show the interquartile range. Letters above the boxplots
 610 show the results from multiple pairwise comparisons of forest class medians. Classes that do not
 611 share a letter have significantly different medians ($p < 0.05$).

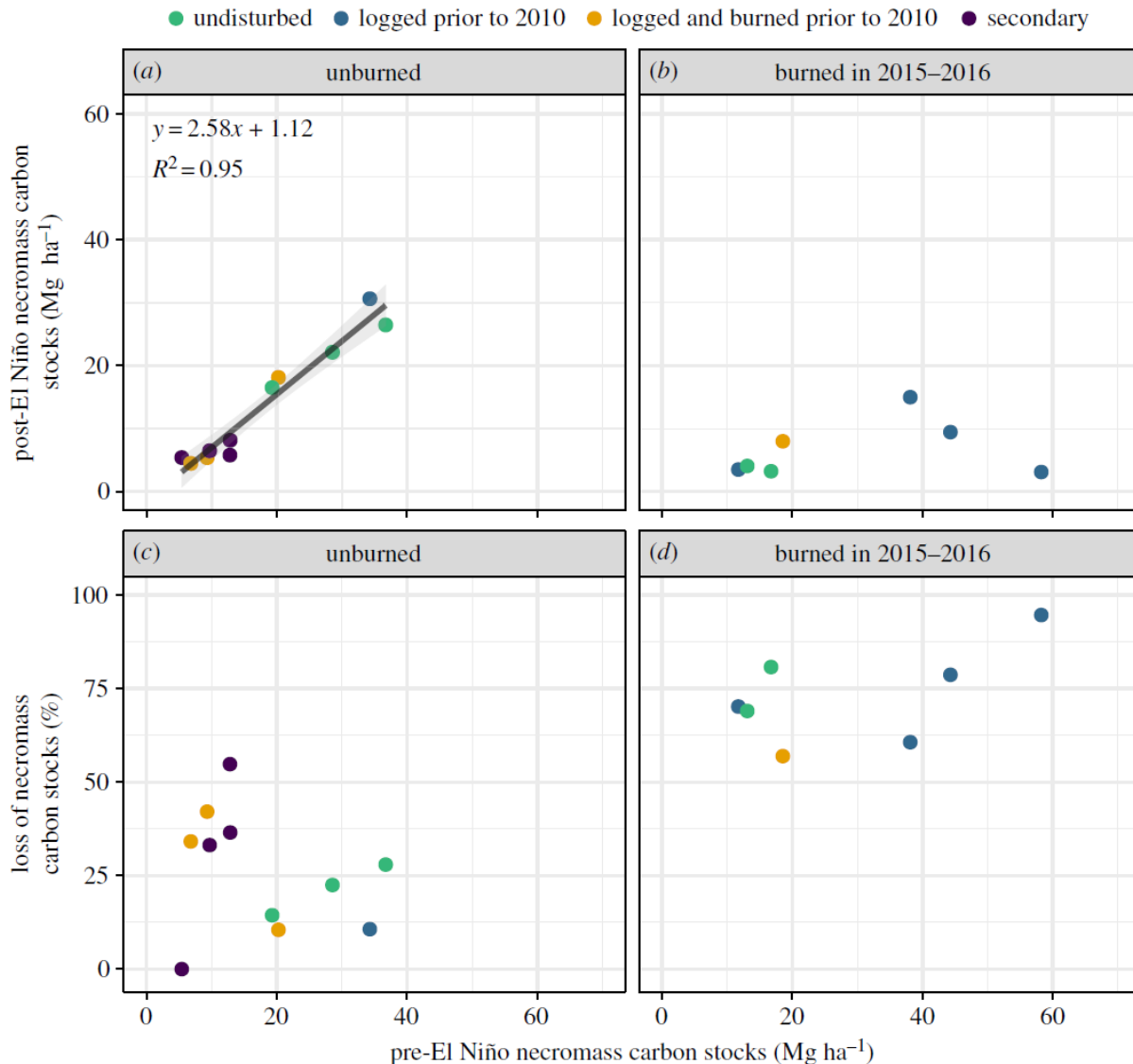
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614 Figure 3. The relationship between percentage reduction in necromass carbon stocks and fire
 615 intensity (a), as measured by median char height, and plot-level estimates of burned area (b) in
 616 human-modified Amazonian forests.

