

# 1 Compositional response of Amazon forests to climate change

2 Running head: Amazon tree community change

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## Abstract

37 Most of the planet's diversity is concentrated in the tropics, which includes many regions  
38 undergoing rapid climate change. Yet, while climate-induced biodiversity changes are widely  
39 documented elsewhere, few studies have addressed this issue for lowland tropical ecosystems.  
40 Here we investigate whether the floristic and functional composition of intact lowland  
41 Amazonian forests have been changing by evaluating records from 106 long-term inventory  
42 plots spanning 30 years. We analyse three traits that have been hypothesized to respond to  
43 different environmental drivers (increase in moisture stress and atmospheric CO<sub>2</sub>  
44 concentrations): maximum tree size, biogeographic water-deficit affiliation and wood density.  
45 Tree communities have become increasingly dominated by large-statured taxa, but to date there  
46 has been no detectable change in mean wood density or water deficit affiliation at the  
47 community level, despite most forest plots having experienced an intensification of the dry  
48 season. However, among newly recruited trees dry-affiliated genera have become more  
49 abundant, while the mortality of wet-affiliated genera has increased in those plots where the  
50 dry season has intensified most. Thus, while changes in compositional dynamics (recruits and  
51 mortality) are consistent with climate-change drivers, these have yet to significantly impact  
52 whole-community composition. Overall, we find that the increase in atmospheric CO<sub>2</sub> appears  
53 to be driving a shift within tree communities to large-statured species and that climate changes  
54 to date will eventually impact Amazon forest composition, but long generation times of tropical  
55 trees mean that the speed of the floristic response is lagging behind the rate of climatic change.

## 56 **Introduction**

57 Tropical forests represent the world's most biodiverse ecosystems, as well as providing its  
58 largest stores of living carbon and contributing more to biomass productivity than any other  
59 biome on the planet. Changes here can therefore have global consequences, potentially  
60 nowhere more so than in Amazonia where between 6,000 and 16,000 tree species exist  
61 (Cardoso *et al.*, 2017, ter Steege *et al.*, 2013) and as much as 100 Pg of carbon is stored in  
62 biomass (Feldpausch *et al.*, 2012). While the physical, chemical, and biological environment  
63 have all been changing over recent decades, it is the changes in climate – both documented and  
64 projected – which are widely expected to cause some of the most profound changes in forest  
65 communities and ecosystem processes (Esquivel-Muelbert *et al.*, 2017a, Thomas *et al.*, 2004).  
66 For example, higher temperatures and intensifying drought may threaten larger trees due to  
67 hydraulic failure (McDowell & Allen, 2015, Rowland *et al.*, 2015), which could eventually  
68 compromise forest biomass and productivity. In Amazonia, because forest diversity is  
69 concentrated in the wetter, least seasonal forests (Francis & Currie, 2003, Gentry, 1988), a  
70 persistent lengthening of the dry season might threaten a large portion of tropical biodiversity.  
71 Here we aim to better understand how Amazonian trees have responded to the last 30 years of  
72 environmental change, by analysing floristic records from long-term tree monitoring in the  
73 Neotropics to assess the potential compositional changes to date.

74 Changes in biodiversity attributed to climate change have already been documented in  
75 a wide variety of ecosystems (e.g. Bowler *et al.*, 2017, Chen *et al.*, 2009), including in some  
76 tropical locations, but so far there is remarkably little evidence of any widespread impacts of  
77 climate change on the composition of tropical ecosystems which harbour much of the planet's  
78 diversity (Duque *et al.*, 2015, Fauset *et al.*, 2012, van der Sande *et al.*, 2016). In contrast, there

79 is evidence for large-scale changes in the structure (i.e., aboveground biomass) and dynamics  
80 (e.g., mortality and productivity) of old-growth tropical forests. In many forests, apparently  
81 undisturbed by humans, both aboveground biomass and the rate of ecological processes such  
82 as growth and recruitment have increased (Brienen *et al.*, 2015, Lewis *et al.*, 2009b, Phillips &  
83 Gentry, 1994, Qie *et al.*, 2017), while in Amazonia increases in mortality have caused a recent  
84 weakening of the biomass carbon sink (Brienen *et al.*, 2015). However, it remains unclear  
85 whether these structural and dynamic changes are also associated with concerted changes in  
86 the species richness and composition of Amazonian forests.

87         In Amazonia, as elsewhere, climate change is a potential leading driver of changes to  
88 the ecosystem. During the last few decades, the climate of Amazonia has become more extreme  
89 – the length of the dry season and its intensity have increased, whilst precipitation has become  
90 more intense during the wet season (Gloor *et al.*, 2015, Hilker *et al.*, 2014). Extreme climate  
91 events in recent years include the three strong droughts within a decade (Erfanian *et al.*, 2017,  
92 Jiménez-Muñoz *et al.*, 2016, Lewis *et al.*, 2011, Marengo *et al.*, 2008, Marengo *et al.*, 2011)  
93 and several large-scale episodes of extreme rainfall (Espinoza *et al.*, 2014, Marengo &  
94 Espinoza, 2016). In addition to the repeated drought events, precipitation has declined in the  
95 south and south east of the basin (25% reduction in rainfall between 2000 and 2012) (Hilker *et*  
96 *al.*, 2014) and higher temperatures are likely to have intensified seasonal evaporative stress  
97 across the basin (Jiménez-Muñoz *et al.*, 2013). These changes are consistent with model-based  
98 predictions (Duffy *et al.*, 2015), implying that the Amazon may already have entered a new  
99 regime of a hotter, more variable climate. The forest has clearly responded to these recent  
100 fluctuations in climate – for example, tree mortality rates increased markedly during and after  
101 drought events causing at least temporary losses of standing biomass (Brienen *et al.*, 2015,  
102 Feldpausch *et al.*, 2016, Phillips *et al.*, 2009, Zuleta *et al.*, 2017). The 2010 drought also

103 impacted on the basin-wide exchange of carbon dioxide between the vegetation and the  
104 atmosphere, with the vegetation becoming a net source of CO<sub>2</sub> during 2010 (Gatti *et al.*, 2014).

105         In addition to the changes in climate, atmospheric CO<sub>2</sub> concentrations have increased  
106 globally from 340 ppm to over 400 ppm over the past 50 years (Conway & Tans, 2016).  
107 Carbon dioxide is also a fundamental resource for photosynthesis and higher concentrations  
108 are expected to stimulate plant growth (Lloyd & Farquhar, 1996). Indeed, the increase in  
109 atmospheric concentrations of CO<sub>2</sub> is a potential driver of the observed increase in  
110 aboveground biomass and turnover rates in tropical forests (Brienen *et al.*, 2015, Lewis *et al.*,  
111 2009a, Pan *et al.*, 2011, Zhu *et al.*, 2016). Additionally, under higher CO<sub>2</sub> concentrations plants  
112 may increase their water-use efficiency with less water being required per unit of carbon fixed.  
113 Thus, by allowing plants to use less water, higher CO<sub>2</sub> concentrations could alleviate the effect  
114 of increasing aridity (Lloyd & Farquhar, 2008, van der Sleen *et al.*, 2015).

115         Interpreting potential shifts in tropical floristic composition and linking them with  
116 possible drivers is a considerable challenge due to the very high diversity of tropical forests  
117 and their large spatial extent. However, if sufficient high-quality, long-term floristic monitoring  
118 is available, then the approach of analysing shifts in a suite of functional traits to describe how  
119 communities change over time can be used to link floristic changes to their drivers (McGill *et*  
120 *al.*, 2006, Violle *et al.*, 2014). For tropical tree species, two largely independent trait axes may  
121 have value in addressing these questions. One axis, the life-history trade-off between growth  
122 and mortality, can be represented by wood density as it is negatively correlated to growth and  
123 mortality rates. This is a reflection of slow-growing trees tending to invest more in wood  
124 structure (Chave *et al.*, 2009, Muller-Landau, 2004, Nascimento *et al.*, 2005, Poorter *et al.*,

125 2010). The other axis is related to the potential size that taxa can attain, representing the  
126 capacity of taxa to compete for light (Falster & Westoby, 2005, Poorter *et al.*, 2005).

