

# Functional susceptibility of tropical forests to climate change

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## 57 ABSTRACT

58 Tropical forests are some of the most biodiverse ecosystems in the world, yet their  
59 functioning is threatened by anthropogenic disturbances and climate change. Global actions  
60 to conserve tropical forests could be enhanced by targeting areas with low levels of functional  
61 diversity and functional redundancy, and therefore with diminished capacity to respond to a  
62 changing environment. Here, we create estimates of plant functional diversity and  
63 redundancy across the tropics by combining a dataset of 16 morphological, chemical and  
64 photosynthetic plant traits sampled from 2461 individual trees from 74 sites distributed  
65 across four continents, together with local climate data for the last half century. Our findings  
66 suggest a strong link between climate and functional diversity and redundancy with the three  
67 trait groups responding similarly across the tropics and climate gradient. We show that drier  
68 tropical forests are overall less functionally diverse than wetter forests and that functional  
69 redundancy declines with increasing soil water and vapour pressure deficits. Areas with high  
70 functional diversity and high functional redundancy tend to better maintain ecosystem  
71 functioning, such as aboveground biomass, after extreme weather events. Our predictions  
72 suggest that the lower functional diversity and lower functional redundancy of drier tropical  
73 forests, in comparison to wetter forests, may leave them more at risk of shifting towards  
74 alternative states in face of further declines in water availability across tropical regions.

## 75 INTRODUCTION

76 Tropical forests are amongst the most biodiverse ecosystems on the planet <sup>1</sup>, they harbour  
77 more than 50% of global biodiversity including between 67-88% of all tree species <sup>2</sup> and are  
78 responsible for more than 30% of terrestrial productivity <sup>3</sup>. Given the large distribution of  
79 tropical forests on earth, small but widespread changes in their tree community composition  
80 can have global impacts in the removal of CO<sub>2</sub> from the atmosphere <sup>4</sup>. Tropical forests are  
81 also essential to help mitigate the effects of climate change, as intact tropical forests are  
82 carbon sinks of around 1.26 Pg C yr<sup>-1</sup> <sup>5</sup>. However, carbon storage can be negatively impacted  
83 by changes in water availability <sup>6</sup>. For example, the Amazon forest, which contains close to  
84 123 Pg C of above and belowground biomass<sup>7</sup> lost 1.2-1.6 Pg C <sup>8</sup> – the equivalent of 1% of its  
85 total carbon stocks <sup>9</sup> – during the extreme drought of 2005 and it is now suggested to be a  
86 carbon source <sup>10</sup>. Besides impacting the carbon storage capacity of forests, changes in climate  
87 mean states and variability are key potential drivers of biodiversity declines around the world  
88 <sup>11,12</sup>. Understanding how climate may affect tropical forests' capacity to store carbon thereby  
89 requires evaluation of how plants respond to drought stress. To do so, the Maximum Climatic  
90 Water Deficit (MCWD) and Vapour Pressure Deficit (VPD) are two fundamental proxies of  
91 hydric stress for plants <sup>13,14</sup>, with increases in VPD leading to greater plant transpiration stress  
92 <sup>15,16</sup>. Although it has been generally expected that communities historically adapted to high  
93 MCWD and VPD should be better adapted to increasing drier conditions, it could also be that  
94 such communities might already be at their climatic physiological limits and thus further  
95 droughts may increase water stress to such an extent that they are driven towards alternative  
96 states <sup>17,18</sup>. To disentangle these two possibilities, evaluating functional trait composition may  
97 provide clues on their possible historical adaptations to water stress conditions <sup>19,20</sup>. Although  
98 changes in MCWD and VPD are prominent features of climate change across tropical forests,

99 detailed analyses that show their relationship with plant morphology/structure, leaf  
100 chemistry and photosynthesis related traits across climatic and elevation gradients at a  
101 pantropical scale remain scarce. Thus, understanding the functional-climatic gradients  
102 relationship is key to disentangling the long-term role of tropical forests for mitigating climate  
103 change and is crucial for deciphering the resilience of key ecosystem properties such as  
104 diversity and carbon stocks under a changing climate.

105 Ecosystem resilience may increase through different pathways, for example, by  
106 species having the same traits that affect a given ecosystem process, such as carbon capture,  
107 but different traits to respond to environmental changes, such as droughts. Arguably  
108 functional traits may respond differently to diverse drivers of change (e.g. temperature or  
109 precipitation change) which may be reflected in trait diversity but not necessarily in species  
110 richness<sup>21</sup> given that there is not always a tight relation between species richness and  
111 functional trait diversity<sup>22, 23</sup>. According to the biodiversity-ecosystem functioning insurance  
112 hypothesis<sup>24</sup>, ecosystem functions should be less affected by a changing environment when  
113 1) the ecosystem possesses both high functional diversity (e.g. large range of trait values; FD),  
114 2) but also a wide set of species with similar functional characteristics<sup>24</sup> conferring the system  
115 with high functional redundancy (FRed)<sup>25, 26</sup>. Thus, in communities with high functional  
116 diversity and high functional redundancy, the loss of a given species is less likely to result in  
117 the disruption of the ecosystem function<sup>27</sup>, as other species will probably continue carrying  
118 out the same functions, substituting the lost species<sup>28, 29</sup>. High FD and high FRed may enhance  
119 the temporal stability of ecosystem functions (e.g., biomass productivity)<sup>30</sup> and thus provide  
120 a buffering effect against environmental changes<sup>24</sup>, conferring higher resilience.  
121 Nonetheless, these hypotheses have never been tested across the tropics, and the role of FD  
122 and FRed for maintaining the tropical forests ability to capture and store carbon remains to  
123 be tested and quantified at this global scale. Quantifying the FD and FRed is crucial to  
124 advancing our understanding of the resilience of these forests in the Anthropocene.

125 Here, we address this knowledge gap by combining a new pantropical dataset of 16  
126 plant traits related to morphology/structure (leaf area, leaf dry and fresh mass, leaf dry  
127 matter content, leaf water content, specific leaf area, leaf thickness, wood density), foliar  
128 nutrients (leaf calcium, potassium, magnesium, nitrogen and phosphorus content) and  
129 photosynthesis (photosynthetic rate, dark respiration). These plant traits are hypothesised to  
130 be of importance for tropical forests to adapt or respond to a drying climate (see Table S1 for  
131 a description of their hypothesised importance). The importance of such traits relies on their  
132 influence on the capacity of species to capture energy for growth and conserve resources (e.g.  
133 water) for survival under stressful environmental conditions, such as droughts, and have been  
134 shown to change in response to a changing climate<sup>31, 32, 33</sup>. The plant traits were collected  
135 from 2461 individual trees belonging to 1611 species distributed across 74 plots that  
136 contained 32,464 individual trees equal to or greater than 10 cm diameter at breast height  
137 from 2497 species (Fig. S1, Table S2, See Methods). The vegetation plots are free of obvious  
138 local anthropogenic disturbance (i.e., far from forest edges, and no evidence of logging or  
139 fires) and cover a wide range of the climatic conditions found across tropical and subtropical

dry and moist broadleaf forests (Fig. S2; Fig. S3). This dataset was combined with estimates of MCWD and VPD from 1958-2017 and of soil chemistry (cation exchange capacity) and texture (clay content) (Fig. S3).

We address three fundamental questions: 1) Does the long-term mean ambient water stress environment (MCWD and VPD) or its changes ( $\Delta$ MCWD and  $\Delta$ VPD) over the last half-century determine current functional diversity (Fig. S3)? First, we examine the relationship between the functional diversity (here calculated as functional dispersion<sup>34</sup>) and redundancy levels across tropical regions. 2) What is the spatial distribution of functional diversity and redundancy across tropical forests? 3) Is there a relationship between functional diversity or functional redundancy and one metric of ecosystem functioning (above ground biomass) during extreme drought events? We expect that: 1) Communities that are found in drier climate conditions and that have experienced stronger decreases in water availability across the last half century will be less functionally diverse but may be more functionally redundant as a result of climate filtering for better adapted traits than communities in less extreme conditions such as wetter forests; 2) Across the full spatial distribution of tropical forests, tropical wet forests communities, which are more species-rich than drier tropical forests, have higher functional diversity given a broader set of ecological strategies available as a result of more stable and favourable climate and soil conditions; 3) There is a positive relationship between functional diversity, functional redundancy and ecosystem functioning (i.e. above ground biomass) as more functionally diverse and redundant communities may attenuate the negative effects of a changing climate and may be therefore be considered to be more resilient.

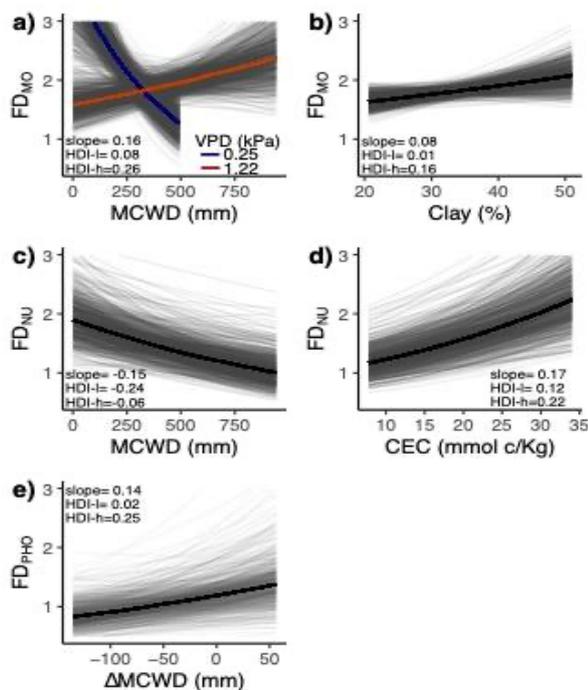
## Results

### Functional diversity and redundancy across tropical forests as a proxy for their susceptibility to climate change

Fundamental knowledge on the climate-FD and climate-FRed relationships across tropical forest ecosystems has been missing. To fill this knowledge gap, we calculated, for vegetation plots distributed across the tropics, the FD and FRed for morphological/structural, leaf chemistry and photosynthetic traits that are hypothesised to be of importance for tropical forests to respond to a drying climate. The selected traits play a role in plant establishment, growth and/or survival<sup>19, 20, 35</sup> (Table S1). Then, we investigated variation in FD and FRed across tropical forests by modelling their relation with MCWD, VPD and their interaction, the  $\Delta$ MCWD and  $\Delta$ VPD and their interaction (see Methods section), where more positive values in MCWD and VPD reflect stronger water deficits. In our models, we also accounted for soil characteristics (see Methods) such as texture (Clay %) and chemistry (cation exchange capacity, CEC). Soils high in clay content may have high water holding capacity over longer periods of time which is important for vegetation under drought conditions<sup>31</sup>. Moreover, it is widely acknowledged that tropical forests in drier regions are generally associated with soils that are richer in nutrients in comparison to wet tropical forests<sup>36</sup>. The feedbacks between soil-rainfall and their effects on plant distributions could be disrupted under a changing climate and therefore have adverse effects on the functioning of tropical

181 forest ecosystems. A principal component analysis (PCA) of climate conditions (long-term  
 182 trends and recent changes) indicated that the first two axes explained 71.3% of the variation  
 183 among plots (Fig. S4a) and the first two axes of the soil-based PCA (with soil chemistry and  
 184 texture) account for 83% of the variation among plots (Fig. S4b).

185 Based on the long-term mean MCWD, our results show that drier tropical forests are  
 186 clearly morphologically less diverse ( $slope = -0.18$   $[-0.31, -0.05]$ , median and 90% highest  
 187 density intervals) than wet forests (Table S2). The effect of MCWD on morphological FD was  
 188 modulated by atmospheric VPD, where the FD of communities with low VPD (blue fitted line  
 189 in Fig. 1a) strongly decreased as MCWD increased, but FD tended to increase with MCWD in  
 190 communities where VPD was high (red fitted line in Fig. 1a). Morphological/structural FD  
 191 increased linearly with increases in clay content ( $slope = 0.08$   $[0.01, 0.16]$ ; Fig. 1b). Foliar  
 192 nutrients FD also tended to decrease towards drier forests ( $slope = -0.15$   $[-0.24, -0.05]$ ; Fig.  
 193 1c). Overall, foliar nutrients FD increased towards communities with higher soil CEC ( $slope =$   
 194  $0.17$   $[0.12, 0.22]$ ; Fig. 1d), while photosynthetic FD also increased towards areas that  
 195 experienced stronger increases in MCWD ( $slope = 0.14$   $[0.02, 0.25]$ ; Fig. 1e) but did not  
 196 respond to the long-term mean MCWD. For the trait groups (morphology, nutrients,  
 197 photosynthesis) for which a clear relationship with climate and soil was found (90% Highest  
 198 Density Interval, HDI, of the posterior distribution does not overlap 0; Table S3), the models  
 199 explained ( $R^2$ ) 44%, 75% and 75% of the variation in morphology/structure, nutrients and  
 200 photosynthetic FD, respectively. The models of FRed as a function of climate and soil  
 201 explained 53%, 73% and 33% of the variation in morphology/structure, nutrients and  
 202 photosynthetic functional redundancy respectively across the tropical forest.



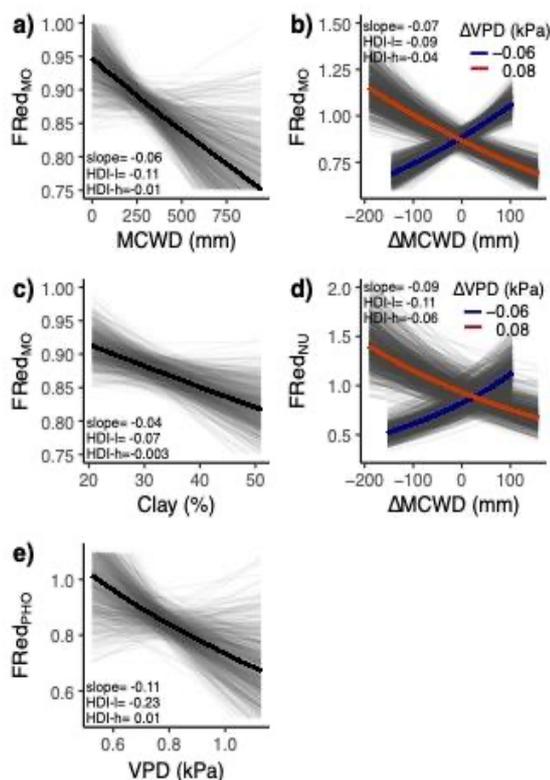
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204 Figure 1. Long-term water availability and its recent changes and soil conditions drive functional diversity of  
 205 morphological (a, b), leaf nutrients (c-d) and photosynthetic (e) plant traits across the tropics. Only climatic  
 206 variables with a clearly important relationship (90% Highest Density Interval, HDI, of the posterior distribution does  
 207 not overlap 0) with functional diversity (FD) are shown. Models for each group (morphology/structure, leaf  
 208 nutrients, photosynthetic) were fitted as a function of long-term and recent changes in climate and of soil chemistry

209 (CEC) and texture (Clay). Thick black lines show the average response and shaded lines show 300 random draws  
 210 from the model posterior distribution representing variability of the expected model fit. The blue fitted line in a)  
 211 shows the effect of MCWD at the lowest value of VPD and the red fitted line at the highest values of VPD. Larger  
 212 positive values in MCWD and VPD reflect stronger water deficits. MCWD: maximum climatic water deficit, VPD:  
 213 vapour pressure deficit, CEC: cation exchange capacity.  $\Delta$ : change. For details about the single traits that form  
 214 each of the groups (MO: morphology/structure, NU: leaf nutrients, PHO: photosynthetic) see Table S1. For full  
 215 statistical results see Table S3.

216 The FRed models (Table S3) showed that redundancy of morphological/structural ( $slope = -$   
 217  $0.06$  [ $-0.11, -0.01$ ]) traits declines with higher long-term mean MCWD and that photosynthetic  
 218 FRed declines as long-term VPD increases ( $slope = -0.11$  [ $-0.23, -0.01$ ]; Fig. 2a and Fig. 2e  
 219 respectively). While redundancy of morphological/structural and foliar nutrients traits  
 220 decreased with increases in MCWD through time ( $\Delta$ MCWD) in areas that also increased the  
 221 most in VPD ( $\Delta$ VPD; Fig. 2b and Fig. 2d red fitted line) the opposite was predicted for areas  
 222 that experienced larger increases in MCWD but smallest increases in VPD (Fig. 2b and Fig. 2d  
 223 blue fitted line). FRed of morphological/structural traits also tended to decrease with  
 224 increases in soil clay content ( $slope = -0.04$  [ $-0.07, -0.003$ ]; Fig. 2c).

225



226

227 **Figure 2. Long-term water availability and its recent changes and soil texture drive functional redundancy of**  
 228 **morphological (a-c), leaf nutrients (d) and photosynthetic (e) plant traits across the tropics.** Only climatic  
 229 variables with a clearly important relationship (90% Highest Density Interval, HDI, of the posterior distribution does  
 230 not overlap 0) with functional redundancy are shown but in e) where the effect of VPD on FRedPHO is marginal.  
 231 Models for each group (morphology/structure, leaf nutrients, photosynthetic) were fitted as a function of long-term  
 232 and changes in climate and of soil chemistry (CEC) and texture (Clay). Thick black lines show the average response  
 233 and shaded lines show 300 random draws from the model posterior distribution representing variability of the  
 234 expected model fit. The blue fitted line in b) and d) shows the effect of  $\Delta$ MCWD at the largest decrease in  $\Delta$ VPD  
 235 and the red fitted line at the larger increase in  $\Delta$ VPD. Larger positive values in MCWD reflect stronger water deficits.  
 236 MCWD: maximum climatic water deficit, VPD: vapour pressure deficit,  $\Delta$ : change. For details about the single traits  
 237 that form each of the groups (MO: morphology/structure, NU: leaf nutrients, PHO: photosynthetic) see Table S1.  
 238 For full statistical results see Table S3.

