1 **Title:**

2 Future CO₂ fertilization of the Amazon forest hinges on plant phosphorus use and

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35 Global terrestrial models currently predict that the Amazon rainforest will continue to 36 act as a carbon sink in the future primarily due to the rising atmospheric carbon dioxide (CO₂) concentration, effectively enhancing its resilience and slowing the pace of climate 37 38 change. Soil phosphorus impoverishment in parts of the Amazon basin limits biomass growth, but the role of phosphorus availability in limiting its future carbon uptake has 39 40 not been considered in global model ensembles, e.g., during the Coupled Model Intercomparison Project for the 5th Assessment Report of the United Nations 41 42 Intergovernmental Panel on Climate Change. Here, we simulate a planned free-air CO₂ 43 enrichment experiment in the Amazon with an ensemble of 14 terrestrial ecosystem 44 models. We show that phosphorus feedbacks reduce the CO₂-induced biomass carbon sink to 79 ± 63 g C m⁻² yr⁻¹ over 15 years, a reduction of ~50% compared to estimates from 45 carbon and carbon-nitrogen models. Our results suggest that the region's resilience to 46 47 climate change may be much smaller than previously assumed. Variation in the biomass 48 C response among the phosphorus-enabled models is considerable, ranging from 5 to 140 g C m⁻² yr⁻¹, due to contrasting assumptions relating to the flexibility in plant phosphorus 49 use and acquisition strategies. The model ensemble involuntarily represents diverse plant 50 51 functional strategies and generates a series of testable hypotheses. Experimental design 52 need to be targeted to reduce the uncertainties around the phosphorus feedback on the 53 CO₂ fertilization effect.

The intact Amazon rainforest acts as a substantial carbon (C) sink, completely offsetting carbon dioxide (CO₂) emissions from fossil fuel combustion and land use change in the Amazon region^{1,2}. Increasing atmospheric CO₂ concentrations from anthropogenic activity may be the primary driving force for the current Amazon net carbon sink^{1,3}, and global models assume that this CO₂ fertilization effect will continue to provide this globally significant ecosystem service into the future^{4–6}. The stimulatory effect of elevated carbon dioxide (eCO₂) on photosynthesis and tree growth has been observed experimentally in greenhouses and in the field in open top chamber and free-air CO₂ enrichment (FACE) experiments. To date, whole-ecosystem-scale experiments (i.e., FACE) have mainly been conducted in the temperate zone and never in the tropics^{7,8}. In these experiments, the eCO₂-induced increase in C uptake is generally low when other factors, such as soil nitrogen (N), are limiting^{9,10}.

65 Over large parts of the Amazon and the tropics worldwide, phosphorus (P), not N, is assumed to be the key limiting nutrient, as most P has been lost or occluded from plant uptake during 66 millions of years of soil pedogenesis^{11,12}. Forests growing on these highly weathered old soils 67 68 may nonetheless be highly productive due to the evolution of multiple strategies for P acquisition and use, enabling tight cycling of P between plants and soils^{13,14}. Despite this 69 knowledge, quantifying the control of P on plant physiology, growth, and plant-soil interactions 70 in global models, and hence its role in the forests' response to eCO₂, remains challenging¹⁵. 71 72 This challenge is exacerbated by the scarcity of observations and distinctive species responses in hyperdiverse tropical forests¹⁶. 73

74 Here, we study the potential interactions between eCO₂ and nutrient (N and P) feedbacks in a mature Amazonian rainforest by simulating the planned AmazonFACE experiment (+200 ppm; 75 76 http://amazon-face.org/) with an ensemble of ecosystem models (n = 14, Extended Data Table 77 3), including three C, five carbon-nitrogen (CN), and six carbon-nitrogen-phosphorus (CNP) models¹⁷⁻²². The AmazonFACE experiment is located in a well-studied, highly productive 78 tropical forest in Central Amazonia^{23,24}, growing on a strongly weathered *terra firme* Ferralsol. 79 This ecosystem represents the low end of the plant-available P spectrum in the Amazon, 80 consistent with \sim 32% of the Amazon rainforest's cover fraction²⁵. In situ measurements were 81 82 used to parameterise the models and to evaluate simulated ambient conditions (Extended Data 83 Table 1, 2). Our aim was to generate *a priori* model-based hypotheses to highlight the state-of-84 the-knowledge and guide measurement strategies for AmazonFACE and other ecosystem 85 manipulation experiments to gain crucial process understanding of P control on the CO₂
86 fertilization effect.

87 Simulated eCO₂ (+200 ppm) had a positive effect on plant biomass C across all models but was 88 weakest in the CNP models (Fig. 1a). The eCO₂ conditions induced average biomass C gains of 163 ± 65 , 145 ± 83 , and 79 ± 63 g C m⁻² yr⁻¹ after 15 years in the C, CN and CNP models, 89 90 respectively (Fig. 1a). Limitations by P thus reduced the predicted biomass C sink by 52% and 91 46% compared to that in the C and CN models, respectively, with considerable variation across 92 and within model groups (Extended Data Fig. 1). Plot inventories at the AmazonFACE site during the 2000s indicate an ambient aboveground biomass sink of 23 g C m² yr⁻¹, with an 93 Amazon-wide¹ estimate of 64 g C m² yr⁻¹. The model ensemble represents ambient conditions, 94 95 such as productivity and LAI, reasonably well but the set of models does diverge on some 96 ecosystem characteristics, such as ambient biomass C increases, which range from 5 to 114 g $C m^2 yr^{-1}$ (see more discussion on ambient model performance in Extended Data Fig. 2). 97