127 Environmental changes could have different impacts along each of these ecological  
128 axes (Chave *et al.*, 2008, Lewis *et al.*, 2009a). Most notably, with more extended or intense  
129 periods of soil water deficit, large trees and those with low wood density may be at greatest  
130 risk of hydraulic failure due to cavitation (McDowell & Allen, 2015, Rowland *et al.*, 2015).  
131 Large trees have been shown to be particularly affected by artificially-imposed drought  
132 (McDowell & Allen, 2015, Nepstad *et al.*, 2007, Rowland *et al.*, 2015) and drought events  
133 (Bennett *et al.*, 2015, Phillips *et al.*, 2010). On the other hand, several observations from  
134 tropical forests show a decline of small understory taxa associated with increases in soil water  
135 deficit increases (e.g. Condit *et al.*, 1996, Enquist & Enquist, 2011, Fauset *et al.*, 2012, Feeley  
136 *et al.*, 2011a). To explain these observations, it has been hypothesized that small taxa have  
137 shallower roots and are therefore be more vulnerable compared to large, deep rooted trees to  
138 long-term drying trends (Condit *et al.*, 1996, Fauset *et al.*, 2012). Although the link between  
139 rooting depth and tree size is still unclear (Stahl *et al.*, 2013), this hypothesis is consistent with  
140 wetter areas tending to have more densely populated understoreys (Malhi *et al.*, 2002, Pitman  
141 *et al.*, 2002) and taller forests being less sensitive to precipitation variability (Giardina *et al.*,  
142 2018). The on-going increase in atmospheric carbon dioxide is also expected to cause changes  
143 in species composition as it is predicted to favour those trees that have greater competitive  
144 capacity to access light (Coomes *et al.*, 2011, Laurance, 2004), consequently increasing the  
145 mean potential tree size within the community (e.g. Laurance *et al.*, 2004) and to favour fast-  
146 growing trees, potentially leading to communities with lower wood density.



147           Given the uncertainty about how tree size relates to responses to a drying climate, the  
148 geographic distributions of species over precipitation gradients offer an alternative source of  
149 information with which to predict and to infer the effects of drought on floristic composition.  
150 The spatial distribution of tree taxa over precipitation gradients has been shown to provide a  
151 valuable proxy for drought-tolerance in observational studies and experiments (Engelbrecht *et*  
152 *al.*, 2007, Esquivel-Muelbert *et al.*, 2017b). If drought is increasingly affecting Amazonian  
153 forests, we might therefore expect concerted shifts in tree communities towards more dry-  
154 affiliated components. A compositional shift towards more dry-tolerant taxa as a consequence  
155 of an increase in moisture-stress has been reported locally for sites in southern Ghana (Fauset  
156 *et al.*, 2012), Central America (Enquist & Enquist, 2011, Feeley *et al.*, 2011a), and parts of the  
157 Amazon (Butt *et al.*, 2014).

158           Here, we aim to quantify the shifts in the floristic composition of Amazonian tree  
159 communities, and test the hypothesis that recent climatic drying is already impacting the  
160 composition of Amazonian forests. The dataset derives from 106 long-term, tree inventory  
161 plots distributed across intact closed-canopy moist forests in lowland Bolivia, Brazil,  
162 Colombia, Ecuador, French Guiana, Guyana, Peru, and Venezuela (Appendix S1). We analyse  
163 monitoring records from as early as 1985 onwards to as recently as 2015, deliberately excluding  
164 any possible influence of the 2015-16 El Niño drought from our analysis. We investigate trends  
165 within the overall community composition, as well as among recruits, trees that died, and in  
166 the growth rate that occurred within each census interval (Figure 1). We analyse compositional  
167 shifts along these three trait axes, which we demonstrate to be independent: life-history (using  
168 wood density as a proxy), potential size, and bioclimatic distribution (Appendix S2). Based on  
169 predictions from plant physiology supported by experimental studies, we expect increases in  
170 dry season duration or intensity to shift floristic composition towards dry-affiliated and taxa

171 with smaller-statured genera with high wood density (McDowell & Allen, 2015, Rowland *et*  
172 *al.*, 2015). Additionally, we examine trends in abundance for individual genera, which allows  
173 us to understand which taxa dominate the changes in functional composition.

## 174 **Methods**

### 175 **Field observations and forest dynamics**

176 We investigate the trends in functional and floristic composition of tree communities  
177 by analysing long-term data from permanent tree inventory plots in the Amazon and adjacent  
178 lowland forests (Appendix S1). A total of 106 South American forest plots from the RAINFOR  
179 network (Malhi *et al.*, 2002), accessed via the ForestPlots.net repository (Lopez-Gonzalez *et*  
180 *al.*, 2011), met our criteria: (i) sampling lowland (< 1000 m.a.s.l), *terra firme*, intact, moist  
181 forests (i.e., where mean maximum cumulative water deficit (MCWD) over the last century is  
182 less negative than  $-300 \text{ mm y}^{-1}$ ); (ii) having been monitored throughout the period of the two  
183 intense dry seasons in 2005 and 2010 (see Supplementary material for analyses including plots  
184 that were not monitored during 2005 and 2010); (iii) having had regular monitoring, thus  
185 excluding any plots where census interval lengths differed by more than 10 years; (iv) having  
186 at least 80% of tree stems identified at least to genus level. The selected plots have a mean area  
187 of 1.25 ha (95% CI = 1.16, 1.35), and have been re-censused on average 7 times, with a mean  
188 census interval of 2.8 years.

189 The long-term plots were monitored following a standardized protocol (Phillips *et al.*,  
190 2016). Full methodological details are given elsewhere (Brienen *et al.*, 2015). In brief, all trees  
191 and palms  $\geq 10$  cm diameter (D) at 1.3 m (or above-buttress) are tagged, identified to the species  
192 level (when possible), have their D measured, and the point of measurement marked and

193 recorded. At every census, trees previously recorded are re-measured, and new recruits - i.e.,  
194 trees that have newly attained 10 cm when the plot is revisited - tagged, measured and  
195 identified, and notes are taken about the individuals that died between censuses. Lianas and  
196 non-woody freestanding plants (*Phenakospermum*) are excluded from our analyses.

## 197 **Climate data**

198 To characterise the change in moisture-stress we calculated temporal trends in  
199 maximum cumulative water deficit (MCWD - Aragao *et al.*, 2007) for each plot. MCWD  
200 represents the most negative value of water deficit (wd), i.e., the difference between  
201 precipitation (P) and evapotranspiration (E) within each year, where for each month (n) wd is  
202 quantified as:

$$\begin{aligned} 203 \quad & \text{If } wd_{n-1} - E_n + P_n < 0; \\ 204 \quad & \text{then } wd_n = wd_{n-1} - E_n + P_n \quad \text{Eq (1)} \\ 205 \quad & \text{else } wd_n = 0 \end{aligned}$$

206 In other words, MCWD is an annual water deficit metric which takes into account both  
207 the length and intensity of the dry season based solely on climatic variables, i.e., ignoring soil  
208 properties. The calculation of MCWD does not necessarily follow the calendar year, as for  
209 tropical forests in the northern hemisphere the annual dry season typically spans two calendar  
210 years (between October and March). Thus, the starting point, i.e., when  $n = 1$ , was defined  
211 climatologically as the wettest month in the first year in the time series (i.e., 1985), rather than  
212 the first month of that calendar year.

213 In addition to annual MCWD, following Feldpausch *et al.* (2016), we also estimated  
214 the intensity of the most extreme dry season between two consecutive censuses, hereafter  
215 termed MCWD<sub>i</sub>. This metric represents a measure of maximum environmental disruption  
216 between two censuses, i.e., the most negative value of annual MCWD between each successive  
217 pair of censuses. Only complete years were considered for this calculation. For the first census  
218 of each plot the MCWD<sub>i</sub> was calculated as the most negative MCWD values within the 3-year  
219 period preceding that census. This time window is equivalent to the mean census interval within  
220 the data (2.8 years).

221 Climate data were obtained from the Climatic Research Unit (CRU), at 0.5° spatial  
222 resolution from 1985 to 2015 (Harris *et al.*, 2014) where evapotranspiration is calculated based  
223 on the Penman–Monteith equation (Allen *et al.*, 1994) using information on temperature, cloud  
224 cover and vapour pressure (Harris *et al.*, 2014). MCWD trends calculated from this ground-  
225 based precipitation data source were consistent with satellite-based data from the Tropical  
226 Rainfall Measuring Mission (TRMM - Huffman *et al.*, 2007) at 0.25° spatial resolution between  
227 1998 and 2010 ( $R^2 = 0.87$ ;  $P < 0.0001$  - see Appendix S3 for more detail). Here we opt to use  
228 ground-based data from CRU as this covers the whole time window of the floristic analyses.