## 239 Mapping functional diversity and functional redundancy across tropical forests

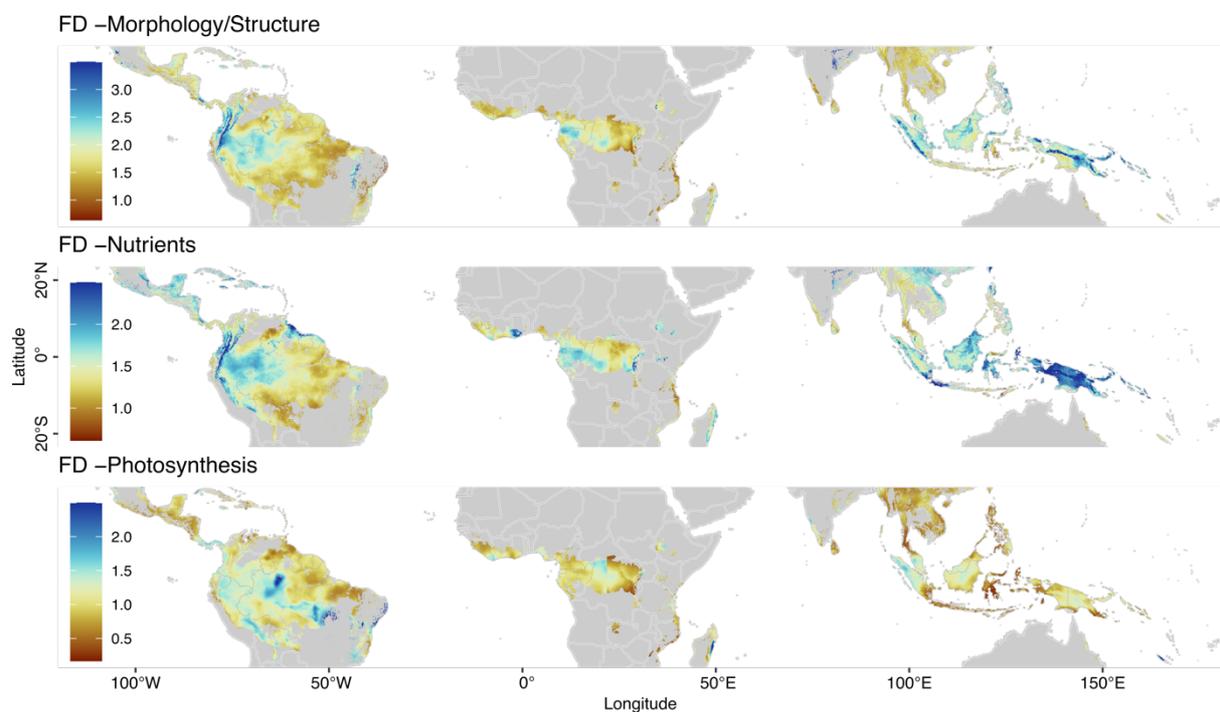
240 Based on our understanding of the relation of FD and FRed of morphological/structural, leaf  
241 nutrients and photosynthetic trait groups with climate and soil (Fig. 1 and Fig. 2), and to fill  
242 the knowledge gap on the pantropical distribution of functional diversity and redundancy we  
243 created pantropical maps of both FD (Fig. 3) and FRed (Fig. 4) distribution. With our map  
244 predictions we aim to uncover the locations of forests with potentially higher and lower  
245 resilience to a changing climate. To this end, we used the statistical models built above (Table  
246 S3) to predict FD and FRed across the pantropical dry and moist broadleaf forests, for which  
247 our field sampling locations have a wide representation of the climatic conditions across those  
248 tropical forests (Fig. S2; Fig. S5 and Fig. S6). Based on the FD and FRed predictions, we  
249 calculated the percent area that had 'low', 'intermediate' and 'high' diversity and redundancy  
250 for each trait group (see methods). We also created bivariate maps that combine the FD and  
251 FRed scores in a single map to visualise where FD and FRed are both maximized and minimized  
252 across the tropics (Fig. 5). We further developed the same statistical models as described  
253 above but by removing from the analysis all plots from each continent (Asia and Australia out  
254 at the same time) to determine which regions have higher contribution to determining the  
255 observed spatial predictions (those of Fig. 5). For morphology/structure, foliar nutrients and  
256 photosynthesis we found high correlations between the bivariate maps developed with the  
257 full dataset and when Asia and Australia were left out ( $r= 0.96, 0.82$  and  $0.94$ ; Fig. S7, Fig. S8,  
258 and Fig. S9 respectively; Also Fig. S10). For morphology/structure and photosynthesis there  
259 were also high correlations between the patterns based on the full dataset and those based  
260 on the one where Africa was removed ( $r= 0.92$  and  $0.93$  respectively; Fig. S7 and Fig. S9  
261 respectively). Low correlations between the maps generated with the full dataset and those  
262 based on smaller datasets depict those regions contributed significantly for the full model  
263 predictions (Fig. S10), which is also correlated to the number of observations available for  
264 each continent (Table S2 and Table S4).

265 As predicted, our results show that wetter tropical forests tend to be more  
266 functionally diverse than drier tropical forests, especially for morphological/ structural traits  
267 and foliar nutrients traits, but also more functionally redundant for foliar nutrients and  
268 photosynthetic traits than drier tropical forests (Fig. 3 and Fig. 4). While FD levels across our  
269 sampling locations are not significantly related to their taxonomic diversity (number of  
270 species, genera and families;  $P\text{-val} > 0.05$ ), FRed<sub>NU</sub> appears to be positively correlated to  
271 taxonomic diversity ( $P\text{-val} < 0.05$ ; Table S5). Our results suggest that given the lower FD (Fig.  
272 3) and FRed (Fig. 4) of drier tropical forests for most of the analysed trait groups, these forests  
273 may be more at risk in the face of further water availability reductions.

274 The bivariate predictions maps combining FD and FRed (Fig. 5) highlight how wet  
275 tropical regions, such as the Western Amazon, Central Africa, and several regions in South  
276 East Asia maintain high functional diversity and high functional redundancy of  
277 morphological/structural (FD<sub>MO</sub> max=3.5, FRed<sub>MO</sub> max=1.5) and leaf nutrients traits (FD<sub>NU</sub>  
278 max=2.5, FRed<sub>NU</sub> max=1.5), and also in several wet regions for leaf photosynthetic traits  
279 (FD<sub>PHO</sub> max=2.5, FRed<sub>PHO</sub> max=1.5). We expect these wet tropical regions to be more resilient  
280 to a changing climate given their large combined FD (Fig. 3) and FRed (Fig. 4). To evaluate

281 which are the different levels FD and FRed across tropical and subtropical dry and moist  
 282 broadleaf forests, we distinguished low, intermediate and high scores based on the range of  
 283 the spatial predictions (Table S6; see methods section). We predicted that only 2.4% of the  
 284 tropical and subtropical dry and moist broadleaf forests have high morphological FD and 2.3%  
 285 high morphological FRed. In contrast, the drier tropical forests show a functional diversity of  
 286 morphological/structural traits that reach only about half of that in the wet tropics ( $FD_{MO}$   
 287  $min \approx 1.5$ ) and some of the lowest FRed ( $\leq 0.6$ ). From the total area of tropical and subtropical  
 288 dry and moist broadleaf forests, 30.4% shows low morphological/structural FD and 5.5% have  
 289 low morphological/structural FRed. Moreover, FD and FRed of leaf nutrients traits are lowest  
 290 to intermediate across the tropical dry forest regions, such as the southernmost parts of the  
 291 forests in Brazil, in parts of Mexico, and West Africa (Fig. 3 and Fig. 4).

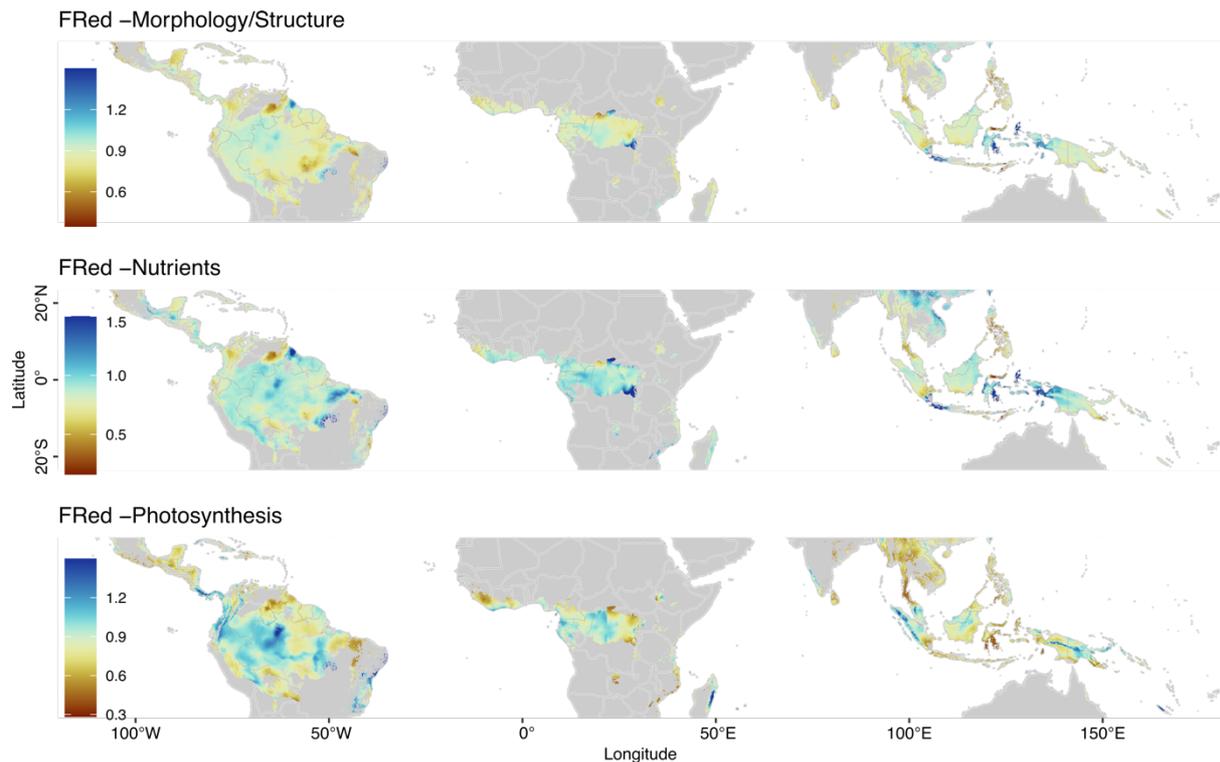
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293

294 **Figure 3. Global predictions of functional diversity (FD) for morphological/structural (top panel), leaf nutrients (middle**  
 295 **panel) and photosynthetic (bottom panel) traits across the tropical and subtropical dry and moist broadleaf forests. Dark**  
 296 **brown colours depict areas where FD is lowest, light brown and light blue where FD is intermediate and dark blue where FD**  
 297 **is predicted to be highest. Functional diversity predictions across the tropics were made using the statistical models for which**  
 298 **details are shown in Table S3. The location of field sites whose data informed this analysis is shown in Figure S5.**

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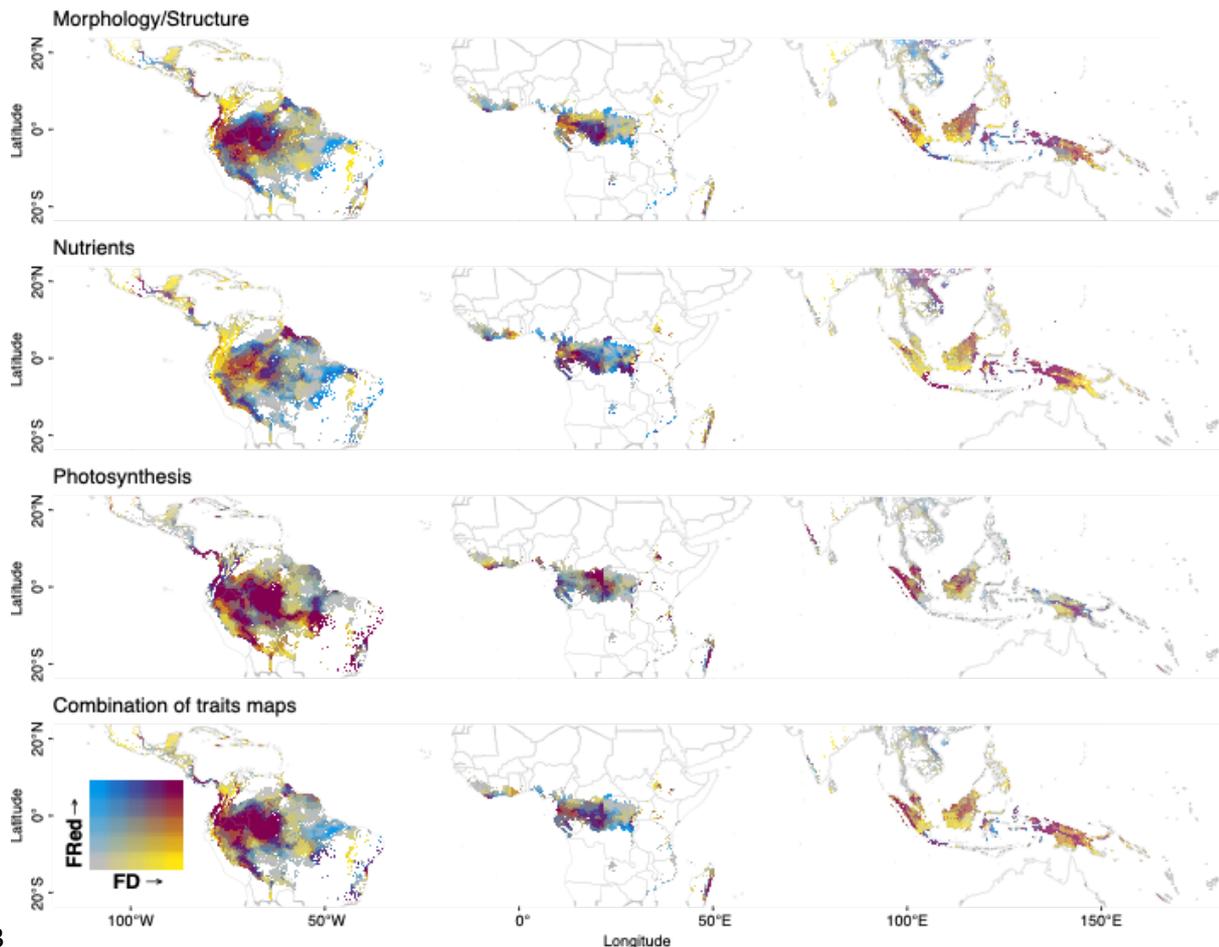


300

301 Figure 4. Global predictions of functional redundancy (FRed) for morphological/structural (top panel), leaf nutrients (middle  
 302 panel) and photosynthetic (bottom panel) traits across the tropical and subtropical dry and moist broadleaf forests. Dark  
 303 brown colours depict areas where FRed is lowest, light brown and light blue where FRed is intermediate and dark blue where  
 304 FRed is predicted to be highest. Functional redundancy predictions across the tropics were made using the statistical models  
 305 for which details are shown in Table S3.

306 While 14.8% of the forest area has low foliar nutrients FD and 3.7% low FRed, 14.1%  
 307 shows high nutrients FD and 7% high FRed. Drier tropical forests in Western Mexico, the  
 308 southern forest portion of Brazil and parts of central and West Africa show intermediate to  
 309 high photosynthetic FD (max=2.5) but they also tend to show intermediate to low levels of  
 310 FRed (FRed<sub>pho</sub> min=0.3). However, photosynthesis FD and FRed do not seem to have a clear  
 311 difference between wetter and drier forests. About 36.8% of the tropical and subtropical dry  
 312 and moist broadleaf forest area is predicted to have low photosynthetic FD and 16.9% to have  
 313 low photosynthetic FRed, while only 2.4% is expected to have high photosynthetic FD and  
 314 6.8% high photosynthetic FRed. Overall, a large amount of forest area has intermediate  
 315 photosynthetic FD and/or FRed levels (60.7% and 76.3% respectively). The bivariate FD-FRed  
 316 predictions show that most tropical forests across West Amazon and Central Africa maximise  
 317 their morphological and photosynthesis FD and FRed, while a smaller area of western South  
 318 America maximises nutrients FD and FRed (Fig. 5). In general forests in drier areas show lower  
 319 FD and FRed combined scores (grey colour; Fig. 5 bottom panel) for the three functional  
 320 groups (morphology/structure, nutrients and photosynthesis) but this is more evident for the  
 321 photosynthesis traits (Fig. 5).

322



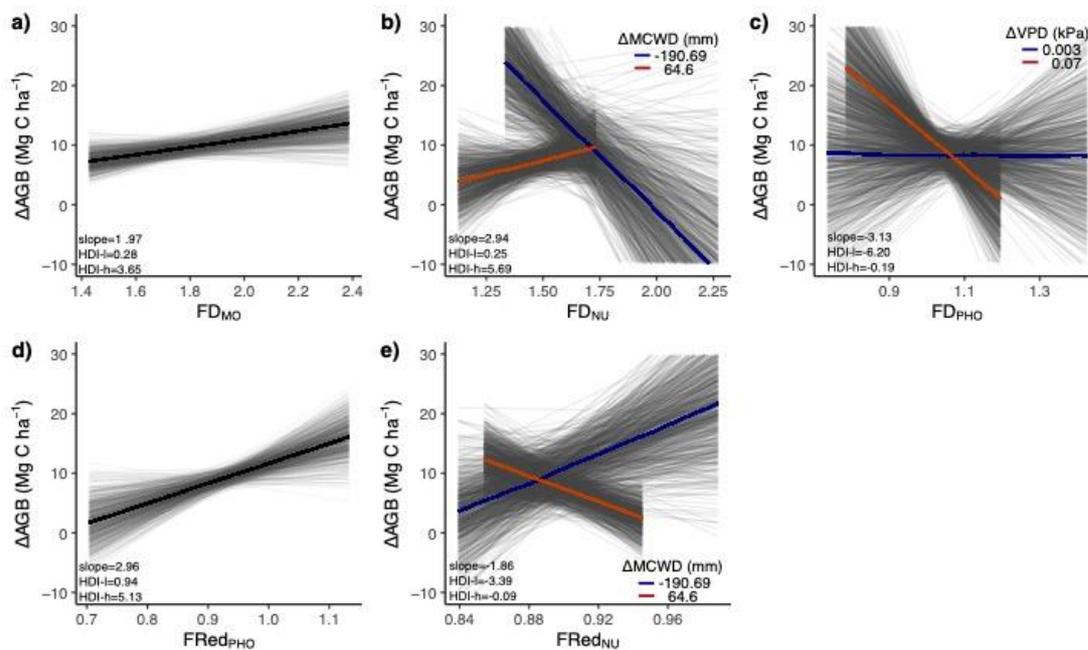
323

324 **Figure 5. Global bivariate maps combining the scores of the Functional Diversity (FD) and Functional Redundancy (FRed)**  
 325 **for morphological/structural (top panel), leaf nutrients (second panel) and photosynthetic (third panel) traits across the**  
 326 **tropical and subtropical dry and moist broadleaf forests. The bottom panel shows the combination of the**  
 327 **morphological/structural, nutrient and photosynthesis bivariate maps, after standardizing (with values 0 to 1) and**  
 328 **summing them to obtain a general bivariate map of global functional diversity and functional redundancy. Purple-red**  
 329 **colours depict areas where both FD and FRed are highest, while yellow points to areas with higher FD and blue to areas with**  
 330 **higher FRed. Gray colours show areas where both FD and FRed are predicted to be lowest. See full details of the statistical**  
 331 **models underlying these predictions in Table S3.**

332 **Testing the link between functional diversity, functional redundancy and resilience in**  
 333 **ecosystem functions under climate change**

334 We tested to what extent the long-term FD and FRed model predictions (Fig. 3 and Fig. 4),  
 335 could capture the functioning of tropical forests after climatic disturbances such as El Niño  
 336 events. By obtaining the above ground biomass data (AGB) from a set of 86 vegetation plots  
 337 in tropical Africa before and after the 2015 El Niño event<sup>37</sup>, we calculated the change in  
 338 aboveground biomass ( $\Delta$ AGB) and modelled it as a function of the predicted long-term FD  
 339 and FRed map scores. Bennett et al.<sup>37</sup> did not detect a strong decline in AGB for most forests  
 340 they analysed after the 2015 El Niño event. We show that, on average, smaller decreases or  
 341 larger increases in AGB (Fig. 6; Table S7) can be found at locations that are predicted to have  
 342 higher long-term FD and FRed of morphology/structure ( $slope= 1.97, [0.28, 3.65]$ ; Fig. 6a) and  
 343 nutrients traits ( $slope= 2.94, [0.25, 5.69]$ ; Fig. 6b) and also higher FRed of photosynthesis traits  
 344 ( $slope= 2.96, [0.94, 5.13]$ ; Fig. 6d) (Table S9). The effect of  $FD_{NU}$  on  $\Delta$ AGB was mediated by  
 345 recent changes in MCWD ( $\Delta$ MCWD), with positive  $FD_{NU}$  effects found in areas that

346 experienced larger increases in mean MCWD (Fig. 6b). There was no strong effect of  $FD_{PHO}$  in  
 347 areas where  $\Delta VPD$  was smaller (blue fitted line in Fig. 6c) but the effect became negative for  
 348 areas where  $\Delta VPD$  was larger (becoming drier, red fitted line in Fig. 6c). The effect of  $FRed_{NU}$   
 349 on  $\Delta AGB$  was mediated by  $\Delta MCWD$  with a positive effect only in regions that experienced  
 350 increases in water availability (Fig. 6e blue fitted line; slope= 2.94 [0.25, 5.69]).