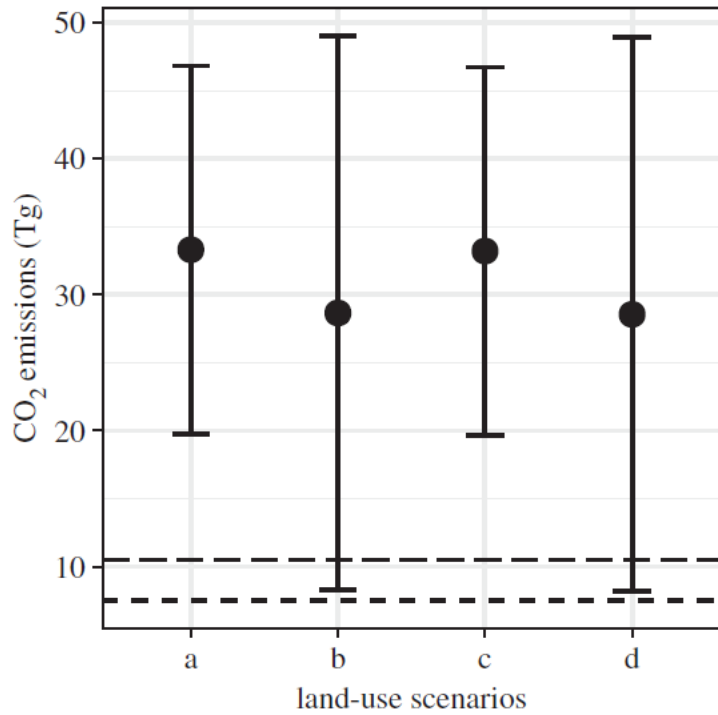
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619 Figure 4. Pre- vs post-EI Niño necromass carbon stocks in unburned control sites (a) and sites
 620 burned in 2015-16 (b), and pre-EI Niño necromass carbon stocks vs post-EI Niño necromass
 621 losses in unburned control sites (c) and sites burned in 2015-16 (d) in human-modified Amazonian
 622 forests. In panel (a) the black line shows the significant ($p < 0.001$) relationship between pre- and
 623 post-EI Niño necromass carbon stocks in unburned sites. The equation for this relationship is
 624 shown in the panel. The grey band represents 1 s.e.m. Note that, due to data limitations, pre- and
 625 post-EI Niño necromass totals are based on coarse and fine woody debris and leaf litter only (i.e.
 626 dead standing stems are not included).