## 229 **Traits**

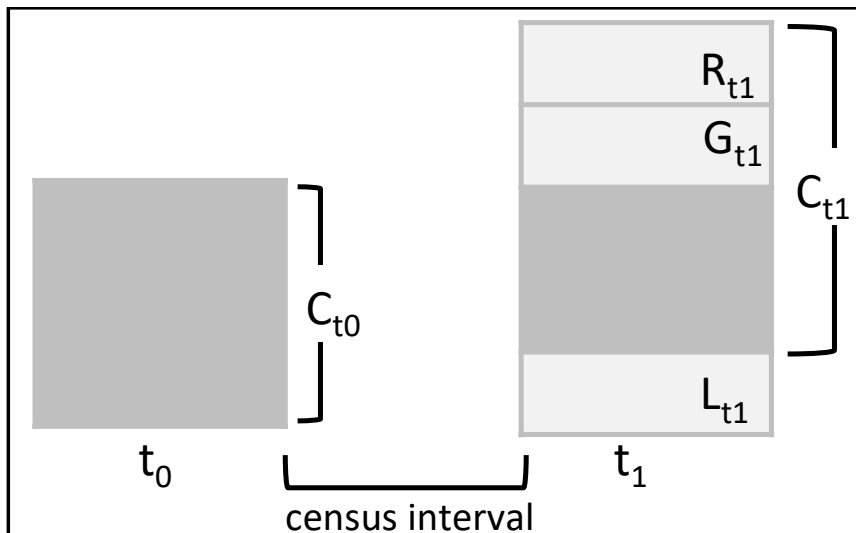
230 We describe Amazonian tree genera in terms of the three basic traits shown in previous  
231 work and in Appendix S2 for our data to represent largely independent axes of fundamental  
232 plant characteristics and each potentially responsive to environmental change: **Potential Size**  
233 **(PS) (cm)**: the 95<sup>th</sup> percentile of the distribution of trees' diameter derived from a set of 530  
234 inventory plots across the Amazon Basin (Fauset *et al.*, 2015); **Water deficit affiliation**  
235 **(WDA) (mm)**: derived from relative abundances across 513 inventory plots distributed along

236 a large gradient of MCWD across the Western Neotropics (Esquivel-Muelbert *et al.*, 2017a).  
237 This metric quantifies the preferred dry season severity for each taxon and is calculated as the  
238 dry season severity (measured as MCWD) where a taxon occurs weighted by the taxon's  
239 relative abundance in each location (Esquivel-Muelbert *et al.*, 2017a). Taxa affiliated to dry  
240 conditions show the most negative values of WDA, whilst the most wet-affiliated ones have  
241 values of WDA equal to zero; **Wood density (WD) (g cm<sup>-3</sup>)**: values were extracted from the  
242 Wood Density Database (Chave *et al.*, 2009, Zanne *et al.*, 2009). There was no indication of  
243 any pairwise relationship among any of the traits: WDA vs. PS ( $R^2 = 8 \times 10^{-3}$ ) WDA vs. WD  
244 ( $R^2 = 5 \times 10^{-4}$ ) and WD vs. PS ( $R^2 = 2 \times 10^{-3}$ ).

245         The diversity of Amazonian flora hinders us from performing consistent species-level  
246 analyses as comprehensive trait data are still missing for the large majority of Amazonian tree  
247 species. Therefore, our analyses were performed at the genus-level and the mean trait value of  
248 the genus was assigned to each individual. Our approach is expected to be adequate to capture  
249 the actual functional shifts in Amazonia as it captures most of the trait variation of Amazonian  
250 trees, which is mostly accounted for at the family and genus level (see Baker *et al.*, 2004,  
251 Coelho de Souza *et al.*, 2016, Fyllas *et al.*, 2009, Patiño *et al.*, 2009). Although genus-level  
252 analyses still of course miss some information on trait variation, analyses at this taxonomic  
253 resolution are potentially more conservative with respect to the hypothesis of environmental-  
254 driven floristic change than analyses at the species level as they use mean genus-level values  
255 instead of (more extreme) species-level values. Results of analyses using species-level traits,  
256 for those taxa where data are available, do not differ from genus-level results (see Appendix  
257 S8).

258 Genus-level trait data were missing for 6%, 9% and 0.04% of all stems for PS, WDA  
259 and WD respectively. For these cases, the mean trait values from the family were used,  
260 following established conventions (Baker *et al.*, 2004, Flores & Coomes, 2011) and  
261 considering the phylogenetic conservatism of PS and WD for Amazonian trees (Coelho de  
262 Souza *et al.*, 2016). For the small proportion of individuals belonging to families for which no  
263 trait information was available, we used average trait values of the community in the same  
264 census was used. For those stems not identified to family level (3.9%), we applied the mean  
265 trait for all dicot individuals of the plot-census during which the tree was recorded. Considering  
266 the low proportion of missing data the imputation technique is unlikely to strongly affect our  
267 results (Penone *et al.*, 2014).

268 Then, to obtain a census-level value for each of the three traits, we scaled the genus-  
269 level traits to the community level by calculating the community-weighted mean (CWM sensu  
270 Diaz *et al.*, 2007) for each trait in each census. For each of the 743 censuses across 106 plots,  
271 the CWM of each of these components was calculated as the mean trait value across the genera  
272 of the community, weighted by (1) the number of stems and (2) the total basal area occupied  
273 by each genus. Community-weighted means were calculated for the whole community and for  
274 each component of forest dynamics, i.e., the recruits (new trees that reach the 10 cm D cut-off  
275 after each census interval), losses (those trees that died within each census interval) and the  
276 basal area gain of those trees that survived the census interval (Figure 1).



277

278 **Figure 1 – Schematic model representing the different components of forest demography.** The box  
 279 on the left represents an inventory plot of a forest community at the first census ( $C_{t0}$ ), whilst the box on  
 280 the right shows the community at the second census ( $C_{t1}$ ). At  $C_{t1}$  recruits ( $R$ ), i.e., those trees that  
 281 attained 10 cm of diameter within the census interval, will now be part of the community analysed.  
 282 Other trees will have died thus leaving the community, here called *losses* ( $L$ ). Those trees from  $C_{t0}$  that  
 283 survive through the census interval are expected to grow ( $G$ ). Thus, the basal area of the whole  
 284 community at  $t_1$  is  $C_{t1} = C_{t0} + G_{t1} + R_{t1} - L_{t1}$  and the net flux between  $t_0$  and  $t_1 = G_{t1} + R_{t1} - L_{t1}$ . Here  
 285 we investigate the trends in the characteristics and identity of genera within these components of forest  
 286 demography. This figure represents dynamics in basal area terms; similar logic can be applied for stem-  
 287 based analyses. Note that in this case we would not be interested in the growth of trees surviving from  
 288  $t_0$  to  $t_1$ , and so the net flux would be represented as  $R_{t1} - L_{t1}$ .

### 289 **Analytical approach**

290 We investigated changes in functional (mean potential size, water deficit affiliation and  
 291 wood density) and floristic composition (relative abundance of individuals within different  
 292 genera) by assessing trends over time of these quantities for each plot and their Amazon-level  
 293 mean.

### 294 ***Trends in functional composition***

295 We investigated functional trends for the different components of forest demography  
 296 (i.e., whole tree community, recruits and trees that died - Figure 1). These functional trends

297 were quantified using (1) the bootstrapped mean and 95% CI of plot level linear regression  
298 slopes of the community weighted mean (CWM) as a function of time, averaged across all  
299 plots, and (2) linear mixed effect models (LMM) of CWM as a function of time with plot  
300 identified as a random effect, using function *lmer* from the R package *lme4* (Bates *et al.*, 2015).  
301 Whilst the first approach provides information of the overall mean trend across all plots, in  
302 which the uncertainty estimate is derived using a non-parametric approach, the second  
303 approach gives an estimate of the trend over the whole period (1985-2015), accounting for  
304 potential changes in which plots are analysed over different time windows along the 30-year  
305 period.

306 The bootstrapped mean and confidence intervals were calculated from the linear slopes  
307 of CWM (i.e., mean plot level traits) for each plot where the CWM in each census (*j*) is a  
308 function of the date when the census took place (time):

$$309 \quad \text{CWM}_j \sim \beta_1 + \beta_2 * \text{time}_j \quad (\text{Eq 2})$$

310 Then, an Amazon-wide weighted mean and the 95% CI were estimated by randomly  
311 resampling values of the plot-level slopes ( $\beta_2$  from Eq. 2) across all plots, 10,000 times. We  
312 further estimate the potential influence of spatial autocorrelation on our results by testing the  
313 correlation between the Euclidean distance in the trends in CWM and the spatial distance  
314 between the plots (Appendix S7).

315 The variation in plot area and monitoring period may be expected to influence plot-  
316 level trends as smaller plots and those monitored for shorter periods are more likely to be  
317 affected by stochastic phenomena, such as tree falls (Fisher *et al.*, 2008). An empirical  
318 investigation of the impact of sampling effort (i.e., length of monitoring period and plot size)



319 on our estimate showed that the variance is expected to scale as a function of the square root  
320 of plot area multiplied by the monitoring period (Appendix S4). Thus, to account for the noise  
321 attributed to sampling effort we used the square root of plot area multiplied by the monitoring  
322 period as weights when calculating Amazon-level mean and confidence intervals of the CWM  
323 slopes.