351

352 Figure 6. The strength of changes in aboveground biomass ( $\Delta AGB$ ) after extreme events such as the 2015 El Niño  
 353 (from Bennett et al. <sup>37</sup>) are related to the local functional diversity (FD; a-c) and functional redundancy (FRed; d-  
 354 e) for sites in Africa. The x axis shows the FD or FRed scores for the morphological/structural (MO), nutrients  
 355 (NU) and photosynthetic (PHO) traits as extracted from Fig. 3 and Fig. 4 and the Y axis shows the relation with  
 356  $\Delta AGB$ . The  $\Delta AGB$  shows a clear relation (90% Highest Density Interval, HDI, does not overlap 0) with the diversity  
 357 indices (Table S7). Thick black lines show the average response and grey shaded lines show 700 random draws  
 358 from the posterior distribution representing variability of the expected model fit. The blue fitted line in b) shows  
 359 the effect of  $FD_{NU}$  at the largest decrease in  $\Delta MCWD$  and the red fitted line at the larger increase in  $\Delta MCWD$ .  
 360 The blue fitted line in c) shows the effect of  $FD_{PHO}$  at the largest decrease in  $\Delta VPD$  and the red fitted line at the  
 361 larger increase in  $\Delta VPD$ . In e) the effect of  $FRed_{NU}$  is shown for the largest decrease in  $\Delta MCWD$  with the blue  
 362 fitted line and the red fitted line shows the effect at the larger increase in  $\Delta MCWD$ . The FD and FRed scores for  
 363 each trait group (i.e. morphology/structure, nutrients and photosynthetic) are predictions extracted from Fig. 3  
 364 and Fig. 4 for the vegetation plots where the  $\Delta AGB$  was collected. Only model covariates with a clear relationship  
 365 with the  $\Delta AGB$  are shown. For full statistical results see Table S7.

## 366 Discussion

367 Changes in forest cover affect the local surface temperature by means of the exchanges of  
 368 water and energy<sup>38</sup>. At the same time climate change is altering land conditions affecting the  
 369 regional climate and in the near future global warming is likely to cause the emergence of  
 370 unprecedented climatic conditions in tropical regions<sup>38</sup>. Therefore, determining the  
 371 distribution of more and less resilient tropical forests (e.g. regarding the maintenance of their  
 372 functioning) to a changing climate and understanding the mechanisms causing such changes  
 373 in resilience is pivotal for the conservation of biodiversity and ecosystem functioning.

374 Theory on niche complementarity predicts that more diverse systems make more  
375 efficient use of ecosystem properties given the complementarity of species in the use of  
376 resources available<sup>39,40</sup>. Such complementarity may also increase the performance of diverse  
377 communities in the face of more stressful environments given facilitative interaction between  
378 species<sup>41</sup>. It can be therefore expected that more functionally diverse and more functionally  
379 redundant communities would experience lower change in performance (e.g. lower  
380 mortality, lower biomass decrease) with changes in environmental conditions (e.g.  $\Delta$ MCWD,  
381  $\Delta$ VPD). In our study we observed that the functional diversity levels are not significantly  
382 related to the taxonomic diversity found in the study sites across the tropics but that  
383 functional redundancy tends to be, especially for redundancy in morphological/structure and  
384 foliar nutrients traits. This points to the role of taxonomic diversity on the possible resilience  
385 of tropical ecosystems. We show that forest communities located in areas with lower soil and  
386 atmospheric water stress are generally more functionally diverse and more functionally  
387 redundant in morphological/structural, nutrients and photosynthetic traits than communities  
388 in drier areas. Such higher functional diversity and higher functional redundancy may be one  
389 reason why such forests have experienced weaker compositional and ecosystem functioning  
390 changes (e.g. carbon capture) as a result of a drying climate in comparison to forests in drier  
391 areas, as shown for forests across water availability gradients in West Africa<sup>31, 32</sup> and the  
392 Amazon<sup>24, 33</sup>. The higher functional diversity in these wetter forests can be the result of their  
393 high water availability (low MCWD and VPD, Table S2)<sup>42, 43</sup>. These conditions facilitate the  
394 adaptation, by means of a varied species morphology and structure<sup>44</sup>, to a diverse set of light  
395 and moisture conditions under and at the canopy. Overall, our results support our expectation  
396 of lower functional diversity in the sites with lower long-term water availability, and are in  
397 agreement with what has been recently found not only for functional diversity but also for  
398 taxonomic and phylogenetic diversity in some local forests<sup>31, 45</sup>. Higher diversity and higher  
399 redundancy in functional traits may enhance ecosystem functioning, such as the ability of  
400 plant communities for carbon capture<sup>46, 47</sup>, and thus show smaller reductions in biomass and  
401 lower mortality<sup>48</sup> under changes in climatic conditions. Our results are consistent with recent  
402 studies carried out in temperate forests<sup>47</sup> and with few tree taxa<sup>25</sup>, which suggest a positive  
403 functional diversity-productivity relationship.

404 Tropical forests that experienced the largest decreases in soil water availability across  
405 the last half century, which corresponds to intermediate to high long-term average MCWD  
406 (e.g. some forests in Panama, Peru and southern Mexico), tend to have high  
407 morphology/structure and nutrients FD and FRed and high photosynthetic FD. The high  
408 functional diversity and high functional redundancy potentially points to the capabilities of  
409 such forests to better withstand the effects of a drying environment than other locations with  
410 low FD and FRed levels. Our findings show that atmospheric water availability (VPD) and its  
411 changes in the last decades mediate the FD and FRed levels across tropical forest ecosystems.  
412 Forests that experienced larger decreases in VPD over the last half century tend to be  
413 functionally redundant in morphological and nutrients traits even with increases in soil water  
414 availability (here the MCWD). However, such forests are not necessarily redundant in  
415 photosynthesis traits. One explanation for this pattern of higher redundancy of forests that  
416 experienced larger increases in MCWD and VPD is that such increases in water stress occurred

417 in a variety of forests which are located all across the long-term mean MCWD and VPD  
418 spectrum (See Table S2). That means that these forests may well be composed of species with  
419 a wide range of functional adaptations to local conditions, adaptations that could have a  
420 possible mechanistic link via leaf phenology<sup>49</sup>, some adapted to long periods of droughts but  
421 also others adapted to high water availability across the year. As tropical forests that  
422 increased the most in soil and atmospheric water availability are located across the long-term  
423 water availability gradient, these forests might be composed of species that have evolved  
424 with different leaf strategies ranging from evergreen to sclerophyllous and deciduous<sup>20</sup>. Leaf  
425 adaptations to different environments may thus also explain the pattern of increasing  
426 diversity and redundancy of leaf nutrients and photosynthesis traits in these forests that  
427 experienced larger decreases in water availability. An important further step in future  
428 analyses will be to include as much information as possible not only on the changes in climate  
429 but also on the contemporary changes in functional diversity and functional redundancy. This  
430 would allow establishing a more direct link between the effects of a changing climate on  
431 forest functioning. Moreover, while our study showed clear relations with proxies of water  
432 availability at a pantropical scale (MCWD and VPD), other environmental variables at fine  
433 scale including local topography and ground water availability may also contribute for  
434 determining local FD and FRed levels.

435 Forests with larger functional diversity and larger functional redundancy pools may be  
436 more resilient to further climate change. Extreme El Niño events bring about higher  
437 temperatures and droughts across tropical regions which can impact the establishment,  
438 survival and persistence of tropical forest vegetation, thus also impacting their functioning<sup>37</sup>.  
439 The 2015-2016 El Niño event did not seem to strongly reduce carbon gains in African tropical  
440 forests. Although we did not measure the functional composition of those tropical forests in  
441 Africa before and after the El Niño event, our modelling framework provides a general  
442 understanding of the functional diversity and functional redundancy of such forest given long-  
443 term climate conditions. Our results show that areas with higher long-term functional  
444 diversity and functional redundancy tended to show smaller decreases or larger increases in  
445 AGB, thus being more resilient to changes in environmental conditions caused by the 2015-  
446 2016 El Niño event. Overall, our results highlight that tropical dry forests, such as those in  
447 drier parts of Mexico, Colombia, south-eastern Amazonia and much of West Africa, which  
448 have experienced high long-term soil water and atmospheric water stress over the last half  
449 century, could be at higher risk than wetter forests of further functional declines given the  
450 projected changes in climatic conditions for the coming decades<sup>50</sup>. Further droughts may  
451 increase the water stress of drier tropical forests, which may already be at their climatic  
452 physiological limits, and could potentially drive them towards alternative stable states<sup>18</sup>. This  
453 is in agreement with recent findings for West African<sup>31</sup> and South American drier tropical  
454 forests<sup>6, 49</sup>, where large and consistent changes in functional diversity<sup>33</sup> and functioning<sup>6</sup>  
455 have been observed. It has been hypothesised that low functional diversity and low functional  
456 redundancy may pinpoint areas that could be less resilient to further changes in  
457 environmental conditions<sup>51</sup>. Recent work in the wet tropics of Australia shows that tree  
458 growth has been reduced the most by positive anomalies in atmospheric water deficits in  
459 drier forests and for species growing faster in drier conditions than in wetter ones<sup>35</sup>. The net

460 carbon sink of tropical seasonal forests has decreased by 0.13 Mg C ha<sup>-1</sup> year<sup>-1</sup> amounting to  
461 carbon losses of 3.4% per year, highlighting how the driest and warmest sites are experiencing  
462 the largest carbon sink declines and becoming carbon sources<sup>6</sup>. Moreover, the effects of a  
463 changing climate on drier tropical forest ecosystems may not only affect tree growth and  
464 survival but also strongly decrease their functional trait space available, possibly also affecting  
465 their functioning<sup>49</sup>. Both the species-level and forest-level differential demographic  
466 sensitivities to a drying climate support this hypothesis of potentially less resilience in already-  
467 drier environments. We also highlight the need for measuring more widely other plant  
468 functional traits that have a more direct link to the availability, accessibility and transport of  
469 water resources such as plant hydraulic traits (e.g. vessel density, P<sub>50</sub>, hydraulic conductivity,  
470 osmotic potential, root size and depth) which are seldom available for most tropical plant  
471 species but that may shed more light into the possible responses of tropical forest to a  
472 changing climate<sup>52, 53</sup>.

473 In summary, this study addresses the need to understand and monitor the responses  
474 of tropical forest ecosystems to climate change, such as the negative impacts of a drying  
475 climate on the capacity of tropical forests to sequester and store carbon. Current models of  
476 ecosystem contribution to climate mitigation lack information on earth systems feedbacks.  
477 Our results show how contemporary climate shapes the functional diversity and functional  
478 redundancy of tropical forest communities. Across the tropics climatic a diverse set of  
479 conditions support a myriad of tropical tree communities with diverse combinations of plant  
480 functional traits and different functional diversity and functional redundancy levels. Tropical  
481 communities more at risk of shifting towards alternative states could be expected to be  
482 currently the ones where lower functional diversity and redundancy is found and that are  
483 under already high water stress, such as in the drier tropical forests. From the ecosystems  
484 conservation point of view, it is of critical importance to inform decisions by mapping tropical  
485 regions in terms of their resilience to future changes in the environment. Conservation efforts  
486 need to prioritise and manage ecosystems accordingly, especially including drier tropical  
487 forests in the conservation agenda, but also considering that wet tropical forests with higher  
488 functional diversity and higher functional redundancy are likely to continue to be long term  
489 carbon stores and be more resilient in the face of climate extremes and pathogens.

## 490 **Methods**

491 **Vegetation plots.** We collected vegetation census data from 74 permanent vegetation plots  
492 that are part of the Global Ecosystems Monitoring network (GEM;  
493 [www.gem.tropicalforests.ox.ac.uk](http://www.gem.tropicalforests.ox.ac.uk))<sup>54</sup>. These plots are located in wet tropical forests,  
494 seasonally dry tropical forests, and tropical forest-savanna transitional vegetation. The  
495 sampled vegetation plots ranged in area from 0.1 to 1 ha, with most (67%) being 1 ha and  
496 only one of them being 0.1 ha (Table S2). The plots are located in Australia, Brazil, Colombia,  
497 Gabon, Ghana, Malaysian Borneo, Mexico and Peru across the four tropical continents (Table  
498 S2). In each plot, all woody plant individuals with a diameter ≥ 10 cm at breast height (DBH)  
499 or above buttress roots were measured. In the plots NXV-01 and NXV-10 in Nova Xavantina,  
500 here onwards referred to as Brazil-NX, the diameter was measured at 30 cm from the ground  
501 level as is standard in drier shorter vegetation monitoring protocols.

502 **Plant functional traits.** We directly collected plant functional trait measurements from the  
503 most abundant species that would cover at least 70% of plot basal area and that were located  
504 in most of the 74 vegetation plots mentioned above ([Fig. S1](#); [Table S1](#)). All traits were  
505 collected following the GEM network standardised methodology across plots. Forest  
506 inventory data were used to stratify tree species by basal area dominance. The tree species  
507 that contributed most to basal area abundance were sampled with 3–5 replicate individuals  
508 per species. Eighty percent or more of basal area was often achieved in low diversity sites  
509 (e.g., montane or dry forests). For each selected tree a sun and a shade branch were sampled  
510 and in each branch 3–5 leaves were used for trait measurements. This represented a total  
511 sample of 2461 individual trees across the tropics ([Fig. S1](#)). We collected plant functional traits  
512 related to photosynthetic capacity  $A_{\max}$  ( $\mu\text{mol m}^{-2} \text{s}^{-1}$ ): light-saturated maximum rates of net  
513 photosynthesis at saturated  $\text{CO}_2$  (2000 ppm  $\text{CO}_2$ ),  $A_{\text{sat}}$  ( $\mu\text{mol m}^{-2} \text{s}^{-1}$ ): light-saturated rates of  
514 net photosynthesis at ambient  $\text{CO}_2$  concentration (400 ppm  $\text{CO}_2$ ),  $R_{\text{Dark}}$  ( $\mu\text{mol m}^{-2} \text{s}^{-1}$ ): dark  
515 respiration. Leaf nutrient concentration traits (%) of Ca: leaf calcium, K: leaf potassium, Mg:  
516 leaf magnesium, N: leaf nitrogen and P: leaf phosphorus. Plant morphological and structural  
517 traits, A ( $\text{cm}^2$ ): leaf area, DM (g): leaf dry mass, FM (g): leaf fresh mass, LDMC (mg/g): leaf dry  
518 matter content, LWC (%): leaf water content, SLA ( $\text{g/m}^2$ ): specific leaf area, T (mm): leaf  
519 thickness and WD ( $\text{g/cm}^3$ ): wood density. Further details of measurements for the Peruvian  
520 Andes campaign are given in Martin et al. <sup>55</sup> and Enquist et al. <sup>56</sup>, for the Malaysian campaign  
521 in Both et al. <sup>57</sup>, and for the Ghana and Brazil campaigns in Oliveras et al. <sup>58</sup>, Gvozdevaite et  
522 al. <sup>59</sup> and for Colombia campaigns in González-M. et al. <sup>49</sup>. For the specific dates of plant  
523 functional traits collection see ref. <sup>60</sup>. For the FD and FRed calculations, as both only accept  
524 one trait value per species, from the individual level plant functional traits, we averaged the  
525 values at species level and when the species had no trait values available, we filled the gaps  
526 by averaging the trait values at the genus level. This protocol allowed us to have at least 70%  
527 of the plot's basal area covered by traits but often more. Thus, in our analysis the inclusion of  
528 plots is trait dependent in the sense that only plots with at least 70% of the BA covered by the  
529 focus trait were included in the analysis (see [Table S2](#)).

### 530 **Community level functional diversity and functional redundancy**

531 We calculated the functional diversity and functional redundancy of morphological/structural  
532 traits, leaf chemistry and photosynthetic traits, which are hypothesised to be of importance  
533 for tropical forests to respond to a drying climate ([Table S1](#)) <sup>14,20</sup>, based on data for species  
534 covering at least 70% of the plot basal area ([Table S2](#)) and following equations from refs. <sup>34,</sup>  
535 <sup>61, 62, 63</sup>. The morphological/structural and nutrient related traits used for this analysis are A,  
536 FM, DM, LDMC, T, LWC, SLA, WD, Ca, K, Mg, N, P; and  $A_{\text{sat}}$ ,  $A_{\max}$  and  $R_{\text{Dark}}$  for photosynthesis.  
537 We did not build an index including all functional traits together as this would make their  
538 interpretation rather difficult as they point to different axes of the global spectrum of plant  
539 form and function<sup>64</sup> and also because of the difference in number of records available for  
540 each trait group. Plant functional trait diversity (FD) was calculated at the plot level using the  
541 functional dispersion metric <sup>34</sup>, which is closely related to the RaoQ <sup>31</sup>, and which represents  
542 the mean distance, in trait space, of each single species to the weighted centroid of all species  
543 <sup>34</sup>. We used the FD as it can handle any number and type of traits, because it is unaffected by

544 species richness, it weighs the values based on the abundance of species, it is not influenced  
545 by outliers and is relatively insensitive to the effects of undersampling<sup>65</sup>. To calculate FD we  
546 applied the equation presented by Laliberté and Legendre<sup>34</sup>:

547 eq. 1 
$$FD = \frac{\sum BA_{ip} z_{ip}}{\sum BA_{ip}}$$

548 where  $BA_{ip}$  reflects the total plot level basal area of species  $i$  in plot  $p$  and  $z_{ip}$  is the distance  
549 of species  $i$  in plot  $p$  to the weighted centroid of the  $n$  species in trait space. The plant traits  
550 were weighted by the relative basal area (in  $m^2$ ) of each of the species in the plot. Therefore,  
551 FD summarises the trait diversity and represents the mean distance in trait space of each  
552 species to the centroid of all species in a given community. All numeric traits were  
553 standardised during the FD calculation.

554 We calculated the functional trait redundancy in the community (vegetation plots),  
555 FRed, as in Pavoine and Ricotta<sup>62</sup> and Ricotta et al. (*Rstar*)<sup>63</sup> and as developed in the  
556 'uniqueness' function of the R 'adiv' package<sup>61</sup>. *Rstar* quantifies how redundant a plant  
557 community is compared to a scenario where all species would have the most distinct trait  
558 values possible. As in the case of FD, *Rstar* as calculated in Ricotta et al.<sup>61, 62</sup> works with  
559 multiple traits and takes into account species abundances. The *Rstar* index is complementary  
560 to the community-level functional uniqueness index *Ustar* described by Ricotta et al.<sup>62</sup> which  
561 is the ratio of the Rao [quadratic diversity](#) index  $Q$ <sup>66, 67</sup>, that accounts for species trait  
562 dissimilarities and the Simpson index  $D$ , which considers the species in the community as  
563 equally and maximally dissimilar. Thus *Ustar* measures the uniqueness of the community in  
564 functional space which is obtained by including interspecies dissimilarities in the calculations  
565 of the index. *Rstar*, which is the complement of *Ustar*, represents thus a measure of  
566 community-level functional redundancy and is quantified as:

567 eq. 2 
$$Ustar = \frac{1-D}{1-Q}$$

568 eq. 3 
$$Rstar = 1 - Ustar$$

569 For an in-depth description of the functional redundancy index see refs.<sup>61, 62, 63</sup>.

570 All above-mentioned analyses were carried in the R statistical environment<sup>68</sup> with the  
571 'FD' and 'adiv' packages.