98 Gross and net primary productivity (GPP and NPP, respectively) are both stimulated by eCO₂ in all models, both initially (after 1 year of eCO₂) and at the end of the simulation. The CNP 99 100 models show the strongest decline over the 15-year period from the initial response due to P 101 limitation (Fig. 1b, c). The final response of NPP to eCO₂ was a 35%, 29%, and 9% stimulation 102 for the C, CN and CNP models, respectively. In general, in the CN and CNP models, nutrient 103 limitation is defined as nutrient demand being greater than nutrient supply. But models differ 104 in their assumptions on how nutrient limitation controls productivity and C allocation in 105 response to eCO_2 , so that divergent responses on plant carbon use efficiency (CUE = NPP / 106 GPP) are simulated (Extended Data Table 3). In some CN models, CUE increases because N 107 limitation is hypothesized to reduce autotrophic respiration (Ra) via lower tissue N content. In 108 contrast, some CNP models (e.g., CABLE and ELM-ECA) assume a direct downregulation of 109 growth or growth efficiency (i.e., NPP) but only a small reduction in GPP, and hence the plant

110 CUE decreases under nutrient limitation (Extended Data Fig. 3). Elevated CO_2 induced higher 111 fine root investments of NPP in some CN and CNP models to aid nutrient acquisition (Fig. 1c; 112 Extended Data Fig. 4). Predicted changes in allocation with eCO₂ cause a general increase in 113 biomass C turnover across all but one of models, partially offsetting the positive biomass C 114 response (Extended Data Table 4). Changes in turnover largely control the long-term future 115 CO_2 effect on the biomass C sink^{26,27}.

116 Plant growth under eCO₂ is lowest in CNP models as the low availability of soil labile P restricts 117 P uptake either immediately (CABLE, ELM-ECA, GDAY) or over time (CABLE-POP, ELM-118 CTC, ORCHIDEE) (Extended Data Fig. 5). We considered the modelled P limitation on plant 119 growth to be realistic, as the models and observations agree on soil labile P being very low 120 (Extended Data Fig. 2). Other observations support the fact that P is extremely critical for plant 121 productivity, such as high leaf N:P ratios of 37 and high plant P resorption (before litter fall) of 122 78% (Extended Data Table 1). P limitation consistently reduces the eCO₂-induced biomass C 123 sink, but there is significant variation among CNP models due to contrasting process 124 representations (Fig. 2; Extended Data Table 3).

125 P shortages downregulate growth (i.e., NPP) in all models, either directly, via photosynthesis, 126 or via a combination of both processes. No model considers P effects on Ra. The major 127 differences among the models relate to how they modify P supply and demand to alleviate plant 128 P shortages, including either (i) enhancing plant P use efficiency (PUE = NPP / P uptake) or (ii) 129 upregulating P acquisition mechanisms. PUE may change if tissue nutrient ratios are flexible, 130 if C allocation changes among tissues with different stoichiometry, and/or if P resorption is 131 variable. Flexible stoichiometry is considered in all CNP models except ELM-CTC, although 132 with varying degrees of flexibility, such that the stoichiometry in CABLE and ORCHIDEE is 133 effectively fixed (Fig. 2). Greater fine root C allocation in response to plant P stress is

134 considered in ELM-ECA, GDAY and ORCHIDEE, and P resorption is a fixed fraction of leaf135 tissue P in all models (Fig. 2).

136 In regards to modelled soil P acquisition mechanisms; three of the six models (ELM-ECA, 137 ELM-CTC, GDAY) consider desorption of P from mineral surfaces (i.e., the secondary or 138 strongly sorbed P pool), whereas the others assume P in those pools to be unavailable to plants. 139 All the models include biochemical mineralization of organic P via phosphatase, but only three 140 (ELM-ECA, ELM-CTC and ORCHIDEE) include the functionality to increase P acquisition 141 via this mechanism under plant P stress (Fig. 2; Extended Data Table 3). Litter and soil 142 stoichiometry are considered with varying degrees of flexibility. Soil labile P limits microbial 143 decomposition rates of litter and soil, so that decomposition is reduced when immobilization 144 demands for P exceed soil labile P availability (Fig. 2; Extended Data Table 3).

Diverging depictions of plant P use and acquisition among the CNP models cause predictions 145 of the eCO₂-induced biomass C sink to range from 5 g C m⁻² yr⁻¹ in CABLE to 140 g C m⁻² yr⁻ 146 147 ¹ in ORCHIDEE (Fig. 3a; Extended Data Fig. 1). Greater plant PUE occurred in four of the models, GDAY, ELM-ECA, CABLE-POP, and ORCHIDEE, for which shifts in tissue C:N and 148 N:P due to eCO_2 led to increases in biomass C:P ranging from ~200 to 1600 g C g P⁻¹ (Fig. 3c). 149 150 Higher fine root investment with eCO₂, at the expense of less "P-costly" wood, offset some 151 increases in PUE in ELM-ECA and GDAY. Although higher fine root allocation was simulated 152 temporarily in ORCHIDEE (Extended Data Fig. 4), investment in wood increased over the full 153 simulation period, as was also the case in CABLE-POP (Fig. 3b).