324 The LMM follows the same logic of the previous analyses with CWM as a linear  
325 function of time:

$$326 \quad CWM_{ij} \sim (\beta_1 + a_i) + (\beta_2 + b_i) * time_{ij} + \varepsilon_{ij} \quad (\text{Eq 3})$$

327 where CWM in plot  $i$  and census  $j$  is a function of the date when the census occurred  
328 (time). Here time is used as a fixed effect and the random components of the model are the  
329 intercept ( $a$ ) and slope ( $b$ ) for each plot and the overall residuals ( $\varepsilon$ ). The slope and intercept of  
330 each plot were included as random effects considering that both the initial trait value  
331 (represented by the plot intercept,  $a_i$ ) and the intensity of change (represented by the plot slope,  
332  $b_i$ ) may differ across plots. An exploration of the influence of sampling effort on the variance  
333 of the residuals shows no weighting procedure to be required for this analytical framework  
334 (Appendix S4).

### 335 ***The influence of climate on functional composition***

336 To explore the potential impact of climate changes on functional change, we tested  
337 whether changes in the community are related to changes in climate. First, we calculated the  
338 linear trend in MCWD and MCWD<sub>i</sub> over the inventory period for each plot. We then used  
339 Kendall's  $\tau$  coefficient to test for the correlation between linear slopes of change in CWMs

340 (composition) and MCWD (climate) for each plot. For the cases where the correlation was  
341 significant, we fit an OLS linear regression with the trends in CWM as a function of trends in  
342 MCWD.

### 343 *Trends in floristic composition*

344 We investigated the influence of individual taxonomic groups on any functional shifts  
345 by analysing the relationship between shifts in abundance and trait values. Trends in relative  
346 abundance for each taxon were calculated following the same procedure applied above to  
347 analyse CWM changes, i.e., by calculating the bootstrapped mean of linear trends and applying  
348 LMM, but here using the relative abundance of each genus as a response variable instead of  
349 CWM. The bootstrap means were calculated from a modified version of Eq 2 applied to every  
350 plot:

$$351 \quad RA_j \sim \beta_1 + \beta_2 * \text{time}_j \quad (\text{Eq 4})$$

352 where RA is the relative abundance of a genus at plot  $i$  and census  $j$ . We then use the  
353 LMM approach by modifying Eq. 3 to:

$$354 \quad RA_{ij} \sim (\beta_1 + a_i) + (\beta_2 + b_i) * \text{time}_{ij} + \varepsilon_{ij} \quad (\text{Eq 5})$$

355 An Amazon-wide slope using each of the methods was calculated for each taxon. The  
356 LMM analysis was restricted to genera that occurred in three or more plots. As for the  
357 functional analyses, each plot in the bootstrap mean following Eq 4 was weighted by the square  
358 root of plot area multiplied by the monitoring period and no weighting procedure was applied  
359 for the LMM approach (Eq 5). Trends in abundance were also calculated for families and  
360 species (Appendix S12).

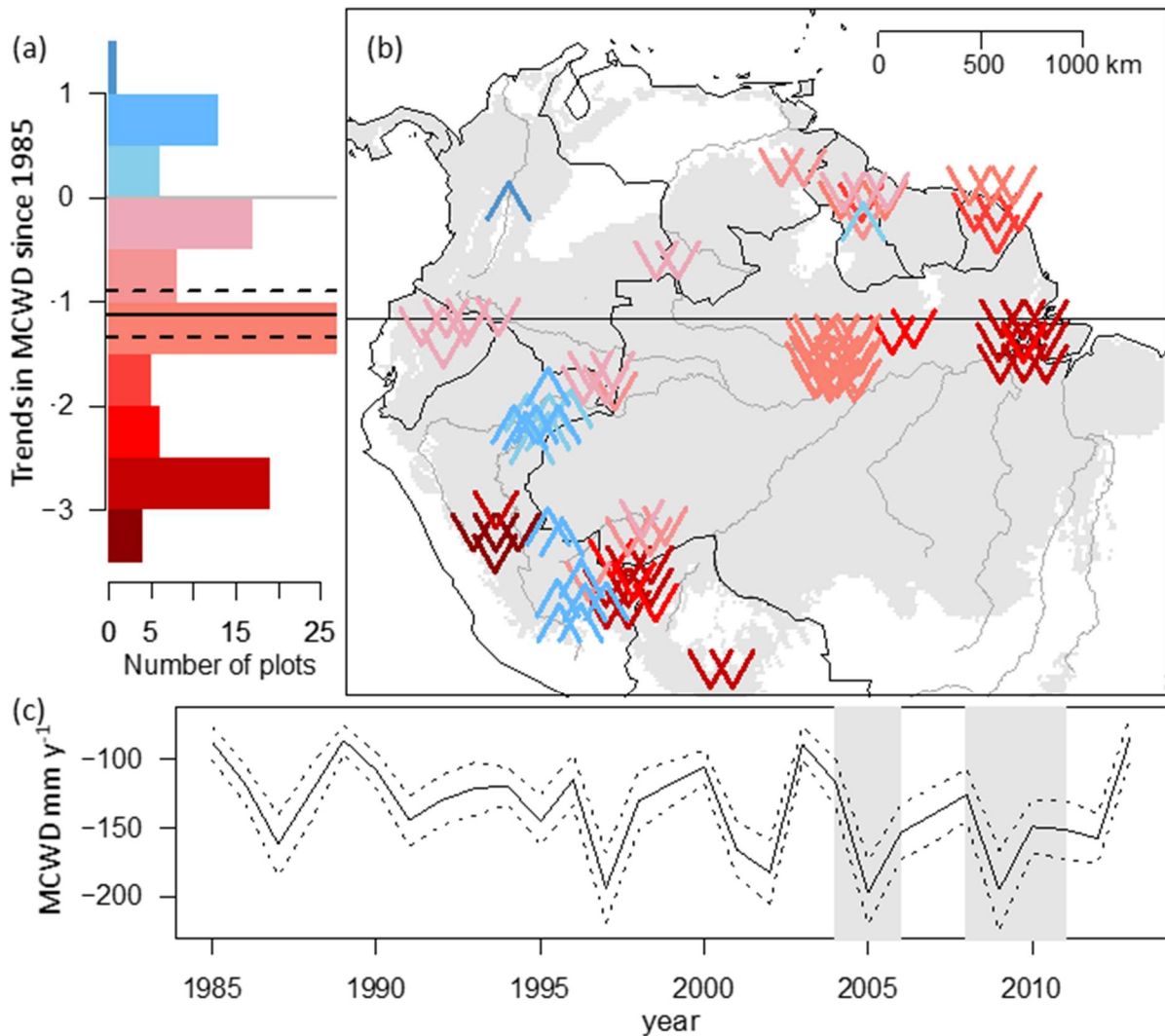
361           Next, we investigated which genera contribute most to the significant functional  
362 changes that were detected. When trends in functional composition were significantly different  
363 from zero (see *Trends in functional composition* for details), we estimated Kendall's  $\tau$   
364 coefficient of correlation between Amazon-wide slopes (calculated for the whole community,  
365 for recruits, and for losses) for each genus and their trait values (WDA, WD or PS). To ensure  
366 that abundance trends were estimated with reasonable levels of uncertainty, we restricted the  
367 investigation of the trends in abundance vs. traits relationship to only include genera within the  
368 upper 20% quantile of abundance across the whole dataset.

369           Finally, we calculated the trends in abundance for four Amazonian functional types  
370 defined by Fyllas *et al.* (2012) using trait information from a subset of the Amazonian species  
371 included in this study. The four Amazonian functional groups (small pioneers, small-statured  
372 non-pioneers, tall pioneers and tall non-pioneers) are based on variety of foliar and structural  
373 traits (Appendix S10) independent from the traits considered in our main analyses. This  
374 therefore provides complementary information to our main analyses.

## 375 **Results**

### 376 **Climate trends**

377 The forests analysed here have on average experienced a strengthening of the dry season, as  
378 measured by maximum cumulative water deficit (MCWD). The plot-level annual MCWD  
379 became more negative by on average 1.1 mm  $y^{-1}$  (95% CI = 1.4, 0.9) since 1985 (Fig. 2). This  
380 represents a marked increase in MCWD across our plots by on average 36% between 1985 and  
381 2014. There are exceptions to the overall drying trend, with some plots near the Andes  
382 becoming wetter during this period (Fig. 2).