## 572 **Climatic and soil data**

573 In order to investigate the role that long-term climate plays on determining the community  
574 trait composition and functional diversity and redundancy across tropical forests we gathered  
575 climatic data on the potential evapotranspiration (PET in mm), precipitation accumulation  
576 (mm) and VPD (kPa) from the TerraClimate project<sup>69</sup> at a spatial resolution of  $\sim 4 \times 4$  km. The  
577 data were obtained for the period from 1958 to 2017. Using the full-term climatic dataset  
578 (1958-2017) we calculated the mean annual VPD, PET, precipitation coefficient of variation  
579 (CV; as a measure of seasonality in water availability) and the maximum climatological water

580 deficit (MCWD). The MCWD is a metric for drought intensity and severity and is defined as  
581 the most negative value of the climatological water deficit (CWD) over each calendar year.  
582 The VPD is an indicator of plant transpiration and water loss<sup>14</sup>. CWD is defined as precipitation  
583 (P) (mm/month) – PET (mm/month) with a minimum deficit of 0. The MCWD was calculated  
584 as in Malhi et al.<sup>13</sup> where  $MCWD = \min(CWD1...CWD12)$ . As a final step we converted the  
585 MCWD so that positive values indicate increases in water stress. We also calculated the  
586 change in the climatic variables ( $\Delta MCWD$ ,  $\Delta VPD$  and  $\Delta CV$ ) between a first period  
587 corresponding to a climatology of 30 years encompassing 1958-1987 and a second period  
588 encompassing the years 1988-2017. The climatology of 30 years to calculate the different  
589 time periods climate was selected as recommended by the World Meteorological  
590 Organization in order to characterise the average weather conditions for a given area  
591 ([www.wmo.int/pages/prog/wcp/ccl/faqs.php](http://www.wmo.int/pages/prog/wcp/ccl/faqs.php)). We also obtained soil texture (percent clay  
592 and sand) and chemistry (soil pH and cation exchange capacity, CEC) gridded data from the  
593 SoilGrids project ([www.soilgrids.org](http://www.soilgrids.org)) and used this as extra covariates in our modelling  
594 framework. We then tested the correlation between all pairs of climatic variables (full-term  
595 and their changes) and also between the soil variables. We observed that MCWD and CV had  
596 Pearson's correlation coefficients  $|>0.70|$  and also CEC and pH and Clay and Sand had  
597 correlation coefficients  $|>0.70|$  (Fig. S11) and we thus dropped CV and its change, Sand and  
598 pH from the analyses as to avoid distorting model coefficients in the modelling stage<sup>70</sup>. We  
599 then carried out a principal component analysis (PCA) using the MCWD and VPD climatic  
600 variables (average of full-term and their changes) and another with the soil variables to  
601 investigate the distribution of the vegetation plots in climate and soil space and to describe  
602 how much of this distribution can be explained by each of these. For the PCA analysis we used  
603 the 'stats' package in R.

## 604 **Statistical analysis**

### 605 ***Functional Diversity and Functional Redundancy statistical analysis***

606 We investigated the variation in morphological/structural, leaf chemistry and photosynthetic  
607 FD and FRed across tropical forests by modelling their relation with mean MCWD, VPD for the  
608 period 1958-2017 and their interaction, the  $\Delta MCWD$  and  $\Delta VPD$  between the first and second  
609 periods and their interaction and soil chemistry (CEC) and texture (Clay%). For the  
610 photosynthesis statistical models, given their lower sample size (n=22; Table S2), interaction  
611 terms were not included and to avoid overfitting we first tested by means of leave-one-out  
612 cross-validation (LOO)<sup>71</sup> if the soil covariates improved or not the models with only climate  
613 information. We found soil data did not improve our models (Table S8) and thus left CEC and  
614 Clay out of the photosynthesis models. We also calculated the relative change (%) in climatic  
615 conditions but this did not improve model predictions (data not shown) and thus we only  
616 present results that include the absolute changes in MCWD and VPD. We included the change  
617 in MCWD and VPD as we wanted to understand if areas that have experienced stronger  
618 changes in climate showed lower or higher functional diversity and functional redundancy  
619 than others that have experienced milder climate changes. In the same way we included the

620 interaction between MCWD and VPD (and also between  $\Delta$ MCWD and  $\Delta$ VPD) as there may be  
621 regions where high values of one of these variables may not be related to the values of the  
622 other, e.g. high MCWD may not be related to high VPD. Prior to the statistical modelling we  
623 centred and standardised (generated z-scores) all climatic and soil variables.

624 We tested for spatial autocorrelation effects in the FD and FRed model residuals using  
625 the Moran's I test and found a significant effect for the photosynthesis and nutrients FD  
626 models and for the FRed nutrients model (Table S9). Thus, for those data we calculated the  
627 spatial distance at which such spatial effect decreased and found that a distance of 2 km was  
628 sufficient. We then generated an ID for each group of plots (group ID) that were at most 2 km  
629 away from each other and included such group ID as a random factor in those statistical  
630 models. As some plots were smaller than 1 ha (Table S2) we included the z-scores of plot size  
631 as a covariate in all statistical models to account for its possible effect. We log transformed  
632 the FD and FRed indices to improve the normality of the data and applied linear mixed-effects  
633 models with a Gaussian error structure accounting for difference in plot size and spatial  
634 autocorrelation as described above under a Bayesian framework. The mixed-effects models  
635 were run with normal diffuse priors with mean 0 and 2.5 standard deviation to adjust the  
636 scale of coefficients and 10 standard deviations to adjust the scale of the intercept, three  
637 chains and 10000 iterations to avoid issues with model convergence. We computed the  
638 highest density intervals (HDI) rendering the range containing the 90% most probable effect  
639 values and calculated the ROPE values using such HDI as suggested in Makowski et al.<sup>72</sup>. The  
640 95% HDI was not used as this range has been shown to be unstable with ESS < 10,000  
641 (effective sample size)<sup>73</sup>. We considered a climatic variable had an important (significant)  
642 effect on the response variable if the 90% HDI did not overlap 0. Posterior density  
643 distributions for all models and covariates included in the models are shown in Fig. S12 and  
644 Fig. S13.

645 Based on the statistical models described above we created spatial predictions of  
646 Functional Diversity (FD) and Functional Redundancy (FRed) at a pantropical scale. We  
647 defined the 'low', 'intermediate' and 'high' FD and FRed groups by defining the range in FD  
648 and FRed values and dividing that range between three in order to allocate the FD and FRed  
649 predicted values to each of these groups and be able to state what is the predicted percent  
650 area of tropical and subtropical dry and moist broadleaf forests with low, medium and high  
651 FD and FRed. We also tested the robustness of the spatial predictions of FD and FRed by also  
652 developing the models by leaving out the data from one continent (South East Asia and  
653 Australia together), fitting the model again, and comparing the resulting spatial predictions  
654 to the full model prediction maps by means of Spearman correlations. In Fig. S14 we also  
655 highlight locations across the tropics with climate and soil conditions outside of our climatic  
656 and soil calibration space, thus not covered by the range in our sampling locations, which may  
657 represent locations where our models are extrapolating the relationships found.

658 ***Relations between Functional Diversity, Functional Redundancy and Aboveground biomass***

659 We obtained the above ground biomass data (AGB) from an independent set of 100  
660 vegetation plots in Africa before (AGB<sub>pre</sub>) and after (AGB<sub>post</sub>) the 2015 El Niño event from  
661 Bennett et al.<sup>37</sup>. The plots from Bennet et al. include censuses from 2000 onward where the  
662 median plot size is 1 ha, the mean initial census was May 2008, with the mean pre-El Niño  
663 census in April 2014, and mean post-El Niño census in February 2017. The plots have a mean  
664 monitoring length pre-El Niño of 8.3 years, with a mean length of the El Niño interval being  
665 2.7 years. To calculate AGB Bennet et al.<sup>37</sup> used the BiomasaFP R package, including the  
666 calculation of the census interval corrections for AGB where Pre-El Niño means of these  
667 variables are time weighted using the census interval lengths. For a full description of the AGB  
668 data see Bennett et al.<sup>37</sup>. We calculated the ΔAGB as:

669 eq. 4  $\Delta\text{AGB} = (\text{AGB}_{\text{post}} - \text{AGB}_{\text{pre}})$

670 Before modelling we eliminated statistical outliers in the AGB values, this is values more  
671 than 1.5 the interquartile range above the third quartile or below the first quartile. We  
672 therefore only used 86 plots in our analysis. We modelled the ΔAGB as a function of the  
673 predicted (see methods above) FD and FRed maps scores from each functional group  
674 (morphology/structure, nutrients and photosynthesis; Fig. 3 and Fig. 4), one model was built  
675 per functional group. Each model included the FD and FRed index (e.g. FD and FRed of  
676 nutrients) and their interaction with ΔMCWD and ΔVPD as to test the effect of a changing  
677 climate on the effects of FD and FRed on above ground biomass change. We accounted for  
678 plot size by including as a covariate in the models and used a Gaussian error structure model  
679 under a Bayesian framework. The ΔAGB statistical models were run with normal diffuse priors  
680 with three chains and 5000 iterations.

681 We carried out all statistical analysis in the R statistical environment<sup>68</sup> using the, ‘rstanarm’,  
682 ‘loo’, ‘bayestestR’, ‘egg’ and ‘BEST’ packages.

### 683 **Data availability**

684 The vegetation census and plant functional traits data that support the findings of this study are  
685 available from their sources (www.ForestPlots.net and gem.tropicalforests.ox.ac.uk/). The processed  
686 community-level data used in this study will be made available in a public repository.

### 687 **Code availability**

688 The main R code used in this study will be deposited in a public repository and can be accessed through  
689 the principal investigator upon request.

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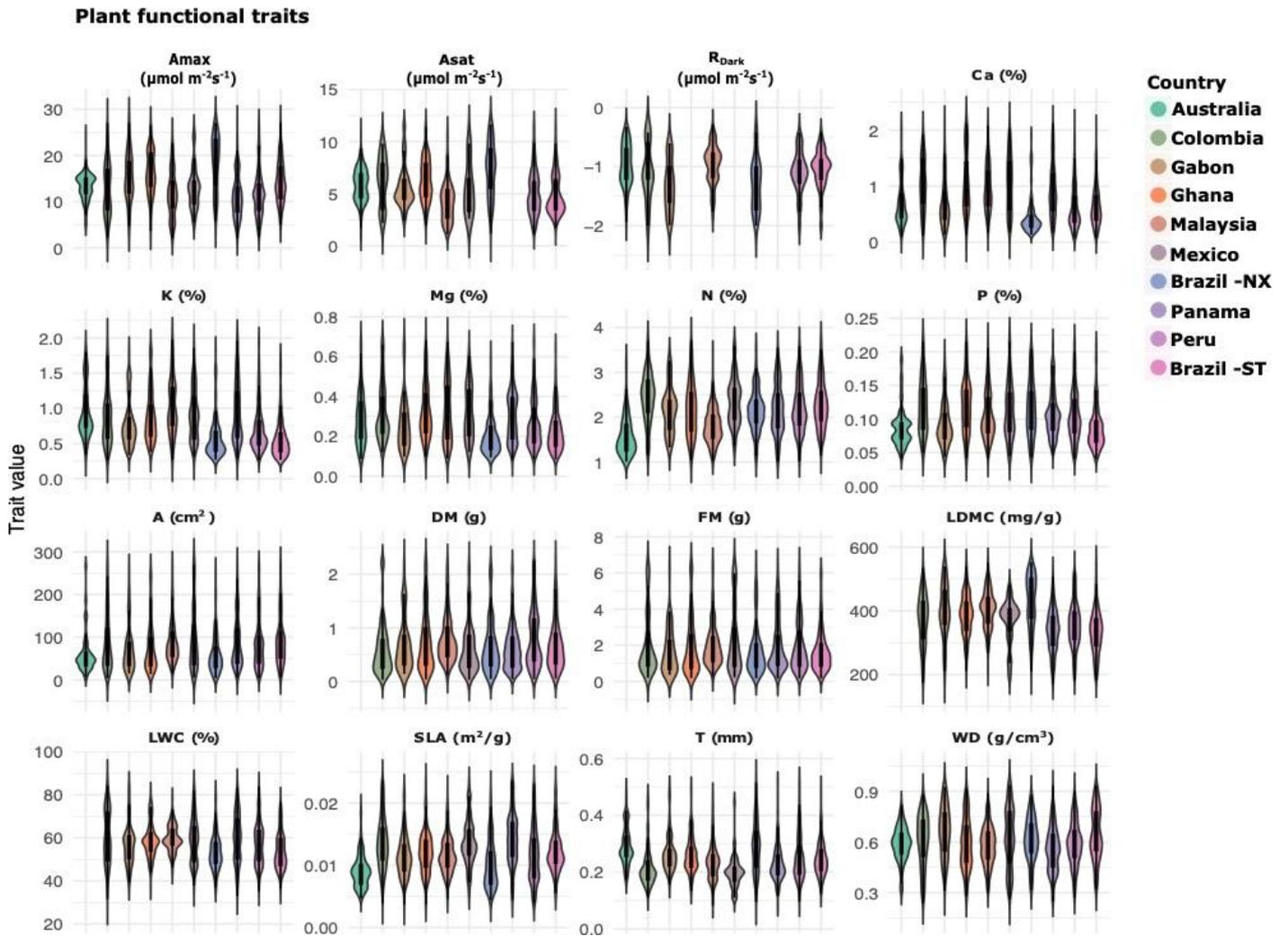
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Supplementary Information

Supplementary figures S1 to S15

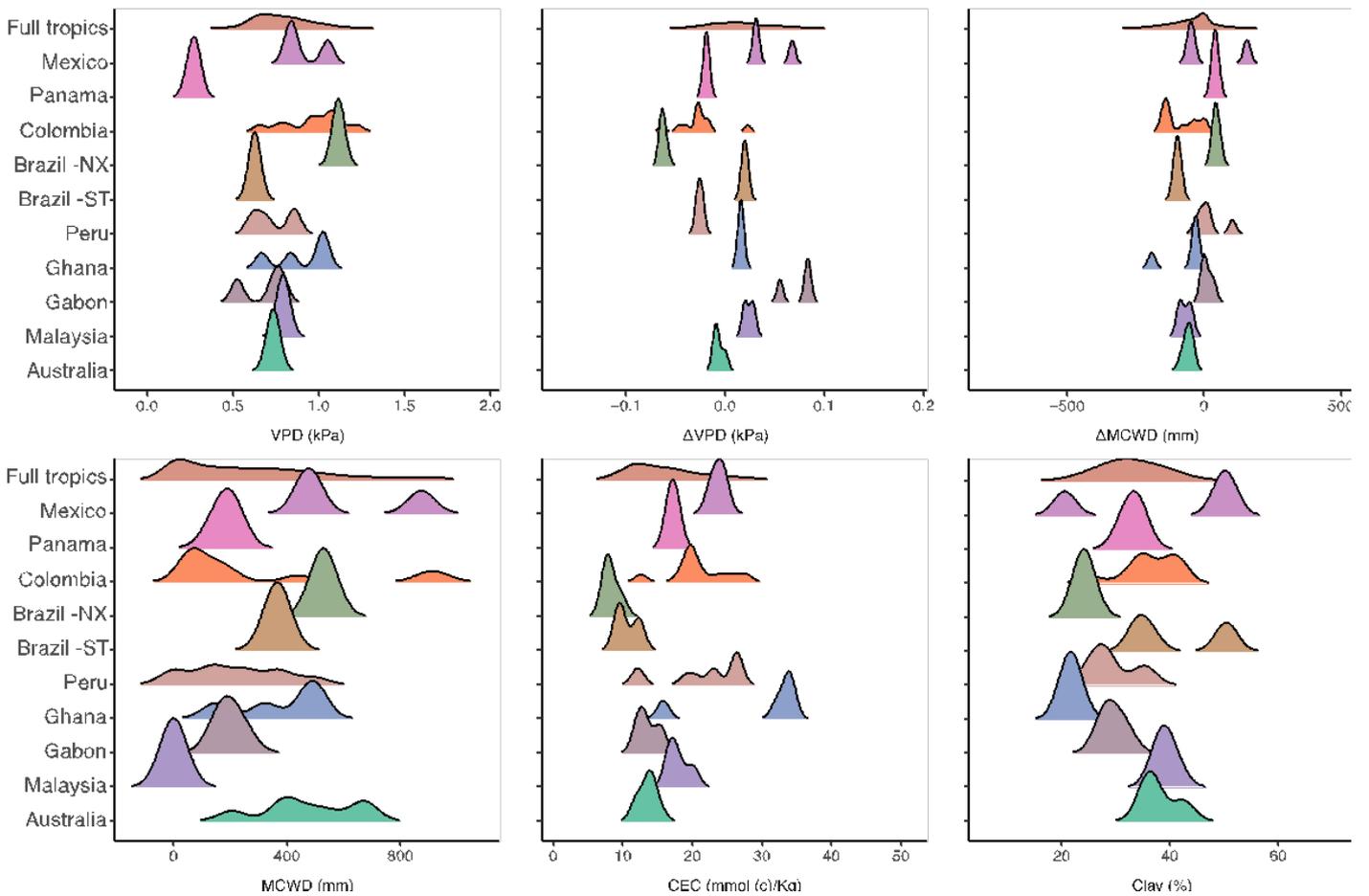
**Functional susceptibility of tropical forests to climate change**

Jesús Aguirre-Gutiérrez et al.

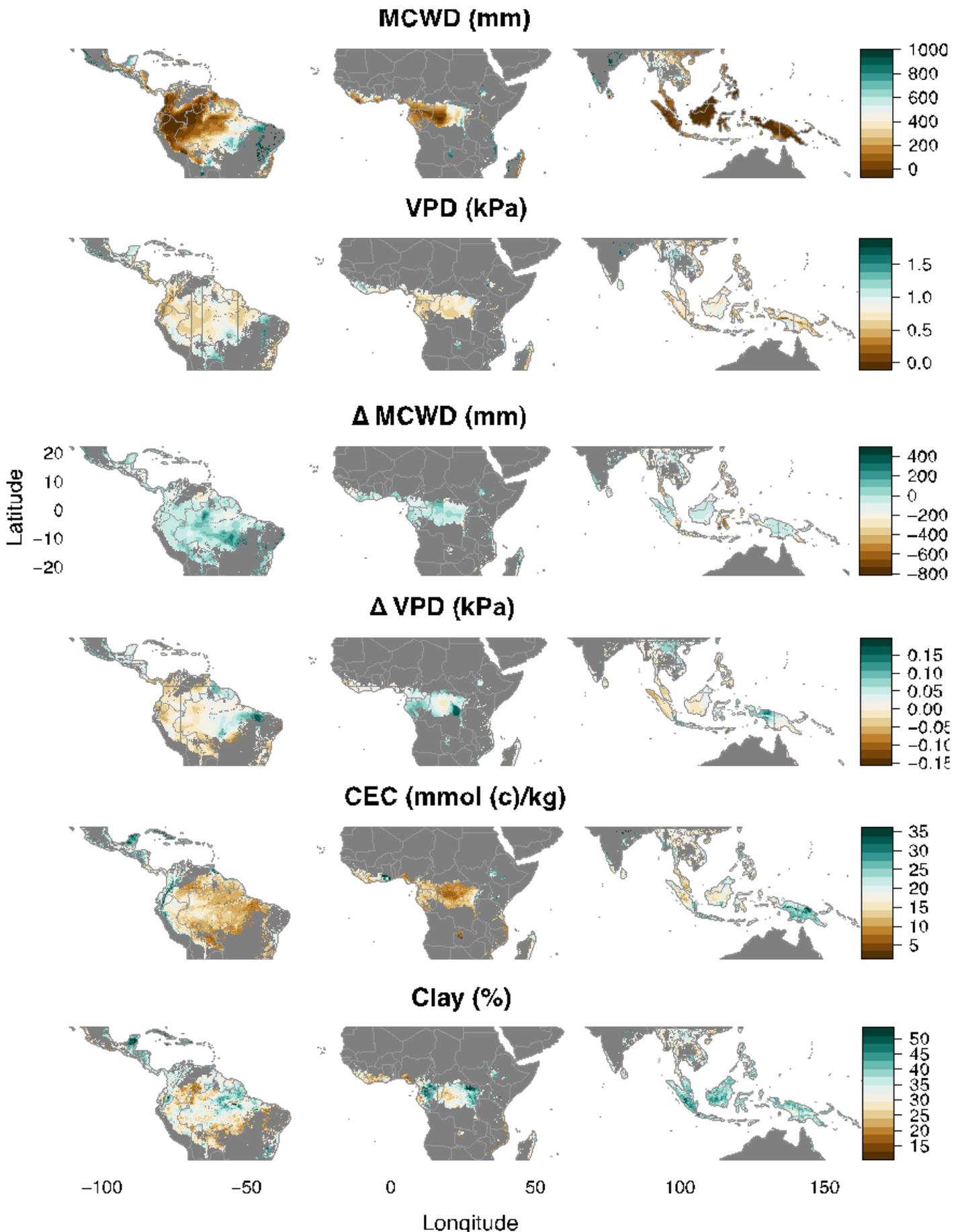


**Figure S1. Violin plots of the plant functional traits and their value ranges across the study area. Plant functional trait values for all functional traits included in the analyses are shown.** The plant functional traits used in the study with raw trait values are shown but these data were log-transformed prior to further analysis. The colours correspond to the field sampling areas where in situ traits collection plots are located; the Y axis shows the raw data values for each functional trait. Photosynthetic traits are  $A_{\text{max}}$ : Light-saturated maximum rates of net photosynthesis at saturated  $\text{CO}_2$  (2000 ppm  $\text{CO}_2$ );  $\mu\text{mol m}^{-2} \text{s}^{-1}$ ),  $A_{\text{sat}}$ : light-saturated rates of net photosynthesis at ambient  $\text{CO}_2$  concentration (400 ppm  $\text{CO}_2$ );  $\mu\text{mol m}^{-2} \text{s}^{-1}$ ),  $R_{\text{Dark}}$ : dark respiration ( $\mu\text{mol m}^{-2} \text{s}^{-1}$ ). Leaf nutrient concentration traits are, Ca: leaf calcium (%), K: leaf potassium (%), Mg: leaf magnesium (%), N: leaf nitrogen (%), P: leaf phosphorus (%). Leaf morphological and structural traits are, A: leaf area ( $\text{cm}^2$ ), DM: leaf dry mass (g), FM: leaf fresh mass (g), LDMC: leaf dry matter content (mg/g), LWC: leaf water content (%), SLA: specific leaf area ( $\text{m}^2/\text{g}$ ), T: leaf thickness (mm), WD: wood density ( $\text{g}/\text{cm}^3$ ). No traits were collected in Mexico and were thus assigned to the vegetation censuses from other locations as explained in the methods section. Brazil -ST: Brazil Santarem, Brazil -NX: Brazil Nova Xavantina.