Flexible biomass stoichiometry altered decomposition dynamics and induced progressive P limitation in response to eCO₂, i.e., litter stoichiometry shifted towards lower quality (less N and P in relation to C), reducing net P mineralization rates from microbial decomposition, causing P to become increasingly unavailable to plants and accumulating in soil organic matter (Fig. 3d, e). Consequently, ecosystem P retention increased marginally in some models as P leaching rates decreased. This plant-soil-microbial feedback slowed the cycling of P in the
ecosystem and exacerbated the initial P limitation (see Ref. ²⁸ for a similar feedback during
pedogenesis).

162 Enhanced plant P acquisition under eCO₂ effectively alleviated P limitation in two CNP models 163 (ELM-CTC and ELM-ECA). In both, eCO₂ increased the liberation of P from the secondary 164 pool, as higher plant P demand and uptake diminished the labile P pool, in turn causing higher 165 desorption rates. P desorption is thus only indirectly, and not mechanistically, enhanced by 166 plants in these models. Biochemical mineralization of P under eCO₂ responded positively in 167 both of the models, but added only notably to additional P acquisition in ELM-CTC (Fig. 3e). 168 Although three CNP models simulated higher fine root investments (ELM-ECA, GDAY, and 169 ORCHIDEE), the actual P uptake return per fine root increment was marginal or came only into 170 effect in the long-term (Extended Data Fig. 6).

171 In summary, the model ensemble encapsulates a range of plausible hypotheses and represents 172 a potential range of biomass C responses to eCO₂ under low soil P availability. At the one end, 173 CABLE assumes no plant-enabled mechanisms to acquire more P and a limited capacity for 174 plants to use P more efficiently, resulting in effectively zero biomass C gain with eCO₂. The 175 remaining models predicted some biomass C gain with eCO₂. Flexible stoichiometry was the 176 key mechanistic response to eCO₂ in four of these models. ELM-CTC had no change in 177 stoichiometry, but nonetheless predicted an increase in biomass C gain under eCO₂ based on an 178 increase in plant P acquisition because of enhanced P mineralization and desorption.

Our results also indicate the control of N availability on modelled plant growth. The CN models simulate increased nitrogen use efficiency (NUE) and biomass C:N ratios, as N uptake was not sufficient under eCO₂ (Extended Data Fig. 5). Direct N limitation of plant growth is, however, not expected, as observations document ample N cycling in the system, e.g., high leaf N contents, indicative δ^{15} N values, high rates of N oxide emissions, and low N retention^{29,30}. Plant N availability may be underestimated in the models, since the plant-available mineral N supply was $<7 \text{ g N m}^{-2}$ across all models, as opposed to 17.5 g N m⁻² observed in the top 10 cm only (Extended Data Fig. 2). These results highlight an important gap in our knowledge related to the dynamics of N availability, and its potential interaction with P dynamics. Future experiments should help reduce the uncertainty surrounding N effects on P limitation, in particular for regions predominantly or co-limited by N.

190 Divergences in the simulated eCO₂ response lead us to the following testable hypotheses:

191 H1. Low soil P availability will strongly constrain future plant biomass growth response to 192 eCO_2 either by downregulating photosynthesis or limiting plant growth directly, or a 193 combination thereof.

H2. Despite the limited soil P supply, plasticity in vegetation stoichiometry and allocationpatterns will allow for some biomass growth under eCO₂.

H3. Plants will increase investments in P acquisition to increase P supply and allow biomass
growth under eCO₂ either via greater P interception through fine root production or via greater
P liberation from P desorption or biochemical mineralization of P.

199 These process- and model-based hypotheses deepen a previously carried out accounting analysis of potential N and P limitation³¹. Furthermore, we add to a model intercomparison 200 carried out in advance of the EucFACE experiment³² by extending the range of plant P 201 202 feedbacks considered across CNP models. This work highlighted H1: two stoichiometrically 203 constrained CNP models predicted that strong P limitation will curtail the growth response to 204 eCO₂ in subtropical Australia. Consistent with this hypothesis, aboveground growth has not 205 increased with eCO_2 in that experiment over the initial years³³. This finding underlines that 206 monitoring efforts need to place a strong(er) focus on belowground carbon allocation and soil 207 nutrient dynamics. Additionally, the model ensemble does not yet consider the P effect on Ra and respiration under different degrees of nutrient limitation need further monitoring during
experiments to further elucidate P effects on the plant C budget and address H1.

210 Nutrient fertilization experiments support H2, as plasticity in leaf stoichiometry at the individual level, along with plasticity in P resorption efficiency, was observed³⁴. Across the 211 Amazon, leaf nutrient assessments indicate a leaf N:P range of 13 to 42 (n = 64) (Ref. ³⁰), which 212 213 place our site, with a community mean ratio of 37, at the high end. GDAY thus predicted the 214 most plausible increase in the leaf N:P ratio from 34 to 38 (Extended Data Fig. 7). CABLE-215 POP and ELM-ECA predicted strong increases in the leaf N:P ratio with eCO₂ but started off 216 with much lower initial values. The degree to which plasticity in stoichiometry and resorption 217 can aid plant PUE in highly P-limited sites that are already at the end of the observed spectrum 218 remains to be seen (H2). Monitoring plant tissue and fresh litter nutrient content in CO₂ and 219 nutrient fertilization experiments will give an indication of the plasticity of these plant use 220 mechanisms in response to eCO₂.