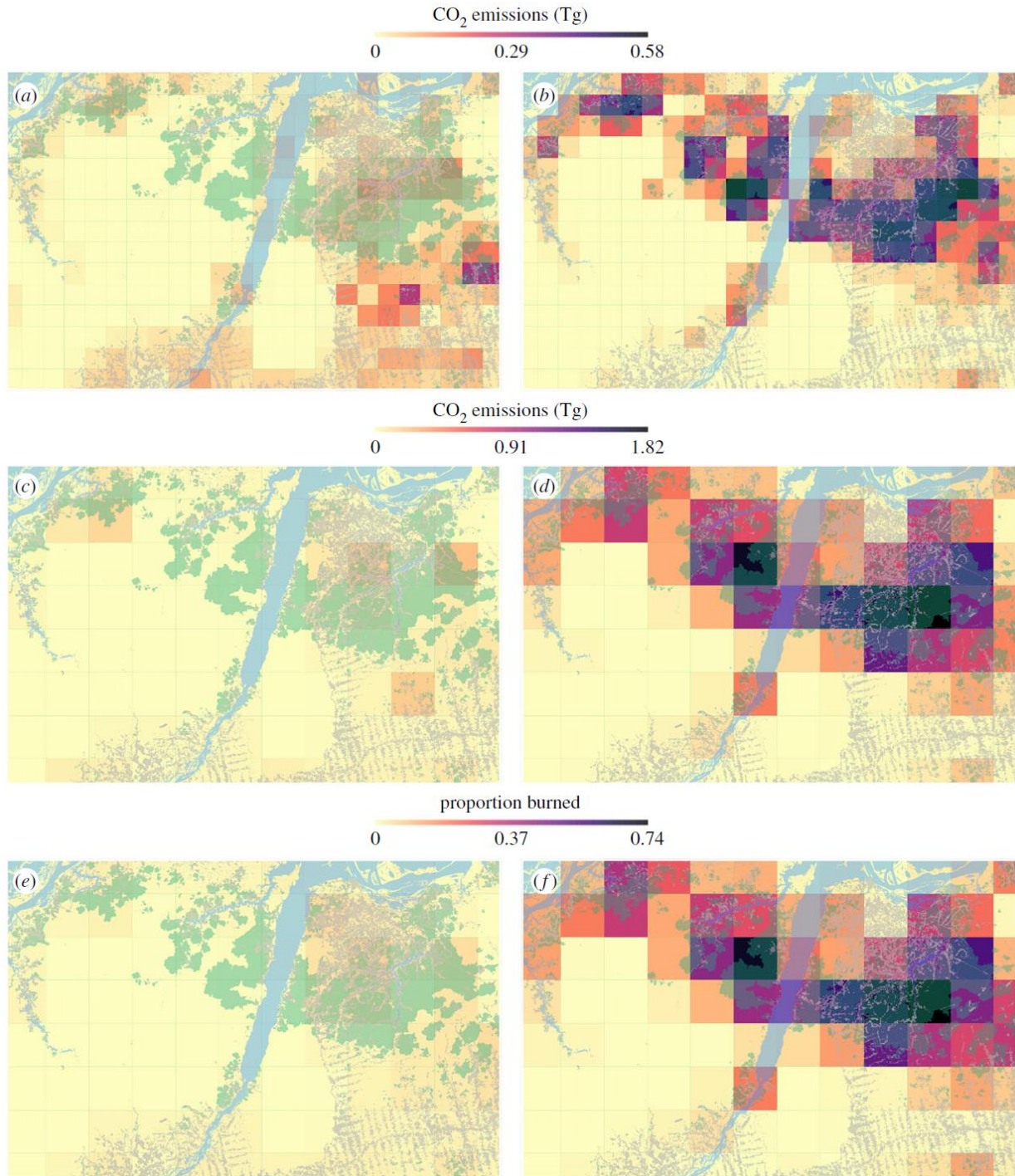
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629 Figure 5. CO₂ emissions for wildfires in central-eastern Amazonian human-modified tropical
 630 forests. Points show expected emissions for four land-use scenarios (see Section 2e and table
 631 S1): a, prim1 + sec1; b, prim2 + sec1; c, prim1 + sec2; d, prim2 + sec2. Error bars show CO₂
 632 emission 95% confidence intervals. Also shown are cumulative CO₂ emissions for our study
 633 region and period from the Global Fire Emissions Database (dotted line) and the Global Fire
 634 Assimilation System (dashed line).

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637 Figure 6: Comparing our findings to those from the Global Fire Assimilation System (GFAS) and
 638 the Global Fire Emissions Database (GFED). CO₂ emissions for our study region and period from
 639 GFAS (a) and our emissions shown at the same scale (0.1 degrees; (b)). CO₂ emissions from
 640 GFED (c) and our emissions shown at the same scale (0.25 degrees; (d)). The proportion of land
 641 burned for our study region and period from GFED (e) and our estimate of burned area shown at

642 the same scale (0.25 degrees; (f)). In all panels, our Landsat-derived fire map is shown in dark
 643 green, deforestation in light grey, and water in blue.

644 Table 1: Forest classifications for pre-El Niño forest disturbance classes and the plot samples in
 645 2010, 2014-15 and 2017. The 2015-16 sample occurred after the extensive wildfires and is a
 646 subset of the 2014-15 sample.

Pre-El Niño forest class	Definition	Necromass assessment (2010)	Monitoring of coarse woody debris (2014-2015)	Burned in 2015-16 and sampled in 2017	Fire intensity and plot burned area (2017)
Undisturbed primary forest	Primary forest with no evidence of human disturbance, such as fire scars or standing tree damage	17	5	2	3
Logged primary forest	Primary forest with evidence of logging, such as logging debris	26	5	4	1
Burned primary forest	Primary forest with evidence of recent fire, such as fire scars	7	0	0	0
Logged-and-burned primary forest	Primary forest with evidence of both logging and fire	24	4	1	4
Secondary forest	Forest regenerating after complete removal of native vegetation	33	4	0	1

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