Climate across the tropics and sampling locations

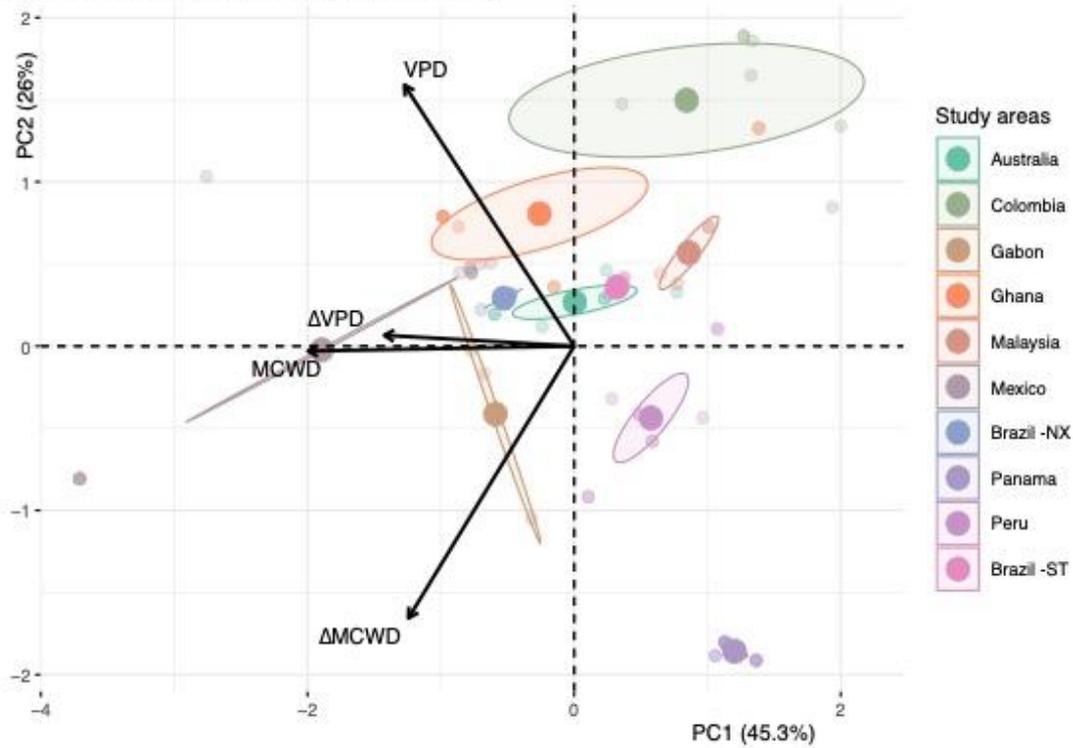


**Figure S2. Density plots of the climatic and soil conditions that encompass each field sampling location where plant functional traits and vegetation censuses were collected.** The top density graph of each climatic and soil variable shows the values found across the tropical and subtropical dry and moist broadleaf forests. VPD: vapour pressure deficit, MCWD: maximum climatic water deficit, CEC: cation exchange capacity,  $\Delta$ : change.

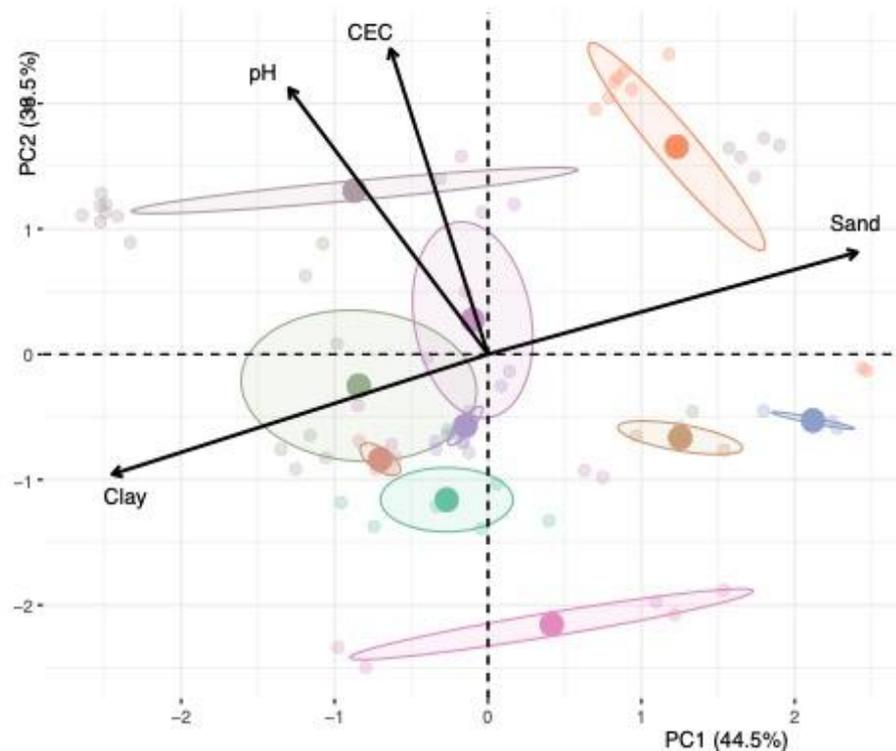


**Figure S3. Spatial distribution of climatic and soil conditions across the tropical and subtropical dry and moist broadleaf forests.** MCWD: maximum climatic water deficit, VPD: vapour pressure deficit, CEC: soil cation exchange capacity, Clay: soil clay content.  $\Delta$ : change.

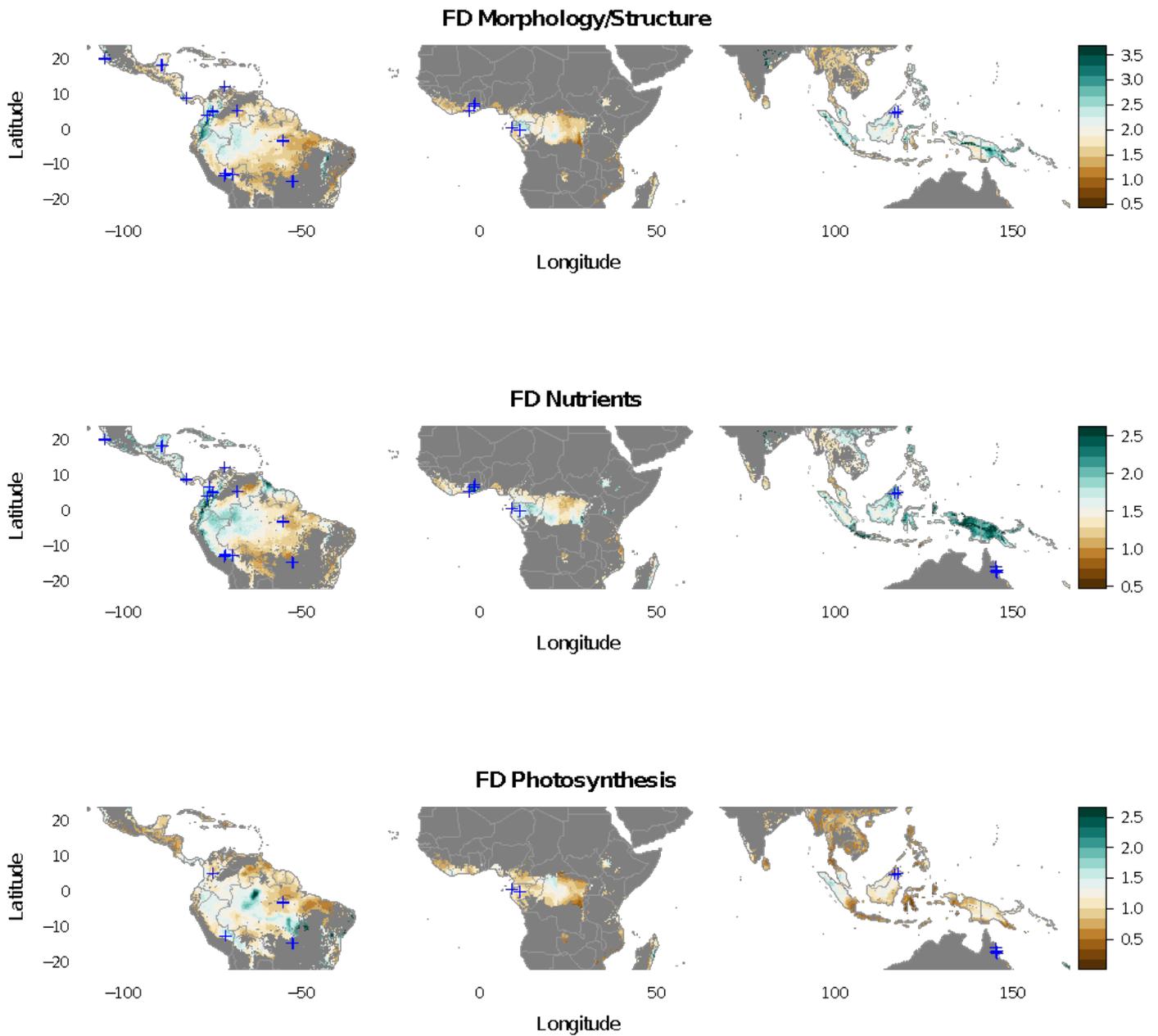
a) PCA of sampling locations in climate space



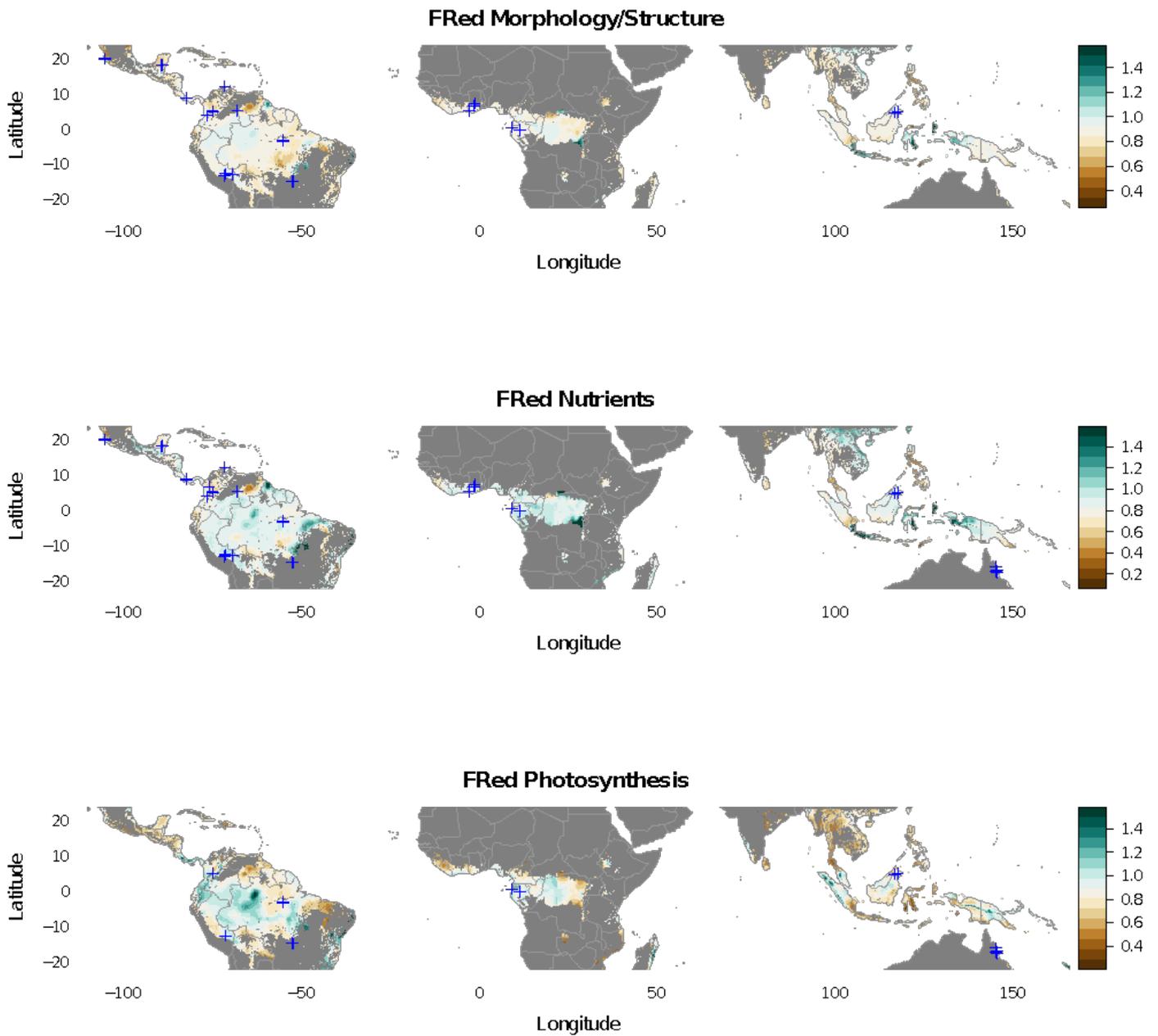
b) PCA of sampling locations according to soil characteristics



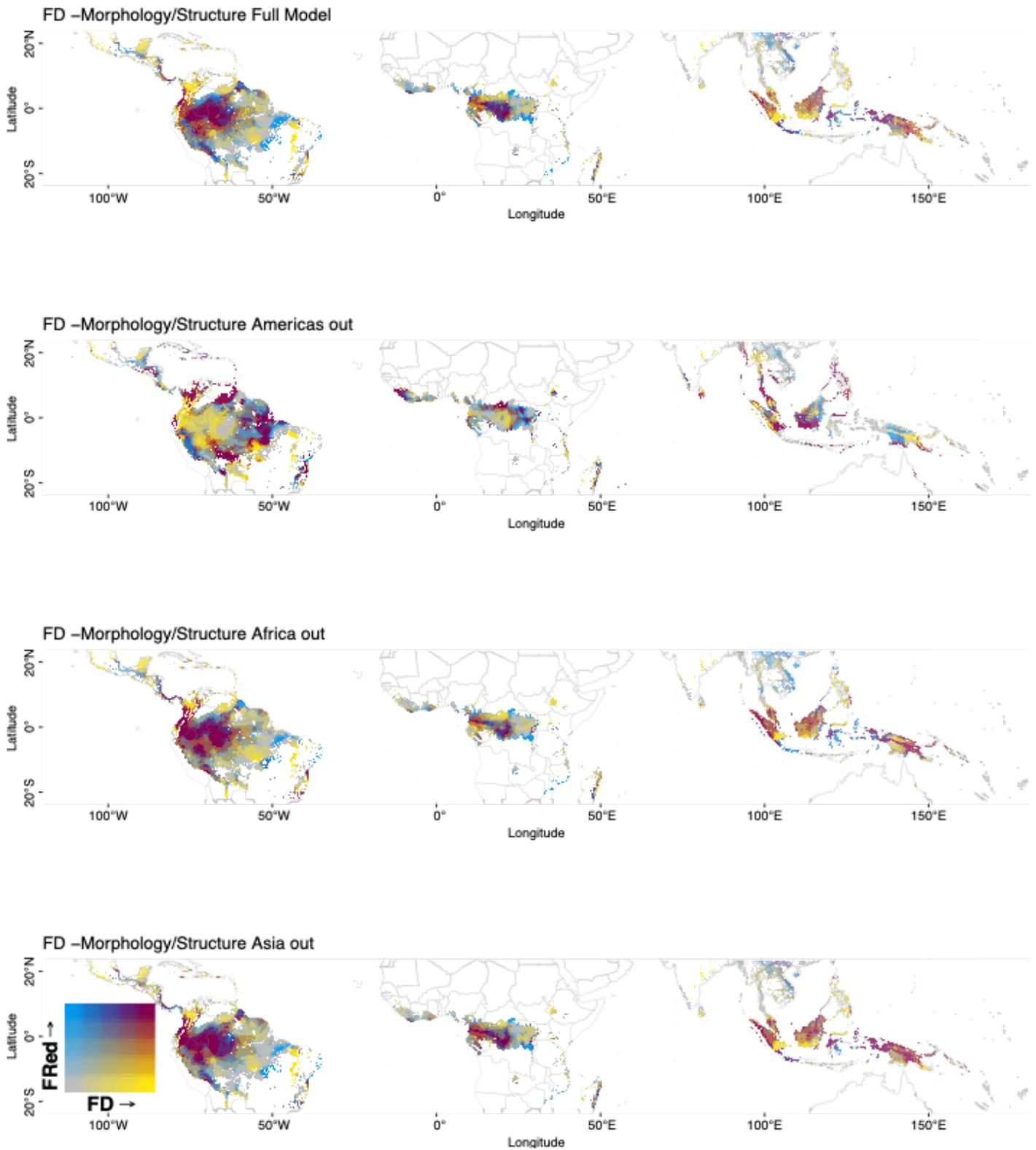
**Figure S4 Principal component analysis of the distribution of the plot locations in climatic (a) and soil (b) space.** MCWD: average Maximum Climatic Water Deficit and VPD: average Vapour Pressure Deficit,  $\Delta$ MCWD and  $\Delta$ VPD: change in MCWD and VPD respectively between the 1958-1987 and 1988-2017 period. MCWD and VPD represent the full-term climatic conditions (1958-2017 period). CEC: cation exchange capacity and soil pH are highly correlated and only CEC is used for further analysis. Clay and sand are highly correlated and only clay is used for further analysis. Coloured ellipsoids in a) and b) encompass 95% of the distribution of the vegetation plots from each field sampling location.