Based on previous observations¹⁰, a number of models assume increased fine root investment, 221 222 as well as higher biochemical P mineralization and P desorption from mineral surfaces, under 223 eCO₂-induced nutrient limitation (H3). The effect of increased fine root biomass on nutrient 224 uptake was limited in our simulations and ambient fine root allocation fractions were highly variable among the models, ranging from 5-30% of NPP (Extended Data Fig. 4, 6). Both these 225 modelled results highlight model deficiencies in belowground processes³⁵. There is evidence 226 227 that phosphatase activity in litter and soil and the presence of low-molecular-weight acids used to liberate P from organic matter or from mineral surfaces increase with plant P demand³⁶. This 228 229 was predicted by ELM-CTC in our simulations, which also showed Amazon-wide that "[with] 230 enhanced phosphatase production, productivity in the highly P-limited areas can be sustained under elevated CO₂ conditions"³⁷. Plants invest in P liberation and acquisition, but if these 231 232 mechanisms can be upregulated under eCO₂ and over what time frame this may occur remain open questions. Quantification of such fluxes is lacking, as are estimates of the associated plant C costs to acquire P via these and other mechanisms, such as mycorrhizal symbiosis^{14,38}. The P gain and C cost for P acquisition mechanisms, as well as the associated plant-soil-microbial interactions, need to be assessed by analyses of soil, microbial and root nutrition, and via novel techniques investigating enzyme and labile C dynamics. Monitoring of belowground fine root dynamics needs to include fine root activity in surface litter, a common phenomenon in Pimpoverished ecosystems in the Amazon, not yet quantified nor considered in models.

240 Previous model projections suggest a sustained fertilization effect of CO₂ on the Amazon C sink but have not considered feedbacks from low soil P availability^{4,5}. Our study demonstrates 241 242 that, based on the current generation of CNP models, the omission of P feedbacks is highly 243 likely to cause an overestimation of the Amazon rainforest's capacity to sequester atmospheric 244 CO₂. Considering P limitation on the CO₂ fertilization effect in future predictions may indicate 245 that the forest is less resilient to higher temperatures and changing rainfall patterns than previously thought^{4,39}. Periods of water deficit may contribute to the eCO₂ fertilization effect 246 on productivity due to its water saving effect³². Our study site experienced years with 247 248 significantly less than average precipitation, e.g. in 2000 and 2009, however, in our simulations 249 this added marginally to the modelled CO₂ effect (Extended Data Figure 8 and 9). Models are 250 not yet very apt to simulate water deficits and their consequences on plant growth and mortality 251 in general, and even more so when precipitation totals are that high⁴⁰. Interactions of water and 252 P availability and their consequences on the CO₂ fertilization effect remain uncertain and need urgent clarification⁴¹. 253

Although P is likely to reduce the biomass C sink response to CO_2 in regions with low plantavailable P supply, our results suggest that plasticity in plant P use and plant P acquisition mechanisms, may enable CO_2 fertilization of biomass growth. The model ensemble may be interpreted as involuntarily representing a range of possible tropical plant functional strategies and growth responses to low phosphorus availability. Responses to eCO_2 are expected to be species-specific, as were plant growth responses to low P supplies in another tropical region¹⁶. The ecosystem-scale response to P limitation under eCO_2 will thus depend on the relative contributions of the various P acquisition and P use strategies across individuals, their interactions and to what extent these processes can be upregulated under eCO_2 . All of which ultimately need to be described and represented in a single model framework in order to accurately predict the Amazon rainforest's response to future climate change.

265 AmazonFACE has the unique opportunity to experimentally address these key areas of 266 uncertainty, not only by integrating the proposed measurements across seasons and at the 267 ecosystem scale but also by assessing species-specific responses to eCO₂ in relation to trait 268 expression. Amazon-wide expression of plant functional strategies may then be inferred by 269 applying the mechanistic interplay between trait expression and edaphic conditions. The key to 270 predicting the future of the world's largest tropical forest under eCO₂ thus lies in obtaining 271 experimental data on, and subsequently modelling, different plant P acquisition and use 272 strategies, as well as their interactions in a competing plant community.

273 END NOTES

274 Author contributions

- 275 D.M.L., A.R., and K.F. conceived the study. L.F., S.G., A.G., F.H., R.N., C.A.Q., K.J.S., and
- 276 O.J.V.-B. collected field data. K.F., D.G., M. de K., M.J., V.H., J.H., F.L., L.M.M., B.P.,
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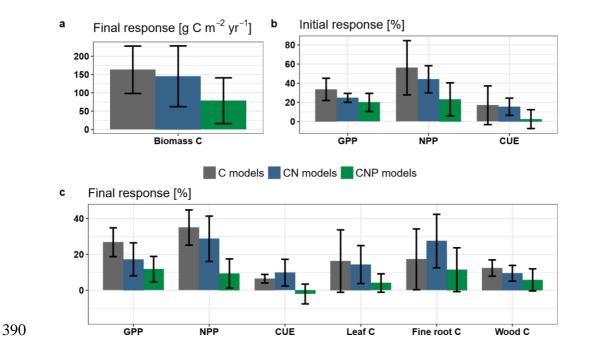
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391 Figure 1: The predicted effect of eCO₂ on biomass C, productivity and biomass