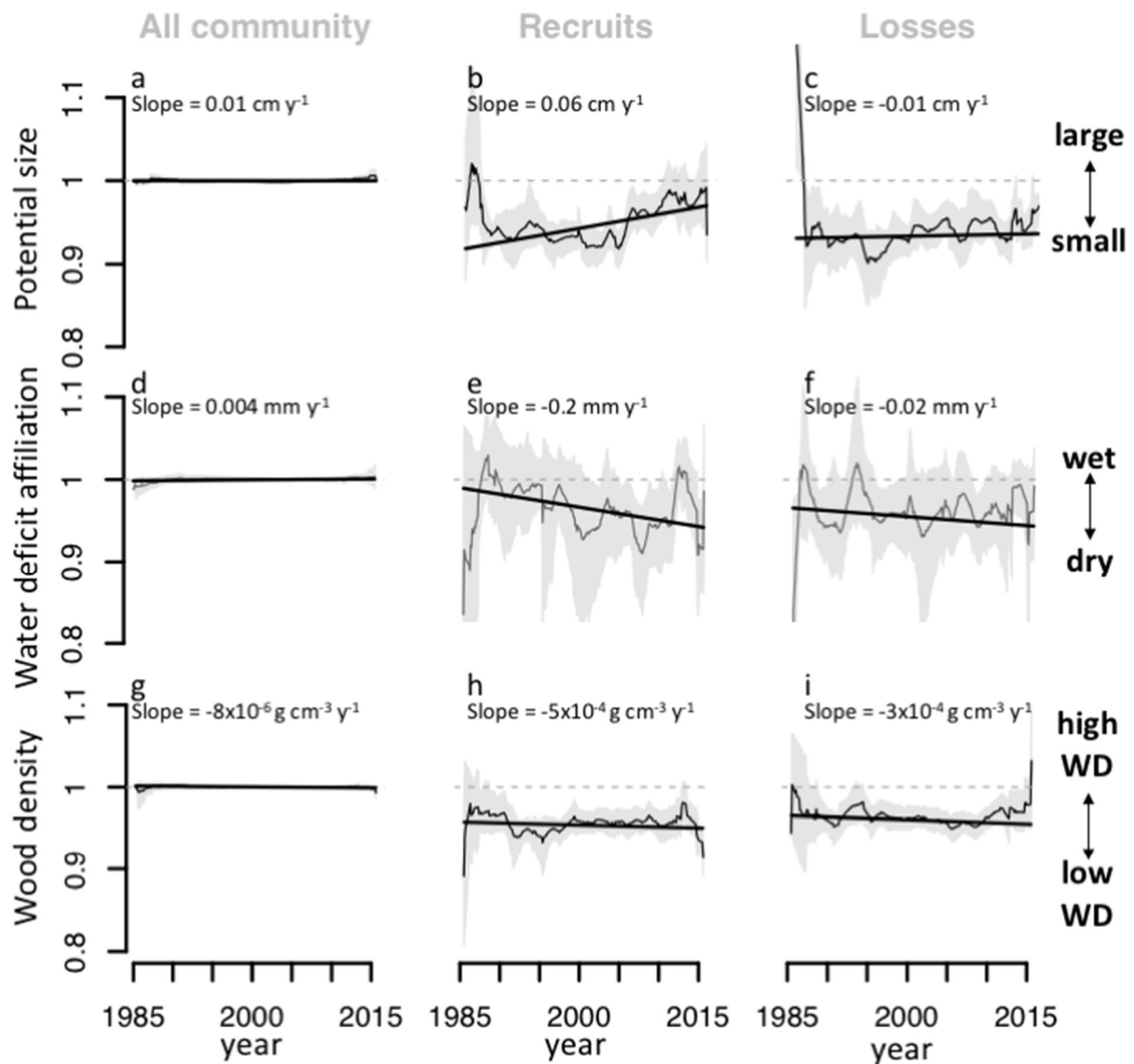
383  
 384 **Figure 2 – Trends in maximum cumulative water deficit (MCWD) across the Amazon Basin. (a)**  
 385 Frequency of annual linear trends in MCWD per plot between 1985 and 2014. Note that for most plots  
 386 the climate has significantly shifted towards more negative MCWD values. Mean change and 95%  
 387 confidence intervals (black solid and dashed lines) across our plots weighting plots by plot area were  
 388 calculated using a bootstrap procedure by resampling the trends in MCWD from all plots 10,000 times  
 389 with replacement. **(b)** Distribution of annual linear trends in MCWD per plot. Arrows pointing down  
 390 (in red) represent locations where MCWD has become more negative over time, i.e., the dry season has  
 391 become more intense. Arrows pointing up (blue) represent less negative values of MCWD meaning that  
 392 moisture stress decreased. The intensity of the colors in (a) and (b) represent the strength of the climate  
 393 trend. Note the difference in scale between drying and wetting trends color bars. **(c)** Mean annual  
 394 MCWD across plots, and 95% CI from resampling among all plots, note lower MCWD values at 2004-  
 395 2005 and 2009-2010 (grey-shaded rectangles).

## 396 **Trends in functional composition**

397 Overall, there has been a significant increase in the potential size (PS) of tree  
398 communities: the community weighted mean (CWM) of PS when weighted by basal area  
399 increased by  $0.03 \text{ cm y}^{-1}$  (95% CI = 0.02, 0.05  $\text{cm y}^{-1}$ ) or  $0.06\% \text{ y}^{-1}$  with basal gains increasing  
400 in PS by  $0.06 \text{ cm y}^{-1}$  (95% CI = 0.01, 0.12  $\text{cm y}^{-1}$ ) meaning that plots have been progressively  
401 occupied by larger statured genera (Table 2). The increase in basal area-weighted community-  
402 level PS holds regardless of the analytical technique, i.e., bootstrapped means or LMM (Table  
403 2, Appendix S6).

404 For the recruits, dry-affiliated genera have become more abundant, with water-deficit  
405 affiliation (WDA) becoming significantly more negative for this segment of the community by  
406  $0.45 \text{ mm y}^{-1}$  (CI 95% -0.9, -0.03  $\text{mm y}^{-1}$ ) or  $0.3\% \text{ y}^{-1}$  (Table 1). This trend was marginally  
407 significant across the basin when calculated using LMM (Appendix S6.1), however it was  
408 observed for 62 out of 102 plots ( $P=0.03$ , two-tailed binomial test) and persisted when our  
409 analyses were repeated across a larger dataset (Appendix S6.2) and when grouping together  
410 nearby plots to account for spatial autocorrelation in the distribution of plots (Appendix S7.2).

411 Among the trees that died within the study period (losses), basal area-weighted wood  
412 density (WD) decreased by  $1 \times 10^{-3} \text{ g cm}^3 \text{ y}^{-1}$  or  $0.16\% \text{ y}^{-1}$  in the LMM analyses (Appendix  
413 S6). This trend, however, was only observed for 53 out of 102 communities, meaning that  
414 positive and negative slopes are equally likely to be observed ( $P=0.8$ , two tail binomial test),  
415 thus it was only marginally significant when using bootstrapped means:  $-1 \times 10^{-3} \text{ g cm}^3 \text{ y}^{-1}$  (90%  
416 CI =  $-2 \times 10^{-3}$ ,  $-5 \times 10^{-6} \text{ g cm}^3 \text{ y}^{-1}$ ). No equivalent significant abundance-based trend for losses in  
417 WD terms was observed (Table 1, Appendix S6).



418  
 419 **Figure 3 – Trends in functional composition between 1985 and 2015 across Amazonia.** The y-axes  
 420 show stem-based community weighted mean (CWM) trends in (a-c) water deficit affiliation (WDA),  
 421 (d-f) potential size (PS) and (g-i) wood density (WD) at genus level. Values are standardized with  
 422 respect to the whole plot population to allow comparison among traits meaning that the value for the  
 423 whole community in the first census is equal to 1. CWM trends are shown for the whole community (a,  
 424 d, g), recruits (b, e, h), and losses (c, f, i). Grey line and grey-shaded area show standardized mean and  
 425 95% CI census-level CWM, which can be influenced by some switching of plots assessed through time.  
 426 Trend lines show linear mixed models (LMM) considering the slope and intercept of plots as random  
 427 effects. Slope values for LMM are shown in each graph - these are not standardized by plot population  
 428 and are shown at a different scale for each trait.

429 **Table 1 – Mean linear slopes in stem-based functional composition in Amazonia.** For each trait, we  
 430 show the bootstrap mean annual changes in community weighted mean (CWM) and 95% confidence  
 431 intervals (CI, in brackets) weighted by the product of the squared root of plot size and monitoring period.  
 432 CWM is calculated using: water deficit affiliation (WDA), potential size (PS) and wood density (WD).  
 433 The analyses were repeated for recruits, losses and the difference between recruits and dead trees (net  
 434 fluxes). Significant trends are in bold, i.e., where 95% CIs do not overlap zero.