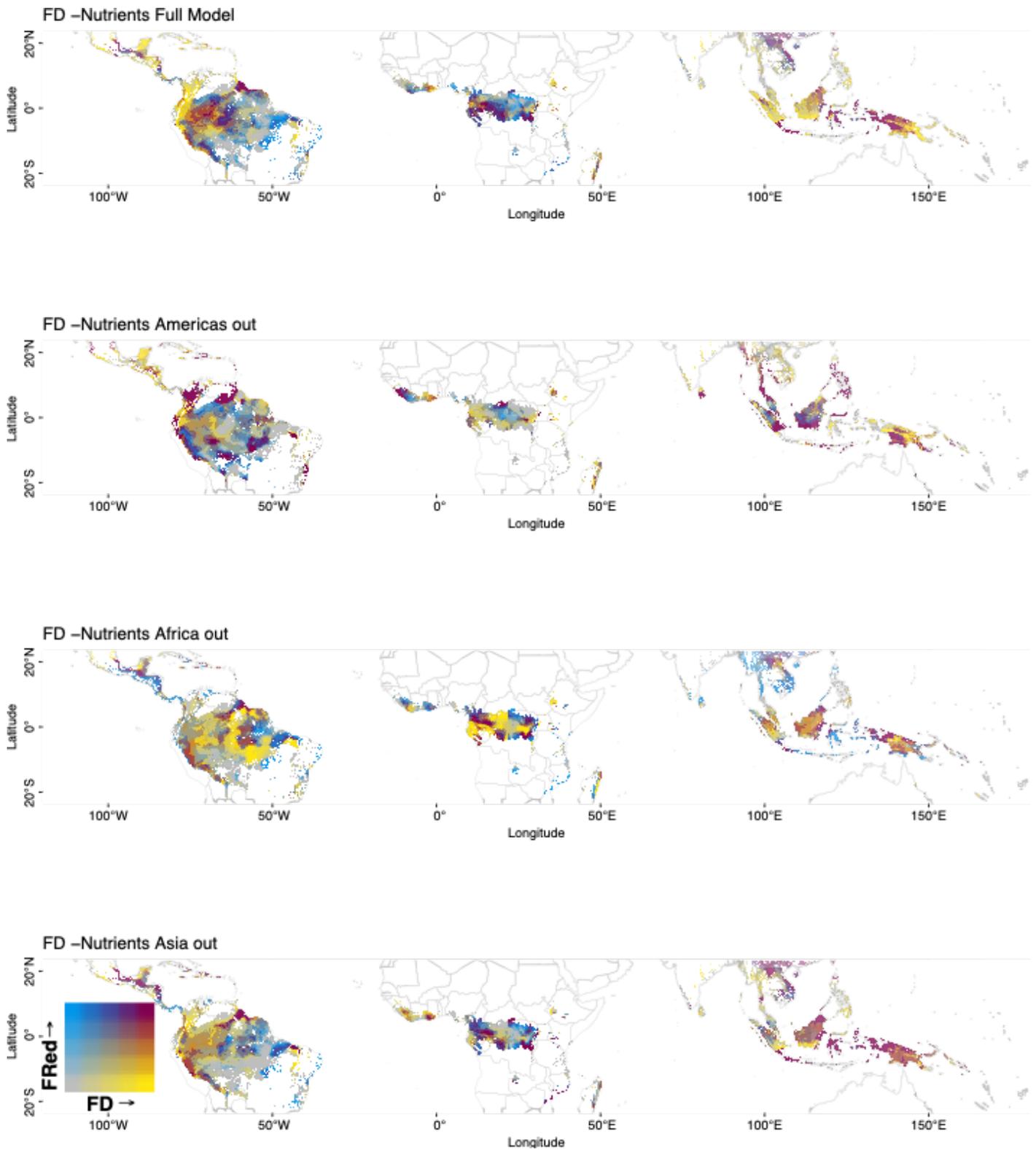
**Figure S5. Spatial predictions of functional diversity (FD) depicting the locations of vegetation plots (blue crosses) that were used to fit the statistical models of morphological/structural (top panel), nutrients (middle panel) and photosynthetic (bottom panel) traits. For details about the plots, their location and climatic and soil conditions see Table S1).**



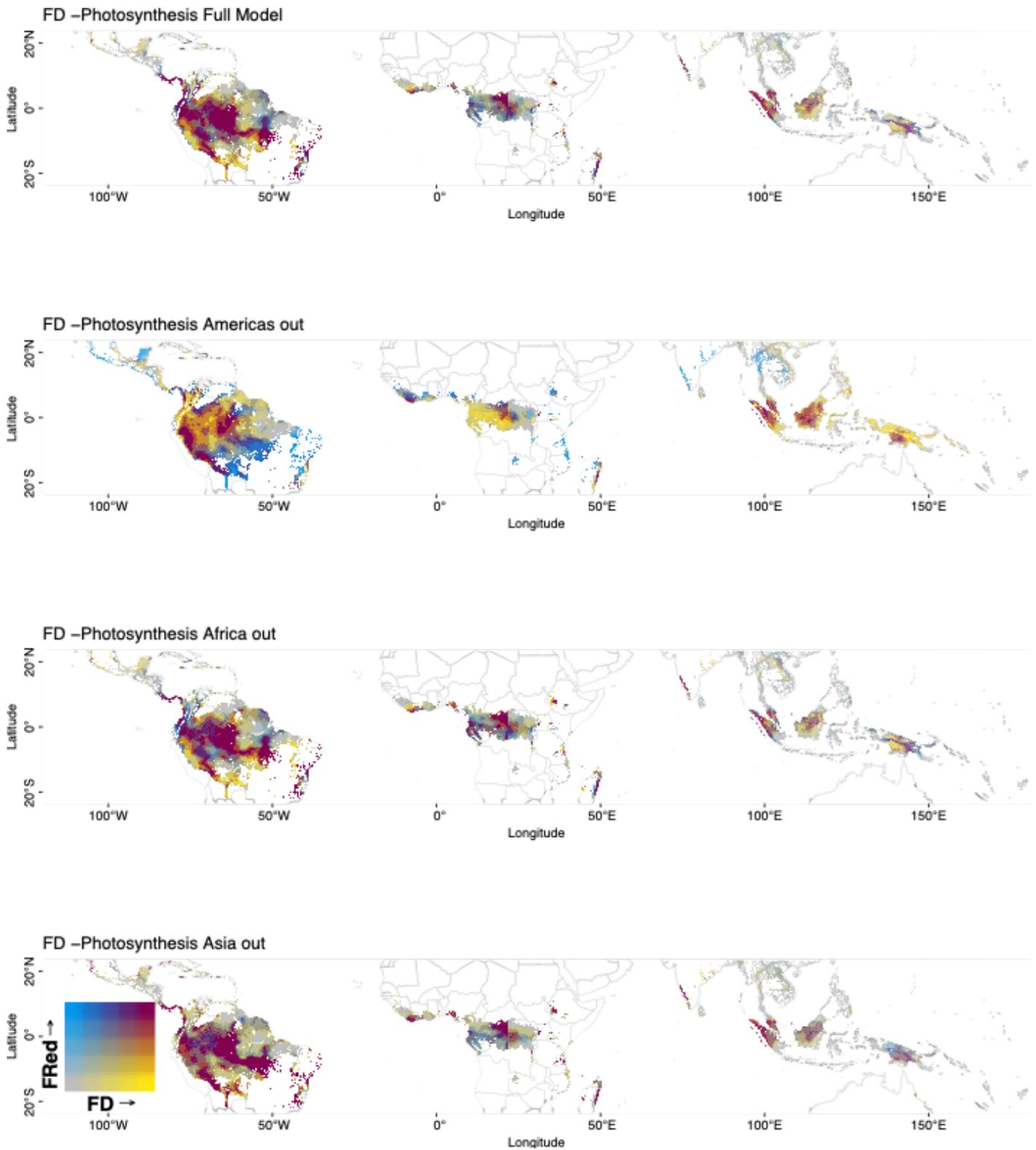
**Figure S6. Spatial predictions of functional redundancy (FRed) depicting the locations of vegetation plots (blue crosses) that were used to fit the statistical models of morphological/structural (top panel), nutrients (middle panel) and photosynthetic (bottom panel) traits. For details about the plots, their location and climatic and soil conditions see Table S1).**



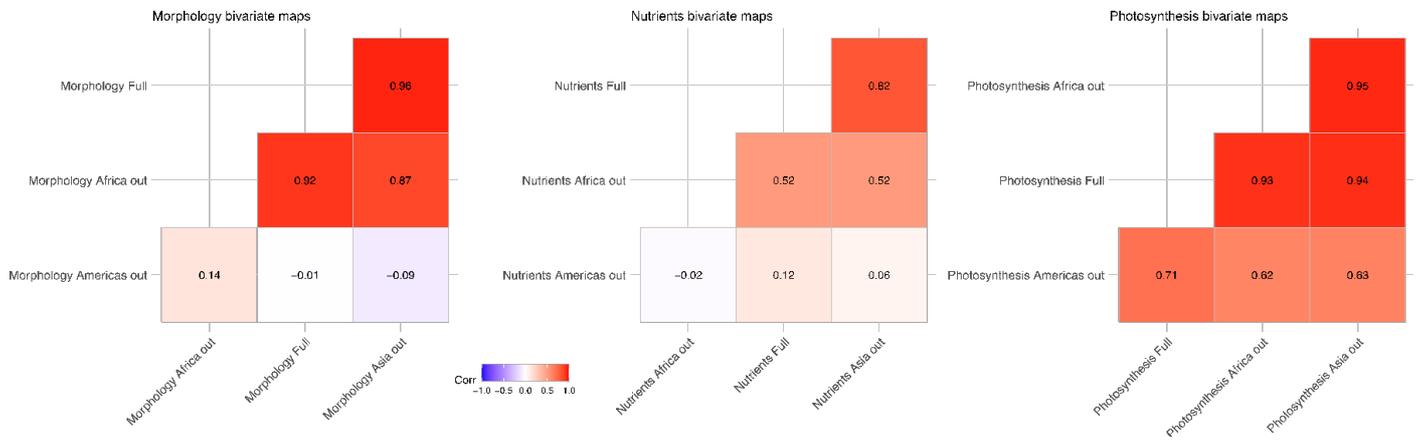
**Figure S7. Bivariate maps combining the functional diversity (FD) and redundancy (FRed) for the morphological traits.** Each map shows the predictions obtained using the full dataset (full model, top panel) and the changes that occur by leaving the plots from each continent out of the model. The second panel shows the spatial predictions when leaving the records from the Americas out of model fitting, the third panel when leaving records from Africa out and the bottom panel when leaving the records from Asia and Australia out from model fitting.



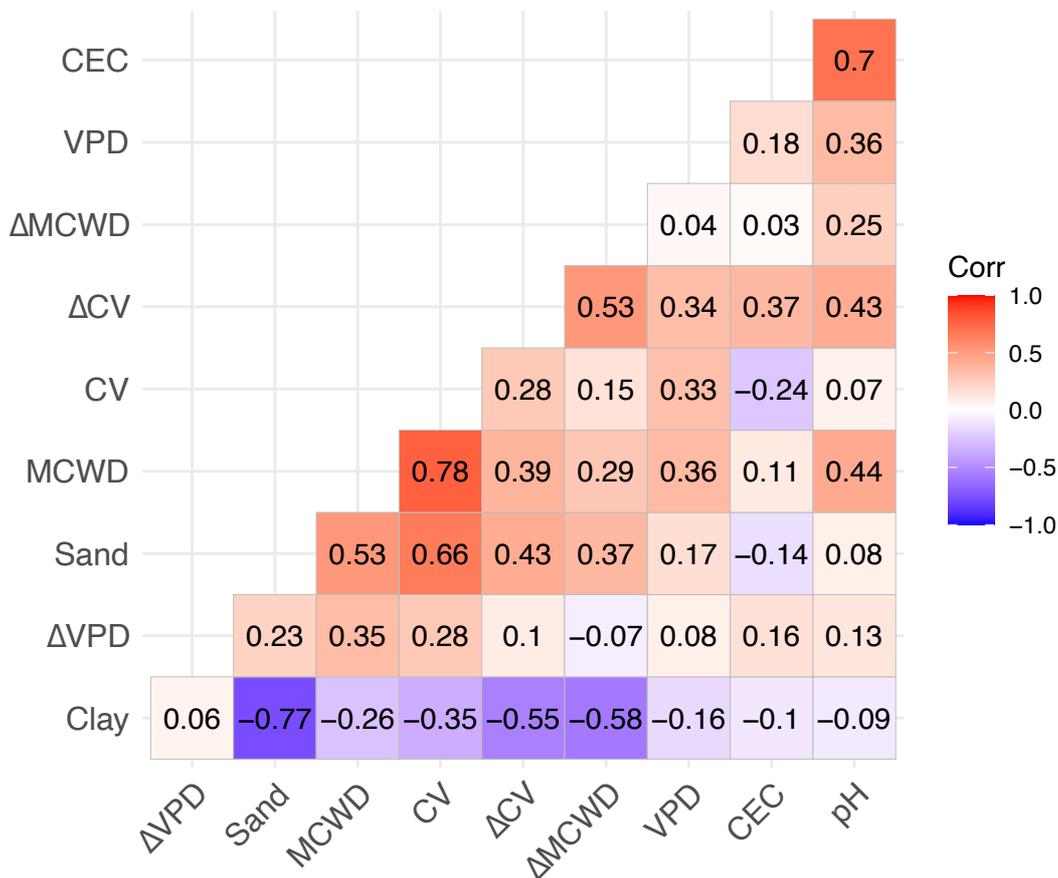
**Figure S8. Bivariate maps combining the functional diversity (FD) and redundancy (FRed) for the nutrients traits.** Each map shows the predictions obtained using the full dataset (Full model) and the changes that occur by leaving the plots from each continent out of the model. The second panel shows the spatial predictions when leaving the records from the Americas out of model fitting, the third panel when leaving records from Africa out and the bottom panel when leaving the records from Asia and Australia out from model fitting.



**Figure S9. Bivariate maps combining the functional diversity (FD) and redundancy (FRed) for the photosynthesis traits.** Each map shows the predictions obtained using the full dataset (Full model) and the changes that occur by leaving the plots from each continent out of the model. The second panel shows the spatial predictions when leaving the records from the Americas out of model fitting, the third panel when leaving records from Africa out and the bottom panel when leaving the records from Asia and Australia out from model fitting.



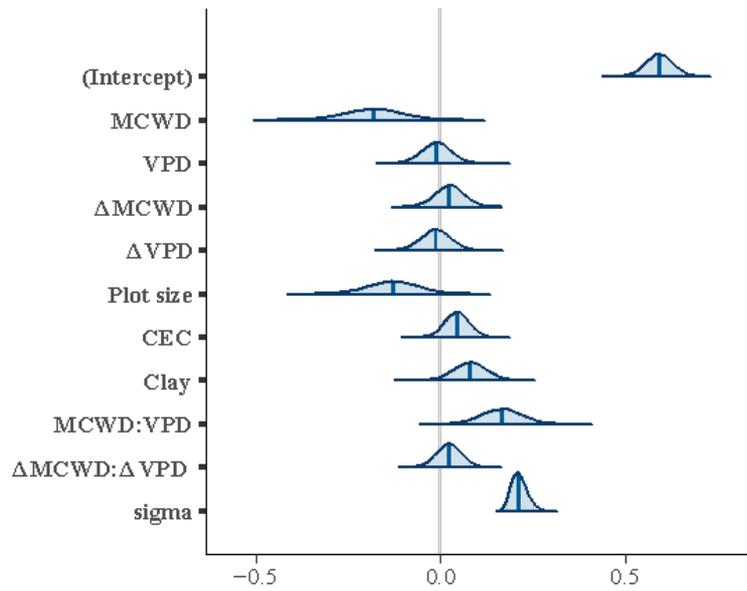
**Figure S10. Correlation coefficients between the full model FD-FRed bivariate spatial predictions and those made when plots from one continent out.** Overall, when the Americas is left out of model fitting the predictions are most different with the full model predictions and this is due to the higher number of records (plots) coming from this area (see also TS4). When data from the Americas is left out from the morphological and nutrients models the correlation with the full models drops dramatically, suggesting plots in the Americas have unique morphological and nutrients composition (FD-FRed) not found in other areas but also reflects the fact that a large part of the plot data is coming from this area.



**Figure S11. Pearson's correlation coefficients between all climatic and soil variables analysed in this study.** Besides the correlation between the coefficient of variation of precipitation (CV) and the maximum climatic water deficit (MCWD), cation exchange capacity (CEC) and pH and soil clay content (Clay) and soil sand content (Sand), all other pairwise comparisons had coefficients below 0.70 (our threshold selected to include or exclude a covariate in the model). VPD: vapour pressure deficit. Δ: change.

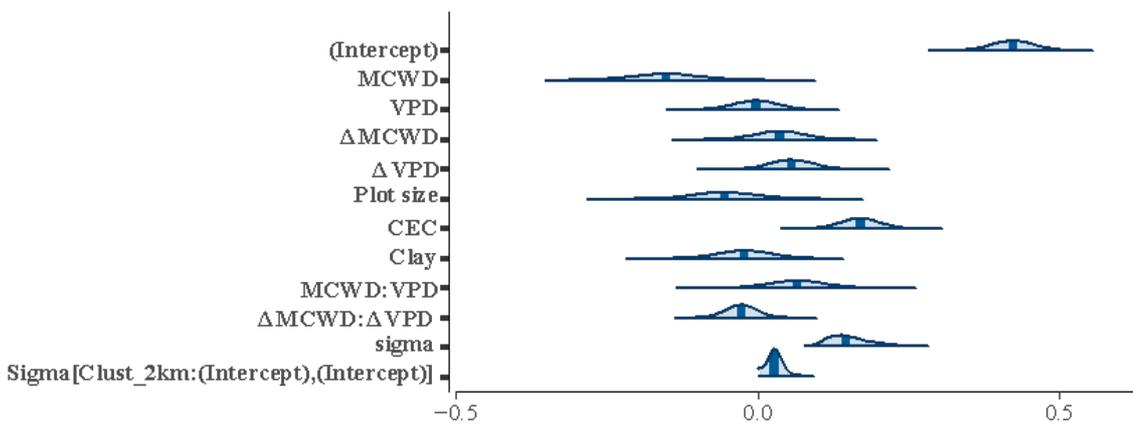
### FD -Morphology/Structure

Posterior distributions with medians and 90% intervals



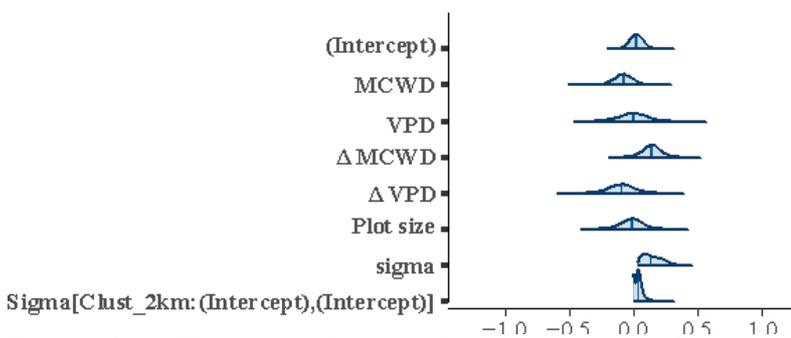
### FD -Nutrients

Posterior distributions with medians and 90% intervals

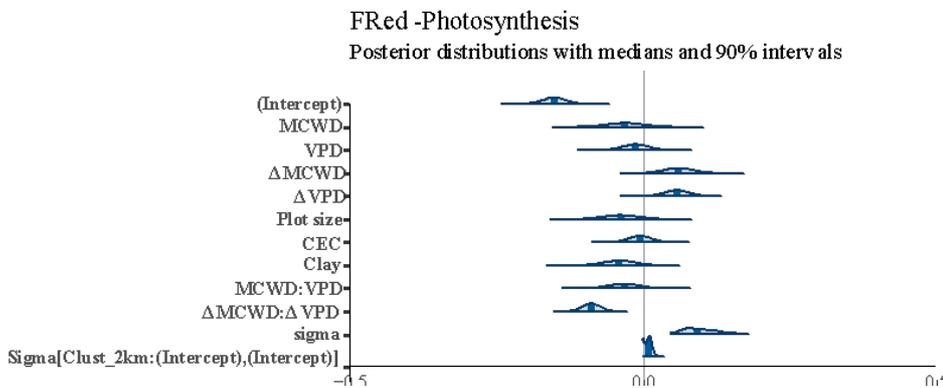
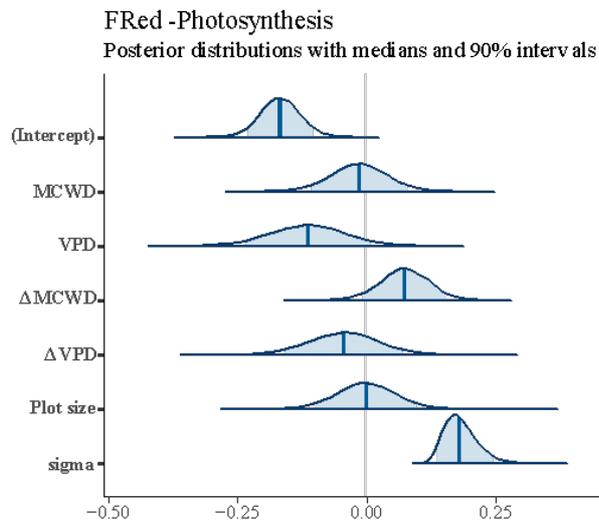
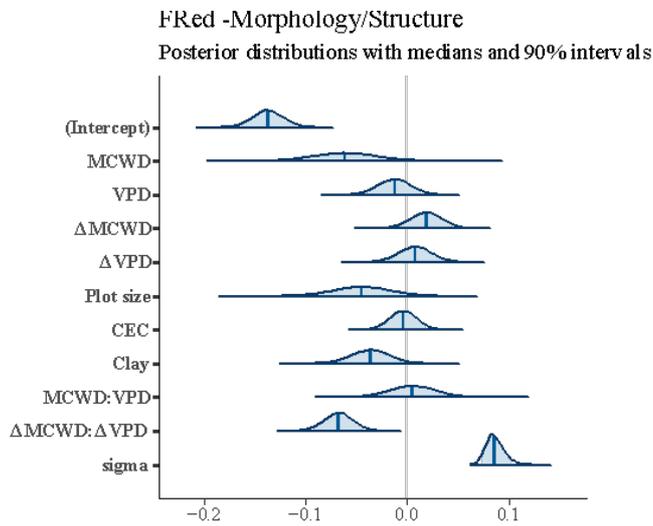