392 **compartments**, averaged over C (grey), CN (blue) and CNP (green) model groups. **a**, The

final absolute response of biomass growth, calculated as the mean annual response over the 15

394 years of eCO₂ per model group in g C m⁻² yr⁻¹. **b**, Initial relative responses of productivity

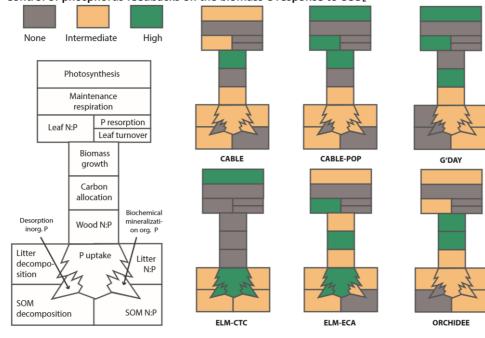
395 (GPP and NPP), and CUE (=NPP/GPP) in %, calculated as the mean response in the first year.
396 c, Final relative responses of productivity and CUE, as well as total leaf, fine root and wood

397 C, calculated as the mean response after 15 years (mean of 13th to 17th year), all in %.

398 Responses to eCO₂ are the differences between the elevated and ambient model run, shown as

mean and standard deviation per model group, individual model outputs are shown in

- 400 Extended Data Figure 1 and 3.
- 401 Control of phosphorus feedbacks on the biomass C response to eCO₂

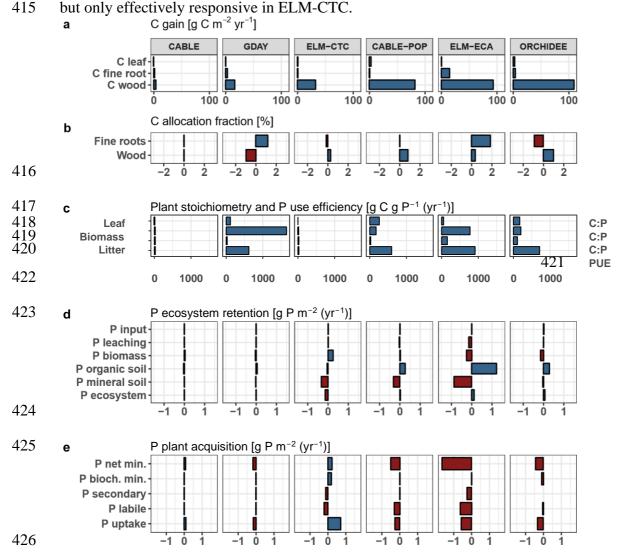


402

403 Figure 2: **Strength of phosphorus feedbacks in controlling the biomass C response**

404 to eCO_2 for the six CNP models. Ecosystem processes are highlighted that depend (or not

- 405 depend) on the P cycle, for which classes (none, intermediate, high) indicate the degree to
 406 which the considered P feedback causes a response of biomass C to eCO₂ in our simulations. P
- 407 limitation causes strong or intermediate downregulation of photosynthesis with eCO₂ across
- 408 all models. Maintenance respiration, leaf turnover and P resorption are not responsive to P
- 409 feedbacks in any of the models. Leaf N:P responds to eCO_2 in most models, but is fixed in
- 410 ELM-CTC, narrowly bound in CABLE, and at its maximum in ORCHIDEE. P limitation
- 411 causes direct downregulation of biomass growth in CABLE, CABLE-POP, ELM-ECA and
- 412 ORCHIDEE. Allocation shifts towards roots to alleviate P limitation is considered in GDAY,
- 413 ELM-ECA and ORCHIDEE. Desorption of P from mineral surfaces is only considered in
- 414 ELM-ECA and ELM-CTC, and biochemical P mineralization is considered in many models,



427 Figure 3: Key responses of biomass C gain, stoichiometry, allocation, and P

428 **dynamics to eCO**₂ **for the CNP models**, contrasted are positive (blue) from negative (red)

429 responses. **a**, Mean annual change in standing leaf, fine root and wood C over 15 years,

430 increasing across models from left to right in g C m^{-2} yr⁻¹. **b**, The mean change in C allocation

- 431 for fine roots and wood in %. **c**, Mean change in tissue stoichiometry in absolute terms in g C
- 432 g P⁻¹ and change in P use efficiency over 15 years in g C g P⁻¹ yr⁻¹. **d**, Mean change in

- 433 ecosystem P input and output (leaching) fluxes in g P m⁻² yr⁻¹ and mean change in final P
- 434 stock in biomass, organic soil, mineral soil and total ecosystem in g P m⁻². **e**, Mean change in
- 435 plant P acquisition processes, including change in net P mineralization, biochemical P
- 436 mineralization and P uptake in g P m⁻² yr⁻¹ and secondary and labile P pools in g P m⁻². For
- both, **d** and **e**, P flux changes are differences of cumulative fluxes after 15 years and P pool
- 438 changes are differences in pools after 15 years.

439 CO₂ fertilization of the Amazon forest hinges on plant phosphorus use and 440 acquisition

- 441 We present here supplementary information to the main text of the study "CO₂ fertilization
- 442 of the Amazon forest hinges on plant phosphorus use and acquisition" by Fleischer et al.,
- 443 submitted to Nature Geoscience.