Community	Potential size (cm y <sup>-1</sup> )	Water Deficit affiliation (mm y <sup>-1</sup> )	Wood Density (g cm <sup>-3</sup> y <sup>-1</sup> )
Whole community	0.01 (-0.002  0.01)	0.01 (-0.03  0.04)	-1x10 <sup>-5</sup> (-9x10 <sup>-5</sup>   6x10 <sup>-5</sup> )
Gains (recruits)	0.07 (-0.03  0.2)	<b>-0.45 (-0.9  -0.03)</b>	-3x10 <sup>-4</sup> (-2x10 <sup>-3</sup>   1x10 <sup>-3</sup> )
Losses	0.1 (-0.01  0.2)	-0.1 (-0.6  0.3)	2x10 <sup>-4</sup> (-7x10 <sup>-4</sup>   1x10 <sup>-3</sup> )
Net fluxes	-0.03 (-0.2  0.1)	-0.45 (-1  0.1)	-7x10 <sup>-4</sup> (-2x10 <sup>-3</sup>   8x10 <sup>-4</sup> )

435

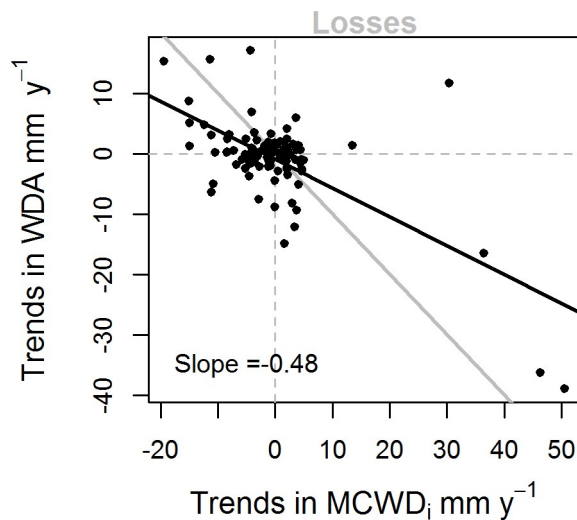
436 **Table 2 – Mean linear slopes in basal area-based functional composition in Amazonia.** As in Table  
 437 1 but showing the results for basal area, see Figure 1 for details.

Community	Potential size (cm y <sup>-1</sup> )	Water Deficit affiliation (mm y <sup>-1</sup> )	Wood Density (g cm <sup>-3</sup> y <sup>-1</sup> )
All community	<b>0.03 (0.02  0.05)</b>	0.01 (-0.04  0.07)	3x10 <sup>-5</sup> (-6x10 <sup>-5</sup>   1x10 <sup>-4</sup> )
Gains (basal area)	<b>0.06 (0.01  0.12)</b>	-0.09 (-0.53  0.2)	-5x10 <sup>-4</sup> (-1x10 <sup>-3</sup>   1x10 <sup>-4</sup> )
Gains (recruits)	0.06 (-0.09  0.19)	-0.08 (-0.7  0.6)	-2x10 <sup>-4</sup> (-2 x10 <sup>-3</sup>   2x10 <sup>-3</sup> )
Losses	0.13 (-0.08  0.33)	-0.33 (-1.2  0.5)	-1x10 <sup>-3</sup> (-2x10 <sup>-3</sup>   3x10 <sup>-4</sup> )
Net fluxes	-0.05 (-0.27  0.2)	0.24 (-0.7  1.19)	9x10 <sup>-4</sup> (-4x10 <sup>-4</sup>   2x10 <sup>-3</sup> )

438

439 **The influence of climate on functional composition**

440 The trends in the intensity of extreme dry events ( $MCWD_i$ ) within each plot were  
441 significantly correlated with trends in the losses of community basal-area WDA (Figure 4) and  
442 the fluxes of basal area WDA (Appendix S9). This indicates that the mortality of large wet-  
443 affiliated trees has increased in plots where the dry seasons have become more extreme. Trends  
444 in climate were also negatively correlated to losses of stem-based WD (Appendix S9). There  
445 was no significant correlation between trends in climate and trends in community weighted  
446 mean of any other trait or segments of the tree community (Appendix S9).



447 **Figure 4 – Relationship between trends in climate and functional composition.** The y-axis  
448 represents plot trends in water deficit affiliation (WDA) per year calculated as the linear slopes of basal  
449 area-based community weighted mean within the losses and x-axis shows the trends in most extreme  
450 dry season within a census interval ( $MCWD_i$ ). The black line represents OLS linear regression and in  
451 the 1:1 line is shown in grey. Note that changes in the tree community are correlated to changes in  
452 climate (Kendall  $\tau = -0.2$ ;  $P < 0.01$ ), i.e., stronger drying trends favour the mortality of wet-affiliated  
453 taxa. Correlations hold when outliers are removed (Kendall  $\tau = -0.4$ ;  $P < 0.05$  when excluding outliers  
454 where climate trend  $> 5 \text{ mm y}^{-1}$  and trends in losses  $> 10 \text{ mm y}^{-1}$ ).

456



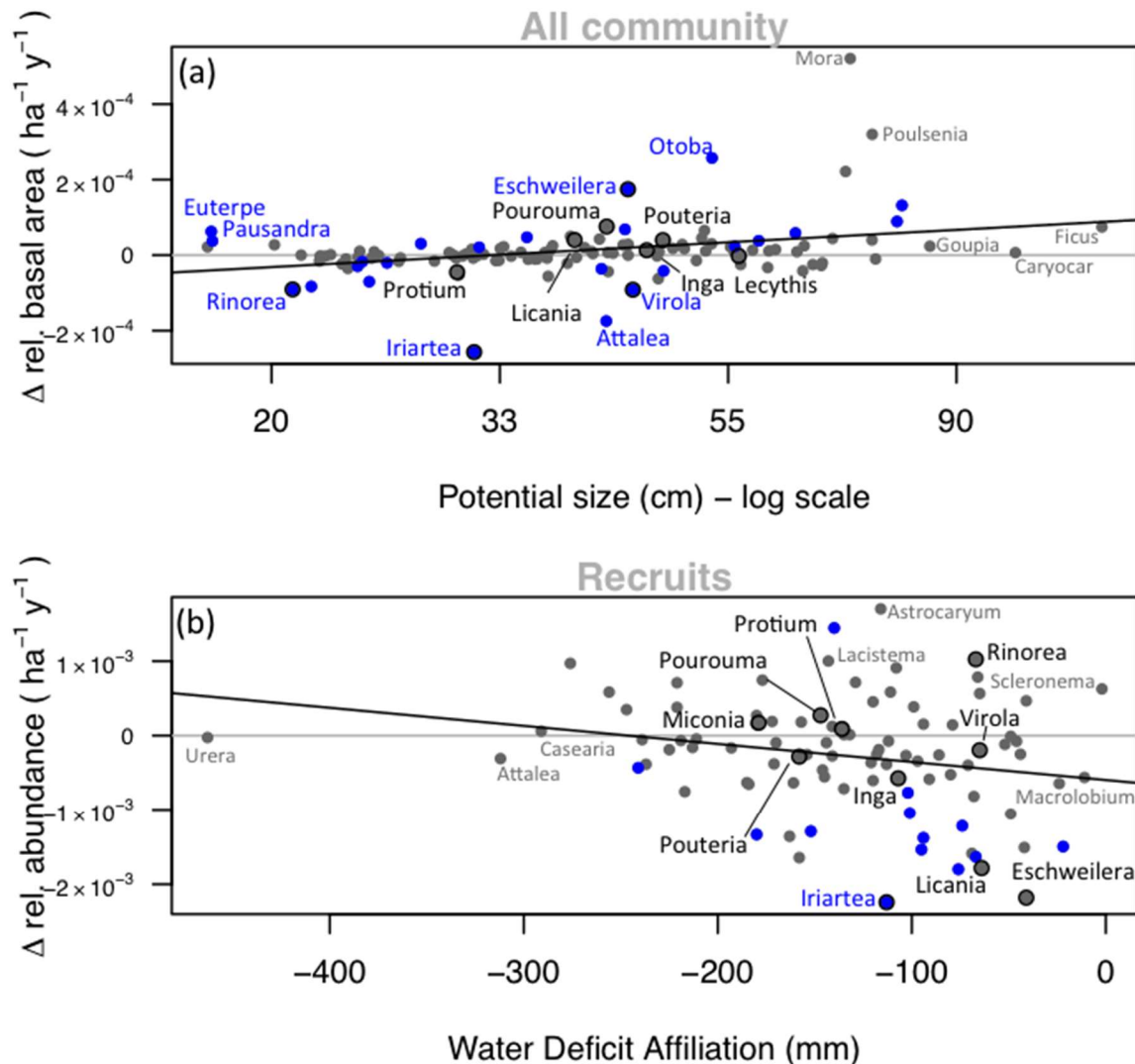
## 457 Floristic trends

458 The floristic changes represented by the linear trends in abundance for individual  
459 genera are generally consistent with the functional changes observed. There has been a notable  
460 increase in the relative abundance of the dry-affiliated genera *Bertholletia*, *Brosimum* and  
461 *Pseudolmedia*, together with sharp decreases for the wet-affiliated *Aparisthmium*, *Fusaea*, *Inga*  
462 and *Mezilaurus*. Some large-statured genera have increased significantly, such as *Mora*,  
463 *Couratari*, and *Eschweilera*. A decrease in smaller-statured taxa, such as *Ouratea*, *Aniba*,  
464 *Marlierea* and *Astrocaryum* is also observed (Appendix S12). Palms (Arecaceae) have  
465 significantly declined in abundance (Appendix S12) overall, with marked declines of  
466 *Oenocarpus* and *Astrocaryum*, even though the hyperdominant palm genus *Euterpe* has  
467 significantly increased in abundance across the basin.