### FD -Photosynthesis

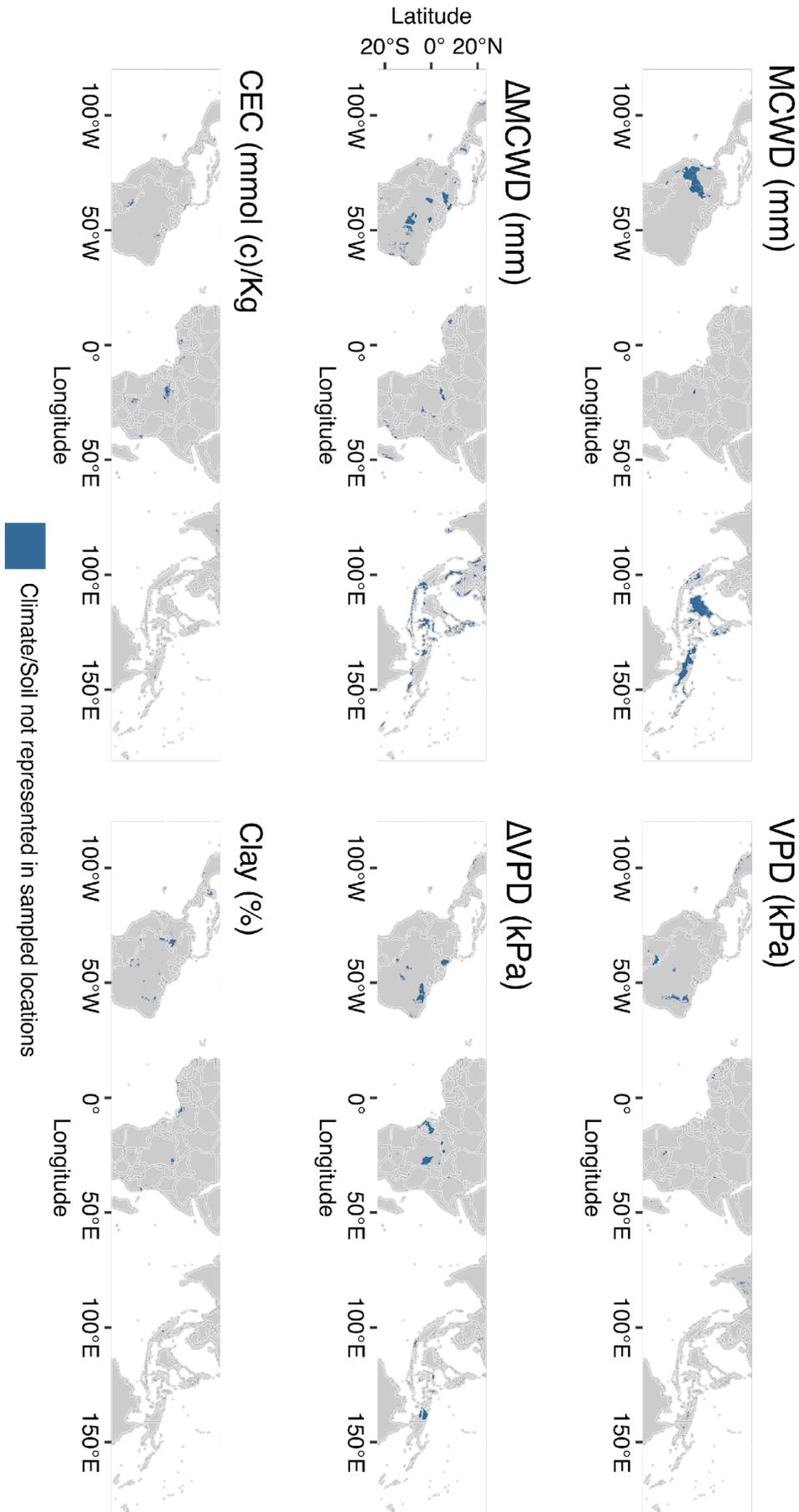
Posterior distributions with medians and 90% intervals



**Figure S12.** The posterior density distribution of the models fitted exploring the effects of long-term and a changing climate and soil characteristics on the functional diversity (FD) of morphology/structure, nutrients(middle panel) and photosynthesis (bottom panel) traits. The posterior density distribution of the random effect (when included in the model) is not shown for clarity purposes. See Table S3 for full statistical details. MCWD: maximum climatic water deficit, VPD: vapour pressure deficit, CEC: soil cation exchange capacity, Clay: soil clay content.  $\Delta$ : change.



**Figure S13. The posterior density distribution of the models fitted exploring the effects of long-term and a changing climate and soil characteristics on the functional redundancy (FRed) of morphology/structure, nutrients(middle panel) and photosynthesis (bottom panel) traits.** The posterior density distribution of the random effect (when included in the model) is not shown for clarity purposes. See Table S3 for full statistical details. MCWD: maximum climatic water deficit, VPD: vapour pressure deficit, CEC: soil cation exchange capacity, Clay: soil clay content.  $\Delta$ : change.



**Figure S14.** The blue colour shows the distribution of locations that contain climatic and soil values out of the range used to fit the statistical models of functional diversity (FD) and functional redundancy (FRed). The results of FD and FRed scores for those areas (in blue) should be interpreted with caution. See Figure 3 and Figure 4 for the FD and FRed spatial predictions. MCWD: maximum climatic water deficit, VPD: vapour pressure deficit, CEC: soil cation exchange capacity, Clay: soil clay content.  $\Delta$ : change.

Supplementary Information: Supplementary Tables S1 to S9

**Functional susceptibility of tropical forests to climate change**

Jesús Aguirre-Gutiérrez et al.

**Supplementary Table S1. Plant functional traits included in the analysis, their description and their hypothesised response and importance under a drying climate.** References are not exhaustive (see end of document for full details of references).

Functional group	Trait	Description	Importance and hypothesised response to a drying climate	References
Morphology and structure	Leaf area: A (cm <sup>2</sup> )	Area of the leaf determined by scanning the adaxial side of the leaf lamina on a flatbed scanner Canon LiDE220®	Relevant as a main light capture mechanism. Higher leaf area could result in more leaf transpiration and thus water loss under a drying climate. Under a drying climate it may increase in deciduous species and expect decreases in evergreens as to limit water loss by transpiration and for increasing cooling.	1,2
	DM: leaf dry mass (g)	Leaf fresh mass calculated as the fresh weight of the recently obtained leaves.	Increasing droughts may cause decreases in leaf dry and fresh mass. Such decreases in leaf dry and fresh mass may have negative implications for biomass productivity.	3
	FM: leaf fresh mass (g)	Leaf dry mass determined after oven drying at 60 °C leaves for 72 hours or until constant weight.		
	LDMC: leaf dry matter content (mg/g)		It is an indicator of leaf defence against drying conditions. It would tend to increase as water stress increases.	4
	LWC (%)	Water content in the leaf determined by subtracting the dry mass content from the fresh mass, multiplying by 100 and dividing by the fresh mass to obtain percentage water content.	Indicator of leaf water stress which can limit photosynthesis and thus productivity. LWC is expected to decline with increasing drought conditions as to avoid leaf water loss.	5
	SLA (m <sup>2</sup> /g)	Specific leaf area calculated as the one-sided area of a leaf divided by dry mass	Important for photosynthetic capacity, light capture, water loss, net assimilation rate, leaf life span. May increase if acquisitive species, e.g. deciduous species, become more abundant with a drying climate.	6,7,8

T (mm)	Thickness of leaf lamina measured by taking four micrometre measurements halfway between the mid-vein and the edge of the leaf, avoiding major secondary veins.	Trade-off between decreasing water transpiration at the expense of higher construction investment. May decrease under a drying climate as a result of increasing in deciduous species which may tend to have thinner leaves. It is expected that thicker leaves become more common under larger water deficits for evergreen species but may decrease for acquisitive deciduous species.	1,2
WD (g/cm <sup>3</sup> ).	Wood density obtained from the oven dried wood mass divided by its fresh volume	Relevant for mechanical strengths, stem vulnerability to xylem cavitation. Expected to be higher in areas with lower water resources, and thus increase with a drying climate.	8,9,10,11
Ca: leaf calcium (%)	Leaf nutrients concentration in percentage obtained from dry leaf samples. On a different branch, all leaves were removed for bulk chemical analysis at different laboratories depending on the traits campaign.	Calcium is a regulator in processes related to growth such as stomatal function, cell division, cell wall synthesis, repair of damage from biotic and abiotic stress. Decreases in Ca are expected under increasing droughts	12
K: leaf potassium (%)		Important role in the regulation of water status, make a major contribution to the osmotic potential of cells and tissues and it is involved in physiological processes, such as photosynthesis, osmoregulation and stomatal movement. Based on recent literature It is expected a decrease in leaf K content with increasing drought.	13,14
Mg: leaf magnesium (%)		Important element for plant growth and photosynthesis which can be impacted by increasing droughts. It has major role in synthesis of proteins, ATP and chlorophyll. It is	15,16

			<p>expected that decreases in Mg may lead to decreases in plant biomass if Mg levels are disrupted by a changing climate.</p> <p>Essential for metabolic reactions involved in light capture, photosynthetic capacity and growth. Restricted availabilities limit plant carbon acquisition and growth. Drought effects may be compensated if nitrogen fixing species (mainly Fabaceae) become more abundant. Following the literature it is expected that leaf nitrogen content will decrease with increasing temperature and droughts.</p>	17,18,19,20
	N: leaf nitrogen (%)			
			<p>Needed nutrient for metabolic reactions that include light capture, related to photosynthetic capacity and growth. Lack of P may limit carbon acquisition and growth. Decreases under a drying climate and possible not strong effect under short term droughts or in wet forests. May be more dependent on soil conditions than on climate.</p>	18,19,20
	P: leaf phosphorus (%)			
Photosynthesis	Amax ( $\mu\text{mol m}^{-2} \text{s}^{-1}$ )	Amax: Light-saturated maximum rates of net photosynthesis at saturated CO <sub>2</sub> . Asat: Light-saturated rates of net photosynthesis at ambient CO <sub>2</sub> concentration. Photosynthetic capacity (light-saturated net assimilation rate) was measured at both saturating CO <sub>2</sub> concentration (2000 ppm CO <sub>2</sub> ; Amax), and at ambient CO <sub>2</sub> concentration (400	Maximum CO <sub>2</sub> assimilation. Index of leaf photosynthetic capacity. Higher for species with fast resources turnover, e.g. deciduous vs evergreens. Increase with abundance of such species. Saturated photosynthetic rate. Index of leaf photosynthetic capacity. Declines with higher temperatures and lower precipitation. However, Asat is also dependent on CO <sub>2</sub> fertilization and N and P levels.	21,22
	Asat ( $\mu\text{mol m}^{-2} \text{s}^{-1}$ )			21,22

RDark ( $\mu\text{mol m}^{-2}\text{s}^{-1}$ )	ppm CO <sub>2</sub> ; Asat) under saturating light conditions and at a temperature of 25 °C using a LICOR 6400-XT. RDark: Leaf dark respiration.	Component of plant carbon balance which can return 40–50% of photosynthetically fixed carbon to the atmosphere. Increases in RDark with increases in temperature and decreases in precipitation.	23,24
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**Supplementary Table S2. Climatic conditions for the full term period (1958-2017) , for its changes between the first (1958-1987) and second (1988-2017) time period analysed and for soil conditions.** The third to fifth columns in the table describe if the plot was included (Y) or not (empty) in the FD and FRed analysis for the different functional groups.

Location	Plot	Functional indices Morphology/Structure	Functional indices Nutrients	Functional indices Photosynthesis	Plot size (ha)	MCWD (mm)	VPD (kPa)	CV (mm)	ΔVPD (kPa)	ΔCV (mm)	ΔMCWD (mm)	CEC (mmol (c)/kg)	Clay (%)	pH	Sand (%)
Australia	EP43		Y	Y	0.5	542.25	0.74	0.73	-0.01	-0.07	-40.06	13.78	42.15	5.00	32.33
Australia	AEP02		Y		0.5	671.04	0.75	0.81	-0.01	-0.06	-46.90	11.99	35.74	4.90	35.23
Australia	AEP03		Y	Y	0.5	671.04	0.75	0.91	-0.01	-0.04	-46.90	11.99	35.74	4.80	42.50
Australia	KRU01	Y	Y	Y	0.1	206.56	0.75	0.67	-0.01	-0.09	-58.22	15.34	42.74	5.10	30.70
Australia	AEP41		Y	Y	0.5	386.28	0.71	0.72	0.00	-0.08	-65.35	14.00	36.41	5.00	39.73
Australia	DRO01		Y	Y	0.9	386.28	0.71	0.69	0.00	-0.08	-65.35	14.00	36.41	5.57	38.60
Australia	ROB06		Y	Y	1	460.43	0.72	0.77	-0.01	-0.06	-85.05	13.70	37.11	5.00	33.27
Brazil -NX	VCR02	Y	Y	Y	1	541.76	1.13	0.83	-0.06	0.01	56.21	9.71	25.19	5.40	58.53
Brazil -NX	NXV01	Y	Y	Y	1	524.20	1.11	0.82	-0.06	0.01	40.41	7.77	23.80	5.40	62.50
Brazil -NX	NXV02	Y	Y	Y	1	524.20	1.11	0.82	-0.06	0.01	40.41	7.77	23.80	5.30	63.80
Brazil -NX	NXV10	Y	Y	Y	1	524.20	1.11	0.82	-0.06	0.01	40.41	7.77	23.80	5.37	63.73
Brazil -ST	363_6	Y	Y	Y	0.25	358.87	0.63	0.61	0.02	0.00	-89.87	9.30	36.69	4.03	51.13
Brazil -ST	363_3	Y	Y	Y	0.25	363.17	0.63	0.62	0.02	0.01	-93.20	9.65	34.03	4.07	53.97
Brazil -ST	363_7	Y	Y	Y	0.25	363.17	0.63	0.61	0.02	0.00	-93.20	9.65	34.03	4.13	46.43
Brazil -ST	261_10	Y	Y	Y	0.25	371.36	0.62	0.64	0.02	0.01	-103.91	12.27	50.40	4.07	33.50
Brazil -ST	261_9	Y	Y	Y	0.25	371.36	0.62	0.64	0.02	0.01	-103.91	12.27	50.40	4.30	32.13
Colombia	Macuire	Y	Y		1	941.62	1.22	0.73	0.02	0.04	0.00	20.05	35.18	6.70	34.33
Colombia	Taminango		Y		1	155.61	0.76	0.44	-0.02	0.00	-43.22	25.81	35.12	5.90	31.63
Colombia	Tuparro	Y	Y		1	204.58	1.13	0.70	-0.02	0.01	-75.96	12.61	25.50	5.23	50.37
Colombia	CardonalLoma	Y	Y	Y	1	60.97	1.00	0.41	-0.02	-0.06	-131.07	21.56	41.54	5.00	27.47
Colombia	CardonalPlana		Y		1	60.84	1.08	0.40	-0.03	-0.07	-135.37	19.48	41.67	5.00	24.97
Colombia	Jabiru	Y	Y	Y	1	60.84	1.08	0.44	-0.03	-0.06	-135.37	19.48	41.67	5.20	24.87
Colombia	Tambor	Y	Y		1	57.41	1.05	0.37	-0.03	-0.07	-140.04	18.15	39.63	5.17	26.70
Colombia	Vinculo	Y	Y		1	80.81	0.65	0.37	-0.03	-0.04	-144.66	23.85	34.67	6.03	27.77
Colombia	Cotove		Y		1	152.12	0.83	0.46	-0.06	-0.05	-152.89	19.65	39.04	5.90	34.13
Gabon	MNG04	Y	Y	Y	1	241.18	0.52	0.68	0.06	0.00	32.87	15.35	28.76	4.87	46.00
Gabon	LPG02	Y	Y	Y	1	173.72	0.74	0.68	0.08	-0.01	0.33	13.15	31.79	5.10	56.17
Gabon	LPG01	Y	Y	Y	1	173.93	0.79	0.67	0.08	-0.01	-0.35	12.14	27.79	4.90	54.10
Ghana	KOG03	Y	Y		1	493.04	1.03	0.60	0.02	0.02	-27.55	34.00	21.10	5.53	49.77
Ghana	KOG04	Y	Y		1	493.04	1.03	0.60	0.02	0.02	-27.55	34.00	21.10	5.63	48.57
Ghana	KOG05	Y	Y		1	493.04	1.03	0.60	0.02	0.02	-27.55	34.00	21.10	5.67	49.20
Ghana	KOG06	Y	Y		1	493.04	1.03	0.60	0.02	0.02	-27.55	34.00	21.10	5.70	50.23
Ghana	KOG02	Y	Y		1	474.96	1.00	0.59	0.02	0.01	-29.66	34.00	21.86	5.73	56.23
Ghana	BOB01	Y	Y		1	322.92	0.84	0.52	0.02	0.01	-35.93	32.23	21.89	5.67	46.73
Ghana	BOB02	Y	Y		1	322.92	0.84	0.52	0.02	0.01	-35.93	32.23	21.89	5.73	48.90
Ghana	ANK01	Y	Y		1	149.27	0.67	0.68	0.02	-0.03	-190.69	15.76	22.87	4.77	65.33
Ghana	ANK03	Y	Y		1	149.27	0.67	0.66	0.02	-0.03	-190.69	15.76	22.87	4.80	65.10
Malaysia	MLA-01	Y	Y	Y	1	0.00	0.82	0.15	0.03	-0.01	-46.76	18.05	39.01	5.00	32.87
Malaysia	MLA-02	Y	Y	Y	1	0.00	0.77	0.16	0.03	-0.01	-54.91	20.09	41.13	5.00	32.13
Malaysia	DAN-04	Y	Y	Y	1	0.00	0.79	0.16	0.02	-0.01	-87.00	16.81	38.21	5.10	29.67
Malaysia	DAN-05	Y	Y	Y	1	0.00	0.79	0.16	0.02	-0.01	-87.00	16.81	38.21	5.07	31.10
Mexico	ME_14_00358	Y			0.25	873.77	1.05	1.12	0.07	0.07	156.99	22.89	20.57	6.10	60.37
Mexico	ME_14_00359	Y	Y		0.25	873.77	1.05	1.12	0.07	0.07	156.99	22.89	20.57	5.80	60.90
Mexico	ME_14_00360	Y	Y		0.25	873.77	1.05	1.12	0.07	0.07	156.99	22.89	20.57	6.10	64.53
Mexico	ME_14_00361	Y	Y		0.25	873.77	1.05	1.12	0.07	0.07	156.99	22.89	20.57	6.00	60.90
Mexico	ME_14_00362	Y	Y		0.25	873.77	1.05	1.13	0.07	0.06	156.99	22.89	20.57	6.00	65.57
Mexico	ME_23_00144	Y	Y		0.25	481.96	0.86	0.57	0.03	0.01	-36.86	22.10	49.24	7.00	32.90
Mexico	ME_23_00143	Y	Y		0.25	475.67	0.85	0.57	0.03	0.00	-43.16	24.24	50.72	7.10	30.87
Mexico	ME_23_00146	Y	Y		0.25	475.67	0.85	0.58	0.03	0.01	-43.16	24.24	50.72	7.07	33.33
Mexico	ME_23_00147	Y	Y		0.25	482.78	0.84	0.57	0.03	0.00	-43.73	23.97	50.70	7.17	33.47
Mexico	ME_23_00148	Y	Y		0.25	482.78	0.84	0.57	0.03	0.00	-43.73	23.97	50.70	7.17	34.13
Mexico	ME_23_00149	Y	Y		0.25	482.78	0.84	0.57	0.03	0.00	-43.73	23.97	50.70	7.27	34.40
Mexico	ME_23_00145	Y	Y		0.25	468.84	0.84	0.57	0.03	0.00	-49.46	24.26	51.00	7.00	32.60
Mexico	ME_23_00151	Y	Y		0.25	470.85	0.82	0.58	0.03	-0.01	-56.44	24.81	49.25	6.93	32.07
Panama	Fortuna-AF	Y	Y		1	210.77	0.28	0.59	-0.02	-0.02	48.42	17.38	35.01	5.10	32.93
Panama	Fortuna-HOR	Y	Y		1	210.77	0.28	0.47	-0.02	-0.03	48.42	17.38	35.01	5.03	32.50
Panama	Fortuna-BON	Y	Y		1	146.78	0.25	0.35	-0.02	-0.02	40.31	17.81	31.30	5.33	38.17
Panama	Fortuna-PAS	Y	Y		1	146.78	0.25	0.39	-0.02	0.00	40.31	17.81	31.30	5.43	40.00
Panama	Fortuna-VERA	Y	Y		1	146.78	0.25	0.39	-0.02	0.00	40.31	17.81	31.30	5.13	32.90
Panama	Fortuna-VERB	Y	Y		1	146.78	0.25	0.40	-0.02	0.00	40.31	17.81	31.30	5.20	33.20
Panama	Fortuna-CHOB	Y	Y		1	202.26	0.28	0.35	-0.02	-0.02	39.09	16.71	33.78	5.10	34.20
Panama	Fortuna-HONA	Y	Y		1	202.26	0.28	0.35	-0.02	-0.02	39.09	16.71	33.78	5.20	34.10
Panama	Fortuna-HONB	Y	Y		1	202.26	0.28	0.35	-0.02	-0.02	39.09	16.71	33.78	5.10	34.47
Panama	Fortuna-PIN	Y	Y		1	202.26	0.28	0.53	-0.02	-0.03	39.09	16.71	33.78	5.00	34.23
Panama	Fortuna-SAM	Y	Y		1	202.26	0.28	0.35	-0.02	-0.02	39.09	16.71	33.78	5.20	33.33
Peru	TAM05	Y	Y		1	152.58	0.84	0.55	-0.02	0.02	104.09	12.13	25.13	4.97	36.67
Peru	TAM06	Y	Y		1	152.58	0.84	0.54	-0.02	0.02	104.09	12.13	25.13	5.07	35.33
Peru	SPD01	Y	Y		1	254.08	0.68	0.45	-0.03	0.07	17.55	26.30	28.39	5.20	32.90
Peru	TRU04	Y	Y		1	254.08	0.68	0.56	-0.03	0.07	17.55	26.30	28.39	5.80	43.80
Peru	SPD02	Y	Y		1	101.53	0.72	0.45	-0.03	0.06	15.69	23.14	33.69	5.13	33.23
Peru	PAN03	Y	Y		1	0.00	0.87	0.41	-0.03	0.06	0.30	18.99	35.94	5.00	28.80
Peru	PAN02	Y	Y	Y	1	0.00	0.87	0.41	-0.03	0.06	0.06	20.46	35.80	5.23	27.23
Peru	ESP01	Y	Y		1	371.90	0.62	0.63	-0.02	0.07	-16.96	26.47	27.07	6.17	36.40
Peru	WAY01	Y	Y		1	371.90	0.62	0.63	-0.02	0.07	-16.96	26.47	27.07	6.30	40.03
Peru	ACJ01	Y	Y		1	494.13	0.59	0.75	-0.02	0.06	-36.10	22.98	28.56	6.20	42.00