The individual models' biomass C responses to eCO₂ are shown in Extended Data
Figure 1, where the absolute and relative effect of eCO₂ on cumulative biomass C is included.
The variation in their predictions among and within the model groups becomes apparent.
While CNP models (in green) generally predict lower biomass C gain with eCO₂ compared to
Conly (grey) and CN models (blue), some CNP models exceed predictions by the other model
groups. Assumptions on how plant P use and P acquisition is dealt with in the models cause
these diverging responses.

- 451 The individual models' performance in representing ambient conditions of key ecosystem 452 variables are shown in Extended Data Figure 2. Models' generally represented ambient 453 conditions well at the study site, such as GPP, NPP and LAI. GPP was lower than observed in 454 some models, while LAI was either over- or underestimated by some models. Considering the 455 uncertainties surrounding field observations, we judged these deviations as acceptable. For 456 biomass C, models diverged noticeably, which is controlled by productivity and turnover 457 dynamics simultaneously. While we have relatively reliable measurements of aboveground 458 biomass C, belowground components remain more uncertain and are not considered in the 459 observational-based estimate here. Models on the other hand consider total biomass C, which adds to the differences among models and observations. Ambient annual biomass C increment 460 461 varied strongly across the models, for which we included the Amazon-wide estimate from 462 Brienen et al. 2015 as an observation (see main text for complete reference). The estimate from our site is lower (see main text), but associated to higher uncertainties due to few 463 464 censuses. For both, biomass C and biomass C increment, there was no clear pattern between
- the model groups, so that we judge that these differences did not control the overallconclusions of our study.

467 The models simulated less than 1.1 g labile P m⁻² to 4 m depth in the ambient run (with the 468 exception of ELM-CTC), which is the plant available soil P. Observations indicate 1.6 g resin 469 P m⁻² to 30 cm depth. Resin P is considered to be directly plant-available, representing the

- 470 modelled soil labile P pool, although direct comparisons are hampered as P fractionations are
- 471 operationally defined. Observations are thus slightly higher but both modelled and observed
 472 values on soil labile P are considered to be very low and the resulting modelled P limitation to
- 472 Values on son rable r are considered to be very low and the resulting modelled r minitation to 473 be realistic
- 473 be realistic.

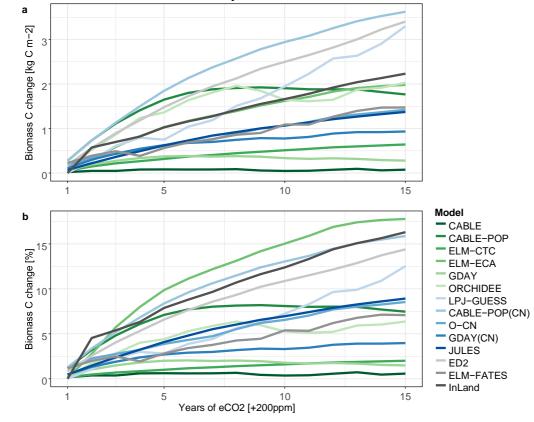
The individuals models' simulation results on the relative eCO₂ effect on primary
productivity (GPP, NPP), plant tissue C stocks and plant CUE are shown in Extended Data
Figure 3. The models' plant C allocation fractions and the respective relative effect of eCO₂
thereon is shown in Extended Data Figure 4. The individuals models' simulation results on

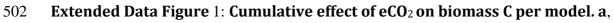
478 the relative eCO_2 effect on N and P uptake, NUE and PUE, as well as plant tissue

479 stoichiometry is shown in **Extended Data Figure 5**.

480 The relationship between eCO₂ induced P uptake, fine root allocation, and the respective 481 return of P uptake per unit fine root allocation for three CNP models are shown in Extended 482 Data Figure 6. The three models (ELM-ECA, GDAY, and ORCHIDEE) simulated a higher 483 fine root investment with eCO₂, but a heightened relative return of P was only achieved 484 temporarily, after some time, or not at all. The absolute effect of eCO₂ on NUE, PUE and 485 stoichiometry for the individual models is shown in Extended Data Figure 7. Both CN and 486 CNP versions of GDAY and CABLE-POP were included in the model ensemble, allowing the 487 N and P effect alone to be inferred. Their respective CN versions, and some other CN models, 488 indicated that N limitation occurred, as leaf and biomass C:N were predicted to increase under 489 eCO2 (Extended Data Fig. 7). The inclusion of both CN and CNP versions for GDAY and 490 CABLE-POP supported the fact that P cycle limitations reduced the eCO₂ induced biomass C 491 sink, as the main comparison across the C, CN and CNP model group indicated.

492 Model driving data of precipitation are plotted as annual precipitation over the course of 493 the 15 year study period in **Extended Data Figure 8**. Precipitation (and other climate) data 494 was derived from the K34 fluxtower, which experienced two years of strong precipitation 495 deficit during the study period, 2000 and 2009. The relative eCO₂ response of GPP and NPP is 496 plotted against annual precipitation in the Extended Data Figure 9 to test for potential 497 interactions of eCO2 and droughts in the study region. While some models show a significant 498 effect of precipitation on the strength of the eCO₂ effect on GPP, the slope of the line is very 499 shallow, so that we can conclude that variations in water availability contributed little to the 500 simulated eCO₂ effect in our study.