468 By analysing abundance trends of different taxa, it is possible to identify which genera  
469 contribute the most to the observed overall changes in functional composition (i.e., PS in basal  
470 area terms for the whole community and WDA stem density for recruits). The correlation  
471 between taxa PS and their trends in basal area was significant (Kendall  $\tau = 0.2$ ; P-value  $< 0.01$ )  
472 and driven by an increase in some emergent and canopy genera such as *Eschweilera*, *Licania*  
473 and *Pouteria*, and a decrease in some sub-canopy and understory genera such as *Iriarteia*,  
474 *Rinorea* and *Oenocarpus* (Figure 5 – Appendix S12). The decrease in WDA within the recruits  
475 was also explained by changes in floristic composition across the Amazon (Kendall  $\tau = -0.16$ ;  
476  $P < 0.05$ ), with declines in the recruitment of new stems of wet affiliated Amazon genera such  
477 as *Mabea*, *Sterculia*, *Swartzia*, *Iryanthera* and *Theobroma* and recruitment increases for dry  
478 affiliates such as *Trema*, *Simarouba* and *Hieronyma* (Appendix S12).

479 Our analyses of the trends in abundance for the functional types defined for Amazonian  
480 trees by Fyllas *et al.* (2012) show small-statured non-pioneer taxa to be significantly decreasing

481 in abundance by 0.29%  $y^{-1}$  (Appendix S10). No significant trend was found for the other  
 482 functional types (small-statured pioneers, tall pioneers, and tall non-pioneers). Note that this  
 483 analysis was limited to the species classified by Fyllas *et al.* (2012) within these four functional  
 484 types, which represent ca. 28% of the total number of individuals within our plots.



485  
 486 **Figure 5 – Floristic changes behind the detected functional shifts.** The y-axes represent mean  
 487 linear slopes of plot level genera relative abundance across the Amazon in terms of number of  
 488 individuals or basal area as a function of time, with each plots' contribution weighted by the square  
 489 root of plot area and monitoring period. Grey horizontal lines indicate zero change. The x-axes  
 490 represent genus-level traits. **(a)** Trends in relative basal area within the whole community vs. potential  
 491 size (cm), plotted in the log scale to facilitate visualization; **(b)** trends in stem relative abundance

492 within the recruits vs. water deficit affiliation (mm). Genera that show confidence intervals not  
493 overlapping zero are shown in blue. Black contour marks the 10 most abundant genera in terms of  
494 number of stems.

## 495 **Discussion**

496 Here we report the first Amazon-wide analyses of temporal trends in functional and  
497 floristic composition of lowland tree communities across 106 Amazonian inventory plots  
498 analysed over three decades. We find evidence of climate-induced shifts in community  
499 composition. Recruits have become more dry-affiliated (Table 1) and the mortality of wet-  
500 affiliated trees has increased in the areas where the drying trend was stronger (Figure 4),  
501 suggesting a direct effect of climate change on functional composition. This compositional  
502 shift is consistent with the detected intensification of the seasonal drought across the majority  
503 of permanent monitoring plots in Amazonia. The trends in potential size (PS) and wood density  
504 (WD) further indicate that changes within the Amazon forest are likely to be a consequence of  
505 a combination of drivers. However, our data also highlight the relative inertia of tropical forest  
506 communities in their ability to respond to environmental changes. For instance, the detected  
507 change in tree communities, with recruits becoming more dry-affiliated by  $0.45 \text{ mm y}^{-1}$ , is  
508 substantially smaller in magnitude when compared to the climate trend of  $1.1 \text{ mm y}^{-1}$ .

509 The functional shifts observed here are mirrored by underlying floristic changes when  
510 our data are analysed in terms of discrete taxonomic units (Figure 5). The genus-level floristic  
511 shifts behind the significant changes detected (Table 1 and 2) illustrates how functional  
512 responses result from actual floristic change across Amazonian communities. However, the  
513 relationships between traits and floristic shifts also show significant scatter, suggesting  
514 idiosyncratic responses of each taxon and the complexity of this highly diverse system.

## 515 **Climate-induced changes in floristic composition**

516           We detected an increase in the abundance of drought-tolerant genera across Amazonia  
517 when analysing the recruitment and mortality within tree communities (Table 1, Figure 4),  
518 consistent with the hypothesis that tree communities are responding to the changes in climate.  
519 Our large-scale results are consistent with tree community shifts towards more drought-tolerant  
520 taxa reported in some neotropical (Butt *et al.*, 2014, Enquist & Enquist, 2011, Feeley *et al.*,  
521 2011b) and west African forest localities (Fauset *et al.*, 2012), and some temperate localities  
522 (McIntyre *et al.*, 2015). Across Amazonia we find that greater mortality of wet-affiliated taxa  
523 over time is related to the degree to which water-stress has increased within each community,  
524 providing direct evidence of the influence of climate on community dynamics (Figure 4). This  
525 only emerged when analysing trends in basal area, indicating that it is driven by the increase in  
526 mortality of large wet-affiliated trees. Indeed, large trees are expected to suffer the most under  
527 drought conditions by being more vulnerable to embolism, and thus more likely to die from  
528 hydraulic failure under drought-stress (McDowell & Allen, 2015, Rowland *et al.*, 2015). In  
529 addition, further supporting the conclusion that this reflects concerted, widespread changes in  
530 Amazon forest mortality, we also found an increase in the potential size of the dead trees when  
531 analyses were repeated considering each cluster of neighbouring plots as a single sample unit  
532 (Appendix S7). Somewhat surprisingly we find losses in stem-based WD to be negatively  
533 correlated to changes in climate (Appendix S9), which suggests that WD may not be a good  
534 proxy of drought vulnerability.

535           Nonetheless our results suggest that other drivers are also causing compositional shifts  
536 in Amazon forests. For example, although we did observe an increase in mortality of large, wet  
537 affiliated trees, consistent with the effect of the 2005 drought (Phillips *et al.*, 2009), somewhat  
538 surprisingly our analyses also show a slight increase in the basal area of potentially large tree

539 genera across the basin. These results contradict the expectations that droughts would  
540 preferably impact larger trees but are in line with the suggestion that smaller-statured trees are  
541 more vulnerable to droughts as they have shallower roots than larger-statured trees (Condit *et*  
542 *al.*, 1996, Fauset *et al.*, 2012, Wright, 1992). Most likely, it appears that the increase in  
543 mortality of large trees in some areas of the basin (Figure 4, Appendix S9) is a consequence of  
544 drought events such as the 2005 drought (cf. Bennett *et al.*, 2015, Phillips *et al.*, 2010), but that  
545 it this mortality has been insufficient to counter a longer-term tendency towards increased basal  
546 area of large-statured taxa across Amazonia.