Brazil -NX: Nova Xavantina; Brazil -ST: Santarem; Malaysia: Malaysian Borneo. Y=yes, used for the FD/FRed calculations. MCWD: maximum climatic water deficit, VPD: vapour pressure deficit, CEC: soil cation exchange capacity, Clay: soil clay content. Δ: change.

**Supplementary Table S3. Models results testing for the relation of functional diversity (FD) and functional redundancy (FRed) with long-term (MCWD and VPD) and changes in climate ( $\Delta$ MCWD and  $\Delta$ VPD) and soil cation exchange capacity (CEC) and clay content (Clay). Important terms (Highest Density Interval does not overlap 0) are highlighted in grey. N refers to the number of vegetation plots used to fit the models. MCWD: maximum climatic water deficit, VPD: vapour pressure deficit, CEC: soil cation exchange capacity, Clay: soil clay content.  $\Delta$ : change.**

Metric	Trait	Parameter	Median	HDI-L	HDI-H	pd	ROPE (%)	Rhat	ESS	R2	N
FD	Morphology / Structure	Intercept	0.590	0.530	0.660	1.00	0.00	1.00	11776.94	0.44	59
		MCWD	-0.180	-0.310	-0.050	0.99	0.01	1.00	6078.76		
		VPD	-0.010	-0.080	0.050	0.60	0.91	1.00	9024.43		
		$\Delta$ MCWD	0.030	-0.040	0.090	0.74	0.81	1.00	13793.30		
		$\Delta$ VPD	-0.010	-0.080	0.050	0.62	0.89	1.00	11322.42		
		Plot size	-0.130	-0.240	-0.020	0.97	0.10	1.00	5927.16		
		CEC	0.050	-0.010	0.100	0.92	0.65	1.00	10472.41		
		Clay	0.080	0.010	0.160	0.96	0.27	1.00	8307.24		
		MCWD:VPD	0.170	0.080	0.260	1.00	0.00	1.00	7965.82		
		$\Delta$ MCWD: $\Delta$ VPD	0.020	-0.030	0.080	0.75	0.86	1.00	11051.42		
	Nutrients	Intercept	0.420	0.370	0.480	1.00	0.00	1.00	6860.33	0.75	70
		MCWD	-0.150	-0.240	-0.060	1.00	0.00	1.00	5386.58		
		VPD	0.000	-0.060	0.060	0.54	0.85	1.00	7137.43		
		$\Delta$ MCWD	0.040	-0.030	0.110	0.81	0.58	1.00	6996.22		
		$\Delta$ VPD	0.060	0.000	0.120	0.94	0.35	1.00	6691.61		
		Plot size	-0.050	-0.140	0.040	0.85	0.42	1.00	5531.48		
		CEC	0.170	0.120	0.220	1.00	0.00	1.00	8388.50		
		Clay	-0.020	-0.090	0.050	0.69	0.70	1.00	6807.73		
		MCWD:VPD	0.060	-0.010	0.140	0.92	0.31	1.00	6358.19		
		$\Delta$ MCWD: $\Delta$ VPD	-0.030	-0.070	0.010	0.86	0.76	1.00	8657.60		
	Photosynthesis	Intercept	0.020	-0.070	0.120	0.67	0.40	1.00	3596.67	0.75	22
		MCWD	-0.080	-0.200	0.060	0.84	0.19	1.00	3653.69		
		VPD	0.000	-0.180	0.170	0.51	0.25	1.00	2404.67		
		$\Delta$ MCWD	0.140	0.020	0.250	0.98	0.01	1.00	3617.61		
		$\Delta$ VPD	-0.090	-0.260	0.070	0.83	0.16	1.00	2635.85		
		Plot size	-0.010	-0.150	0.130	0.55	0.32	1.00	6056.06		
	FRed	Morphology / Structure	Intercept	-0.140	-0.160	-0.110	1.00	0.00	1.00	10032.57	0.53
MCWD			-0.060	-0.110	-0.010	0.97	0.01	1.00	5039.35		
VPD			-0.010	-0.040	0.010	0.78	0.37	1.00	7962.77		
$\Delta$ MCWD			0.020	-0.010	0.050	0.88	0.23	1.00	10881.27		
$\Delta$ VPD			0.010	-0.020	0.040	0.69	0.41	1.00	8045.75		
Plot size			-0.040	-0.090	0.000	0.94	0.07	1.00	4862.01		
CEC			0.000	-0.030	0.020	0.60	0.53	1.00	9195.92		
Clay			-0.040	-0.070	0.000	0.97	0.04	1.00	6962.26		
MCWD:VPD			0.010	-0.030	0.040	0.59	0.33	1.00	6648.54		
$\Delta$ MCWD: $\Delta$ VPD			-0.070	-0.090	-0.040	1.00	0.00	1.00	8911.43		
Nutrients		Intercept	-0.150	-0.180	-0.120	1.00	0.00	1.00	6764.04	0.73	70
		MCWD	-0.030	-0.090	0.020	0.83	0.18	1.00	4501.18		
		VPD	-0.010	-0.050	0.020	0.72	0.37	1.00	5748.85		
		$\Delta$ MCWD	0.060	0.020	0.100	0.99	0.00	1.00	5803.23		
		$\Delta$ VPD	0.060	0.020	0.090	1.00	0.00	1.00	6924.62		
		Plot size	-0.040	-0.090	0.020	0.88	0.15	1.00	4675.90		
		CEC	0.000	-0.040	0.030	0.60	0.47	1.00	6382.34		
		Clay	-0.040	-0.080	0.000	0.94	0.08	1.00	5455.13		
		MCWD:VPD	-0.030	-0.080	0.010	0.88	0.18	1.00	5391.84		
		$\Delta$ MCWD: $\Delta$ VPD	-0.090	-0.110	-0.060	1.00	0.00	1.00	6591.10		
Photosynthesis		Intercept	-0.170	-0.230	-0.100	1.00	0.00	1.00	11858.06	0.33	22
		MCWD	-0.010	-0.110	0.080	0.60	0.19	1.00	8177.61		
		VPD	-0.110	-0.230	0.01	0.94	0.04	1.00	7547.91		
		$\Delta$ MCWD	0.070	-0.010	0.160	0.93	0.05	1.00	9917.27		
		$\Delta$ VPD	-0.040	-0.160	0.070	0.74	0.13	1.00	7617.03		
		Plot size	0.000	-0.100	0.100	0.51	0.18	1.00	8701.47		

**Supplementary Table S4. Relation between the number of records used to fit the FD and FRed models and the correlation between the resulting binary maps constructed with the full dataset and with records from the Americas, Africa or Asia left out.** There is in general a high overall correlation between the number of records used to fit the models and the correlation between the full model and continent out bivariate FD-FRed maps (see Figure 5 and Figures S2-S4).

Index	Trait	Comparisons	Overall correlation	Records used	Correlation with full model
FD	Morphology/Structure	Full model	0.99	59	1.00
		Americas out		14	0.21
		Africa out		49	0.95
		Asia out		55	0.98
	Nutrients	Full model	0.81	70	1.00
		Americas out		23	0.34
		Africa out		58	0.47
		Asia out		59	0.86
	Photosynthesis	Full model	0.51	22	1.00
		Americas out		13	0.65
		Africa out		19	0.94
		Asia out		12	0.97
FRed	Morphology/Structure	Full model	0.99	59	1.00
		Americas out		14	-0.50
		Africa out		49	0.91
		Asia out		55	0.94
	Nutrients	Full model	0.99	70	1.00
		Americas out		23	-0.57
		Africa out		58	0.48
		Asia out		59	0.71
	Photosynthesis	Full model	0.65	22	1.00
		Americas out		13	0.23
		Africa out		19	0.99
		Asia out		12	0.84

**Table S5. Relationship between FD and FRed levels and taxonomic diversity at the plot level.**

<b>Index</b>	<b>Trait group</b>	<b>Taxonomical comparison</b>	<b>Correlation</b>	<b>Pval</b>
FD	Morphology/Structure	Species	0.02	0.90
		Genus	0.06	0.64
		Family	0.12	0.37
	Nutrients	Species	0.02	0.88
		Genus	0.08	0.51
		Family	-0.04	0.74
	Photosynthesis	Species	0.30	0.18
		Genus	0.41	0.06
		Family	0.50	0.02
FRed	Morphology/Structure	Species	0.57	<0.001
		Genus	0.59	<0.001
		Family	0.56	<0.001
	Nutrients	Species	0.49	<0.001
		Genus	0.49	<0.001
		Family	0.43	<0.001
	Photosynthesis	Species	0.36	0.10
		Genus	0.36	0.10
		Family	0.19	0.39

Correlation: Pearson correlation coefficient; P-val: Significance of the correlation

**Supplementary Table S6. Percentage of the study area with low, intermediate and high functional diversity and functional redundancy scores.** For details about the methodology to obtain the % values show see the methods section in the main text.

Index	Trait	Low (%)	Intermediate (%)	High (%)
FD	Photosynthesis	36.8	60.7	2.4
	Nutrients	14.8	71.1	14.1
	Morphology/Structure	30.4	64.1	5.5
FRed	Morphology/Structure	5.5	92.2	2.3
	Photosynthesis	16.9	76.3	6.8
	Nutrients	3.7	89.2	7.0

**Supplementary Table S7. Linear models results explaining the change in AGB after the 2015 El Niño event in African tropical forest.** The original data on pre and post El Niño AGB was obtained from Bennet et al. 2021. We modelled the change in AGB as a function of the morphological/structural, leaf nutrients and photosynthetic functional diversity (FD) and redundancy (FRed) map scores (extracted from Figures 3 and 4 in the main text) and their interaction with changes in MCWD and VPD. Several parameters using from the different trait groups have a clear effect (Highest Density Intervals (HDI) do not overlap 0) on the changes in AGB.

Trait	Parameter	Median	HDI-L	HDI-H	pd	ROPE (%)	Rhat	ESS	R2	N
Morphology / Structure	Intercept	9.66	8.2	11.1	1.00	0.00	1.000	8051.41	0.18	86
	FD	1.97	0.28	3.65	0.97	0.05	1.000	4014.49		
	FRed	-1.78	-3.55	0.15	0.94	0.12	1.001	3814.73		
	ΔMCWD	-0.9	-2.52	0.75	0.81	0.36	1.001	3984.14		
	ΔVPD	-1.05	-2.89	0.73	0.83	0.30	1.000	4673.00		
	Plot size	-0.25	-1.51	0.97	0.63	0.61	1.000	7001.04		
	FD:ΔMCWD	-0.43	-2.71	1.95	0.62	0.36	1.000	5010.76		
	FRed:ΔMCWD	-0.07	-3.06	3.1	0.51	0.29	1.001	3776.35		
	FD:ΔVPD	-1.42	-3.24	0.33	0.91	0.20	1.001	3358.34		
FRed:ΔVPD	-0.46	-3.3	2.5	0.60	0.28	1.001	3876.24			
Nutrients	Intercept	10.89	9.4	12.4	1.00	0.00	1.000	5441.02	0.19	86
	FD	-1.79	-3.69	0.06	0.94	0.10	1.000	4233.05		
	FRed	-0.89	-2.12	0.39	0.88	0.34	1.000	7212.75		
	ΔMCWD	-2.33	-4.03	-0.57	0.99	0.00	1.001	4690.78		
	ΔVPD	-1.03	-2.69	0.79	0.83	0.30	1.000	4371.06		
	Plot size	-0.92	-2.21	0.39	0.88	0.33	1.000	6570.48		
	FD:ΔMCWD	2.94	0.25	5.69	0.96	0.03	1.000	5389.38		
	FRed:ΔMCWD	-1.87	-3.39	-0.09	0.96	0.08	1.000	4873.43		
	FD:ΔVPD	-0.94	-2.71	0.74	0.81	0.33	1.000	4521.17		
FRed:ΔVPD	-0.69	-2.89	1.55	0.69	0.34	1.000	5166.57			
Photosynthesis	Intercept	8.44	6.89	9.96	1.00	0.00	1.000	5675.56	0.19	86
	FD	-4.13	-10.27	2.22	0.86	0.08	1.001	2072.73		
	FRed	2.96	0.94	5.13	0.99	0.00	1.001	2850.44		
	ΔMCWD	-0.86	-5.89	4.27	0.61	0.18	1.001	2650.77		
	ΔVPD	0.25	-2.33	2.62	0.57	0.35	1.001	2689.94		
	Plot size	-0.21	-1.43	0.98	0.62	0.64	1.000	7324.20		
	FD:ΔMCWD	0.77	-0.74	2.3	0.81	0.41	1.000	3439.71		
	FRed:ΔMCWD	-0.85	-2.5	0.75	0.81	0.37	1.000	3613.87		
	FD:ΔVPD	-3.13	-6.2	-0.19	0.96	0.03	1.000	3598.22		
FRed:ΔVPD	0.47	-1.66	2.73	0.65	0.37	1.001	3019.23			

HDI: highest density interval, l: low, h: high, pd: probability of direction, Rhat: potential scale reduction statistic, ESS: effective sample size. MCWD: maximum climatic water deficit, VPD: vapour pressure deficit, CEC: soil cation exchange capacity, Clay: soil clay content. Δ: change.

**Supplementary Table S8. Leave-one-out comparisons results comparing models for the same Index and trait group with and without soil data.** The inclusion of soil data improved model outcome for morphology/Structural and Nutrients models but not for the Photosynthesis models. The best model was selected as the one with the lowest LOOIC.

Index	Trait	Climate	Soil	ELPD diff	ELPD LOO	SE ELPD LOO	P LOO	SE P LOO	LOOIC	SE LOOIC
FD	Morphology/Structure	Yes	Yes	0	11.35	5.56	10.93	2.70	-22.71	11.12
		Yes	No	-0.84	10.51	6.09	9.47	2.86	-21.03	12.18
	Nutrients	Yes	Yes	0	6.00	5.41	38.61	4.17	-11.99	10.83
		Yes	No	-7.49	-1.50	5.91	46.18	4.97	2.99	11.81
	Photosynthesis	Yes	Yes	-2.31	-7.29	6.91	25.49	6.41	14.57	13.82
		Yes	No	0	-4.98	7.56	28.72	7.20	9.95	15.13
FRed	Morphology/Structure	Yes	Yes	0	87.44	6.71	9.57	2.03	-174.87	13.41
		Yes	No	-4.65	82.78	7.08	7.85	1.80	-165.56	14.15
	Nutrients	Yes	Yes	-0.24	71.63	9.79	19.09	4.87	-143.27	19.57
		Yes	No	0	71.87	9.57	18.14	4.76	-143.75	19.14
	Photosynthesis	Yes	Yes	0	25.11	3.67	9.89	2.40	-50.22	7.35
		Yes	No	-0.06	25.05	4.03	7.91	2.22	-50.10	8.05

LOOIC: Leave one out information criterion; ELPD LOO: Leave one out expected log predicted density; ELPD diff: difference in expected log predicted density; P LOO: Effective number of parameters; SE LOOIC: standard error of LOOIC; SE ELPD LOO: Standard Error of ELPD; SE P LOO: Standard error of P.

**Supplementary Table S9. Moran I results of model residuals for models for FD and FRed fitted with and without a random factor.** The random factor accounted for the distance between sampling locations and grouping the sampling locations based on a distance where spatial autocorrelation (if existent) diminished. See the methods section in the main text for an in full explanation.

Index	Trait	RF included	Observed	Expected	sd	P value
FD	Photosynthesis	N	-0.44	-0.05	0.22	0.08
		Y	-0.40	-0.05	0.23	0.13
	Nutrients	N	0.30	-0.01	0.11	0.00
		Y	0.06	-0.01	0.11	0.49
	Morphology/Structure	N	0.10	-0.02	0.12	0.36
		Y	0.06	-0.02	0.12	0.51
FRed	Photosynthesis	N	-0.30	-0.05	0.22	0.25
		Y	-0.33	-0.05	0.22	0.21
	Nutrients	N	-0.22	-0.02	0.11	0.07
		Y	-0.23	-0.02	0.11	0.05
	Morphology/Structure	N	-0.02	-0.02	0.12	0.98
		Y	-0.05	-0.02	0.12	0.81

References for Table  
S1

Names

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