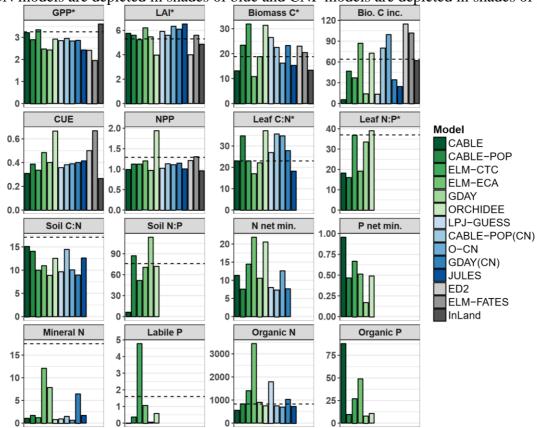




501

503 Absolute cumulative effect on biomass C in kg C m^{-2} , and **b**, relative cumulative effect on

biomass C in %. See legend for individual model names. C-only models are in shades of grey,
CN models are depicted in shades of blue and CNP models are depicted in shades of green.

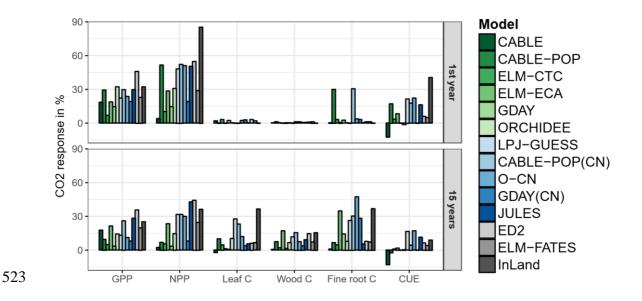


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507 Extended Data Figure 2: Ambient model conditions compared to in situ

508 observations. Individual models' values are mean conditions over the ambient simulation. 509 Horizontal dotted lines indicate observations when available (see sources in Extended Data 510 Table 1). Measurements marked with a ? were provided to modelers beforehand. C fluxes (GPP, NPP) are in kg C m⁻² yr⁻¹, biomass C is aboveground only in kg C m⁻², and biomass C 511 512 increment in g C m⁻² yr⁻¹. The observational estimate for biomass C increment is based on the Amazon-wide estimate from Brienen et al. 2015 (64 g C m⁻² yr⁻¹ for the 2000s, C.I. 45-78 g C 513 514 $m^{-2} yr^{-1}$). CUE is calculated as the ratio of NPP per GPP. LAI is in m^2/m^2 . Leaf and soil 515 stoichiometry are ratios of C, N and P content in dry matter, respectively. Leaf stoichiometry 516 was parameterised only in some models (see Extended Data Table 2). Fluxes of net N and P 517 mineralisation are in g N/P m⁻² yr⁻¹. Soil mineral N pool and labile P pool (both considered plant-available), as well as soil organic N and P pool, are in g N/P m⁻². Observations for soil 518 nitrogen content are based on top 10 cm, and for labile P on top 30cm. Modeled values are 519 520 based on a soil depth of 4m. See legend for individual model names. C-only models are in shades of grey, CN models are depicted in shades of blue and CNP models are depicted in 521

522 shades of green.



524 Extended Data Figure 3: Relative effect of eCO₂ on GPP, NPP, leaf C, wood C, fine

- 525 **root C and plant CUE.** Shown are initial effects (1st year) on top and final effect after 15
- 526 years of eCO_2 (mean of 13th to 17th year), both in %. See legend for individual model names.

527 C-only models are in shades of grey, CN models are depicted in shades of blue and CNP

528 models are depicted in shades of green.

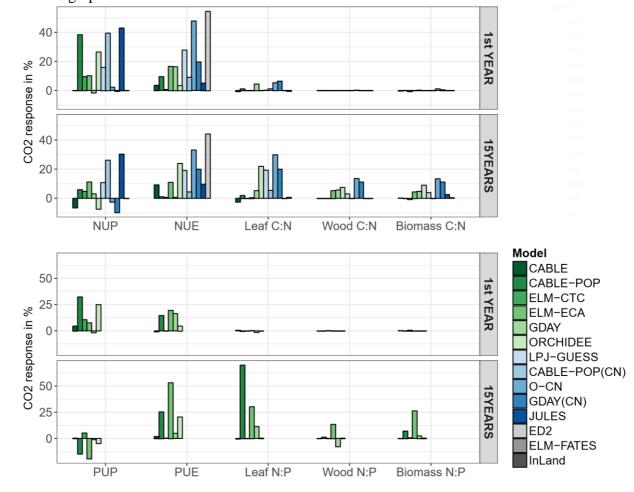
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530 Extended Data Figure 4: Ambient C allocation to plant tissues and the effect of eCO₂

531 thereon. Mean and standard deviation of ambient C allocation to leaf, wood, coarse and fine

- root per model in % (top), and annual effect of eCO₂ on C allocation fractions over 15 years
- 533 per model in % (bottom). See legend for tissue compartments; leaf is displayed in green, wood
- in red, coarse root in dark blue and fine root in light blue. Note individual y-axis scaling inbottom graph.