#### 547 **Additional drivers of compositional change**

548 Larger trees have greater competitive capacity and are anticipated to gain  
549 disproportionately with additional resources (Coomes *et al.*, 2011, Enquist *et al.*, 2009, Enquist  
550 *et al.*, 1999). The increase of atmospheric CO<sub>2</sub> potentially provides a parsimonious explanation  
551 for the observed relative increase in large-tree genera (Table 2). If the increase in atmospheric  
552 CO<sub>2</sub> of ca. 5% per decade since the 1980s (Tans, 2016) is stimulating plant growth or increasing  
553 water-use efficiency, then taxa that tend to compete better for light, notably larger trees (Poorter  
554 *et al.*, 2005), are likely to gain a greater competitive advantage (Falster & Westoby, 2003).  
555 Although further investigation is needed to confirm this hypothesis, our results show an  
556 increase in basal area of large-statured taxa (Figure 3; Table 2) and a decrease in abundance of  
557 non-pioneer small-statured taxa (Appendix S10), both consistent with the expectations from  
558 increased competition. Additionally, the relative increase of larger genera is also observed in  
559 the broader dataset including the fringes of Amazonia (*Extended Amazonia* see Supplementary  
560 material), which supports the inference of a ubiquitous driver of compositional change. Our  
561 observations are also in line with a series of stand-level studies that show increases in above  
562 ground biomass, growth, mortality and recruitment across Amazonia – all trends expected as

563 an outcome from increased atmospheric CO<sub>2</sub> (Brienen *et al.*, 2015, Phillips & Gentry, 1994,  
564 Phillips *et al.*, 1998).

565         While considerable interest has focussed on the atmospheric and climatic changes,  
566 particularly drought, other environmental changes may be important. Conceivably one or more  
567 of these could have pervasive impacts on mature forests across the basin to rival or exceed any  
568 climate impacts. Amazonian forests have been hypothesized to be recovering from previous  
569 disturbances that are either natural (Chambers *et al.*, 2013, van der Sande *et al.*, 2016) or  
570 human-driven, particularly in pre-Colombian times (McMichael *et al.*, 2017). If this is the case,  
571 we would expect the forest to be following a successional trajectory characterised by a shift  
572 from pioneers (low wood density) to mature forest species (high wood density) (e.g., Chave *et*  
573 *al.*, 2008, Connell & Slatyer, 1977, Lewis *et al.*, 2009a). While the observed relative increase  
574 in basal area of larger taxa is consistent with widespread recovery from disturbance (Chave *et*  
575 *al.*, 2008, Wright, 2005), the 106 Amazonian inventory plots show no significant shift in wood  
576 density (WD) across the whole community, or perhaps more importantly, among the recruits  
577 (Table 2). We note that our WD data (Chave *et al.*, 2009, Zanne *et al.*, 2009) provide a less  
578 than perfect insight into actual change given that there is likely to be additional spatial and  
579 intra-generic variation (Baraloto *et al.*, 2010, Patiño *et al.*, 2009) that we cannot account for.  
580 However, WD is considerably conserved across the phylogeny, and genus-level wood density  
581 has been found to be adequate to distinguish between late successional and pioneer genera  
582 (Coelho de Souza *et al.*, 2016). Moreover the only functional group that has clearly *lost* ground  
583 over our monitoring window are the short-statured non-pioneers which are the best adapted to  
584 low light, late-successional environments (Appendix S10). Compositional analyses further  
585 suggest that some pioneers are increasing, most notably an increase of 3.4% ha<sup>-1</sup>y<sup>-1</sup> in the  
586 relative abundance of *Cecropia*, a key early successional taxon (Appendix S12), which

587 typically dominates in early stages of succession but declines at later stages of the successional  
588 trajectory (Zalamea *et al.*, 2012). The increase in the abundance of light-demanding taxa may  
589 be a consequence of an acceleration in the canopy gap dynamics caused by the increase in  
590 baseline mortality rates (Baker *et al.*, 2016, Brienen *et al.*, 2015). Finally, if these forest plots  
591 are recovering from the impact of Amazonian peoples who favoured especially useful species,  
592 then we might expect domesticated taxa *sensu* Levis *et al.* (2017) to now be decreasing in  
593 abundance following the relaxation of this anthropogenic influence. No such trend is observed  
594 in our data (Appendix S11).

595         There has been considerable concern regarding the ecosystem impacts of widespread  
596 removal of large-bodied frugivores. In particular, it has been repeatedly suggested that hunting  
597 will or may have already altered tree composition in tropical forests (e.g. Doughty *et al.*, 2016,  
598 Osuri *et al.*, 2016, Peres *et al.*, 2016, Peres & Palacios, 2007, Terborgh *et al.*, 2008) via  
599 dispersal failure of zoochoric trees (Chapman & Chapman, 1995). These tend to have high  
600 wood density and large stature, so a recruitment failure is predicted to lead to a reduction in the  
601 prevalence of both of these traits and thus in Amazonian biomass (Bello *et al.*, 2015, Peres *et*  
602 *al.*, 2016). This study was designed to understand floristic dynamics in intact Amazonian  
603 forests and not to evaluate the effects of hunting pressure, which is likely to more strongly  
604 affect areas adjacent to rural communities, roads and rivers (Peres & Lake, 2003). However,  
605 the increase in potential size and the lack of change in wood density within the recruits (Figure  
606 3) contradict expectations of the hunting hypothesis as a driver of recent community  
607 composition change in intact forests, which, again, does not rule out the possibility of hunting  
608 pressure causing shifts in composition in particular locations where this activity is stronger.

## 609 **The pace of change**

610 Changes in tree communities are expected to substantially lag behind environmental  
611 changes as trees are sessile and long-lived (Blonder *et al.*, 2017, Davis, 1989, Hubbell, 2001,  
612 Lenoir *et al.*, 2008, Svenning & Sandel, 2013). Our results are consistent with this prediction.  
613 In other systems where climate gradients are almost unidirectional it is possible to assess the  
614 speed at which communities are expected to be moving across spaces to follow climate  
615 (Devictor *et al.*, 2012), but this is not the case for precipitation in Amazonia where precipitation  
616 regime is heterogeneous at multiple spatial scales. However, by ensuring that climate and  
617 water-deficit affiliation are calculated in the same scale we can compare the degree to which  
618 climate and communities are changing. Across Amazonia, plots have undergone an average  
619 drying trend of  $-1.1 \text{ mm y}^{-1}$  MCWD (Figure 2). Notably, change in tree communities did not  
620 keep pace with the change in climate - the mean trend in water-deficit affiliation for the whole  
621 community is two orders of magnitude smaller ( $0.01 \text{ mm y}^{-1}$ , Table 1), with confidence  
622 intervals overlapping zero. However, a much shorter lag is observed when analysing the net  
623 fluxes, i.e., recruits – deaths ( $-0.45 \text{ mm y}^{-1}$ , Table 1), indicating that although responses are  
624 slow, this system has some dynamic capacity to respond to changes in climate.

625 The observed pace of change is a reflection of the nature of these communities.  
626 Recruitment and mortality of trees  $\geq 10 \text{ cm D}$  averaged 9 trees per hectare per year between  
627 1985 and 2010 across the basin (Brienen *et al.*, 2015). Considering that in our data mean stem  
628 density is  $520 \text{ trees ha}^{-1}$  and mean plot-monitoring length is 14 years, we can expect by the  
629 final census an accumulated turnover of  $\approx 24\%$  of stems. Thus, we should expect *a priori* that  
630 whole community-level composition would be only weakly affected by changes over the  
631 measurement period and would instead largely reflecting legacy effects of recruitment and  
632 mortality processes occurring decades prior to the onset of the monitoring period (Davis, 1989).



633 Our results provide empirical evidence of the inertia within this system and clearly raise  
634 concerns about whether forests here will be able to track further climate change anticipated  
635 over coming decades.

636 This study provides the first Amazon-wide picture of functional and floristic dynamics  
637 over the last 30 years. Models have predicted a strengthening of the dry season over the  
638 Amazon (Boisier *et al.*, 2015, Joetzjer *et al.*, 2013), and an increase in water-stress as a  
639 consequence of rising temperature (Pokhrel *et al.*, 2014). But there have been few attempts to  
640 account for changes in composition, which may modulate the whole forest ecological impact  
641 of ecophysiological drivers such as increasing vapour pressure deficit (Levine *et al.*, 2016,  
642 Sakschewski *et al.*, 2016). The velocity and the magnitude of compositional changes presented  
643 here should be considered in attempts to model the dynamics of these forests under future  
644 climate. Our results show that a slow shift towards a more dry-affiliated Amazonia is  
645 underway. If such a floristic shift is substantial enough to increase the resilience of Amazon  
646 tree communities to future droughts, it will still come with a price in terms of tree biodiversity,  
647 since wet-affiliated restricted taxa represent the majority of Amazonian tree flora (Esquivel-  
648 Muelbert *et al.*, 2017a). Furthermore, although our results demonstrate that changes in  
649 composition are possible, the inertia intrinsic to these communities means that they will  
650 substantially lag behind climate change. Droughts are continuing to impact the basin (Erfanian  
651 *et al.*, 2017, Jiménez-Muñoz *et al.*, 2016). If this lag persists, intact Amazonian forests may be  
652 increasingly dominated by sub-optimally adapted trees in terms of their preferred climate  
653 space, potentially threatening the ability of these ecosystems to provide key services such as  
654 protecting biodiversity and sequestering and storing carbon.

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