537 Extended Data Figure 5: Relative effect of eCO₂ on N and P uptake, NUE and PUE,

538and biomass stoichiometry per model. Shown are initial effects (1st year), and final

539 effects after 15 years of fumigation (mean of 13th to 17th year), for N uptake (NUP), N use

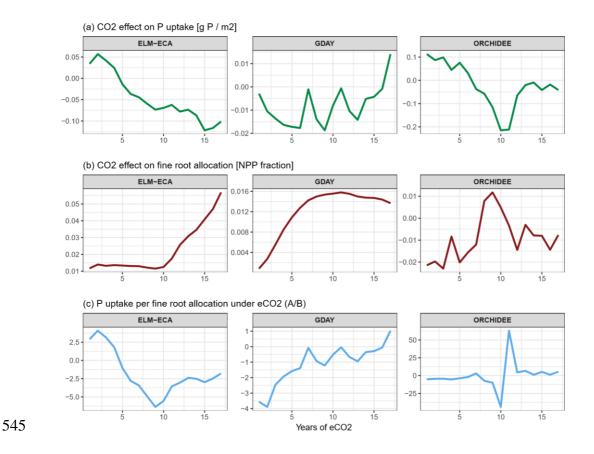
efficiency (NUE), leaf C:N, Wood C:N, and biomass C:N for all CN and CNP models, in %
(top). Further displayed are P uptake (PUP), P use efficiency (PUE), leaf N:P, wood N:P, and

541 (top). Further displayed are P uptake (POP), P use efficiency (POE), leaf N:P, wood N:P, and 542 biomass N:P for all CNP models, in % (bottom). See legend for individual model names. C-

543 only models are in shades of grey, CN models are depicted in shades of blue and CNP models

544 are depicted in shades of green.

536

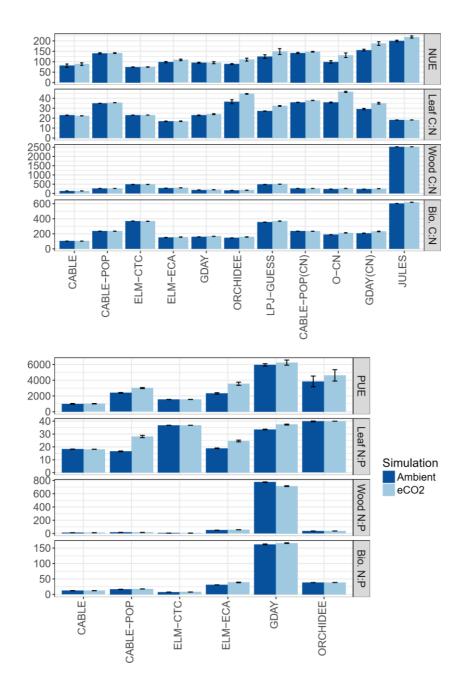


546 **Extended Data Figure** 6: **Effect of CO**₂ **on P uptake, fine root investment and the**

547 **resulting P uptake per fine root investment. a**, CO₂ effect on P uptake, **b**, CO₂ effect on

548 fine root allocation, and **c**, P uptake gain per fine root investment (a/b). Shown for the three

- 549 CNP models that predict higher fine root investment with eCO₂, see plot title for individual
- 550 model names.



551

552 Extended Data Figure 7: Absolut CO₂ effect on nutrient use efficiency and biomass

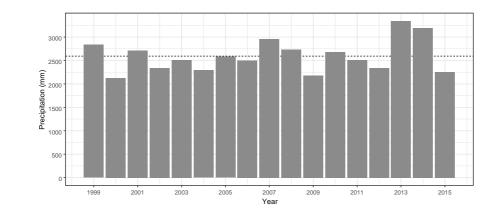
stoichiometry per model. Shown are the absolut difference between ambient and eCO₂

simulation run at the end of the 15 year simulation experiment (mean and standard deviation

of 13th to 17th year) for nitrogen use efficiency (NUE), leaf C:N, wood C:N, and plant

biomass C:N for CN and CNP models (top), and for phosphorus use efficiency (PUE), leaf
N:P, wood N:P, and plant biomass N:P for CNP models (bottom). See x-axis for individual

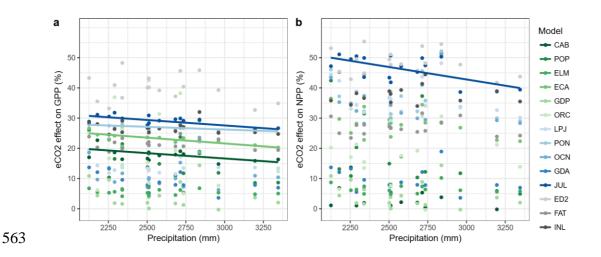
558 model names.



560 Extended Data Figure 8: Annual precipitation from the fluxtower K34, used as

561 model driving data. Shown are sums of annual precipitation in mm, note that years

represent Southern hemisphere growing season, i.e. 01/07/year to 30/06/year+1.



564 **Extended Data Figure** 9: Effect of precipitation on the individual models' eCO₂

effect on GPP and NPP. a, eCO₂ effect on gross primary production (GPP) (in %) and b,
eCO₂ effect on net primary production (NPP), both against sum of precipitation (in mm)
throughout the experimental phase (1999-2015). See legend for individual model names. Conly models are in shades of grey, CN models are depicted in shades of blue and CNP models
are depicted in shades of green. Only significant (p₁0.05) linear regression lines are drawn in
the respective colour per model.

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559