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1 **Nutrient availability as the key regulator of global forest carbon balance**

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26 **Summary paragraph**

27 Forests strongly affect climate through the exchange of large amounts of atmospheric CO₂¹.
28 The main drivers of spatial variability in net ecosystem production (NEP) on a global scale
29 are, however, poorly known. Since increasing nutrient availability increases the production of
30 biomass per unit of photosynthesis² and reduces heterotrophic³ respiration in forests, we
31 expected nutrients to determine carbon sequestration in forests. Our synthesis study of 92
32 forests in different climate zones revealed that nutrient availability indeed plays a crucial role
33 in determining NEP and ecosystem carbon-use efficiency [CUEe, i.e. the ratio of NEP to
34 gross primary production (GPP)]. Forests with high GPP exhibited high NEP only in nutrient-
35 rich forests (CUEe = 33 ± 4%; mean ± SE). In nutrient-poor forests, a much larger proportion
36 of GPP was released through ecosystem respiration, resulting in lower CUEe (6 ± 4%). Our
37 finding that nutrient availability exerts a stronger control on NEP than on carbon input (GPP)
38 conflicts with assumptions of nearly all global coupled carbon cycle-climate models, which
39 assume that carbon inputs through photosynthesis drive biomass production and carbon
40 sequestration. An improved global understanding of nutrient availability would therefore
41 greatly improve carbon cycle modeling and should become a critical focus for future research.

42

43 **Main Text**

44 The net ecosystem production (NEP) of an ecosystem represents its C balance at daily to
45 decadal scales. Despite considerable study, the main drivers of NEP are still unclear. Climate
46 ^{4,5}, climatic trends ⁶, nitrogen deposition ^{7,8}, disturbance and management ^{8,9} have been
47 suggested to influence NEP. These studies, however, were either unable to explain a
48 substantial percentage of the spatial variability in NEP or collected data in a restricted subset
49 of climatic space, indicating that it is not yet known what factor(s) most strongly govern NEP,
50 one of the critical pathways by which terrestrial ecosystems feedback to climate.

51 At the ecosystem scale, nitrogen deposition has been suggested to enhance the NEP of
52 forests ^{3,7}. Nutrient availability is indeed a key variable explaining patterns of carbon
53 allocation in forests; nutrient-rich forests exhibit higher biomass production (BP), biomass
54 production efficiency (BPE, defined as BP-to-GPP ratio) and shoot-to-root biomass
55 production ratio ². By converting a larger fraction of GPP to woody biomass and thereby
56 increasing the residence time of the assimilated carbon (C), forests growing on more fertile
57 soils can be expected to exhibit higher NEP. Carbon-use efficiency at the ecosystem level
58 (CUEe), defined as NEP of an ecosystem per unit of GPP, measures the proficiency of an
59 ecosystem to store C absorbed from the atmosphere. We thus hypothesize that both NEP and
60 CUEe increase with increasing nutrient availability in forest ecosystems.

61 To test this hypothesis, we updated and analyzed a global forest data set of mean annual
62 carbon flux [GPP, ecosystem respiration (Re) and NEP], stand biomass, stand age and
63 information on management. The resulting data set of 92 forests included scattered data from
64 1990 to 2010 from boreal, temperate, Mediterranean and tropical forests ⁹ (Supplementary
65 Fig. 1). We added all published information on the nutrient status of these forests and we
66 classified them as forests with high nutrient availability (without apparent nutrient limitation)
67 and low nutrient availability (apparently strongly nutrient-limited, sensu Vicca et al. ²,
68 considering a holistic combination of availability of nutrients and soil characteristics). We

69 based the nutrient availability classification on a multivariate factor analysis containing
70 information about soil type, soil and foliar nutrient concentrations (N, P), soil pH, soil C:N
71 ratio, nitrogen deposition and mineralization, history of the stand, specific reports of nutrient
72 availability and an assessment by the principal investigator of the site (Supplementary Table
73 1). This analysis clearly separated nutrient-rich from nutrient-poor forests (Supplementary
74 Fig. 2). We also established a medium category that was used for additional testing; it
75 contained forests with information indicating moderate availability of nutrients or with few
76 information about their nutrient status. Mean annual temperature and precipitation (MAT,
77 MAP) from the WorldClim database¹⁰ and water deficit (WD) derived from MODIS
78 evapotranspiration time series (MOD15A2 product) were used as climatic predictors. We then
79 used generalized linear models to disentangle the effects of climate, management and stand
80 age from those of nutrient availability on NEP and CUEe (see Methods for details on datasets
81 and methodology).

82 NEP in nutrient-rich forests averaged $33 \pm 4\%$ (mean \pm SE) of GPP, whereas nutrient-
83 poor forests only accumulated $6 \pm 4\%$ of the photosynthesized carbon (CUEe in Fig. 1,
84 difference = $27 \pm 7\%$, ANOVA $P < 0.001$). Only nutrient-rich forests showed a clear positive
85 relationship between GPP and NEP (Fig. 1). In contrast, nutrient-poor forests channelled a
86 larger proportion of GPP into Re (Fig. 2), with NEP being almost independent of GPP. Higher
87 nutrient availability thus appears to channel C fixed by GPP toward storage in biomass and
88 soils, rather than being respired back to the atmosphere.

89 A common protocol in eddy covariance CO₂ flux studies is to estimate GPP by adding Re
90 (e.g. extrapolated from nocturnal measurements) to the measured net ecosystem exchange
91 (NEE, a proxy for short-term NEP). In this protocol any error in Re would therefore be
92 directly propagated into a biased estimation of GPP, potentially imposing a spurious
93 correlation between GPP and Re^{11,12}. This correlation, however, in addition to being
94 irrelevant on an annual scale¹³, was present in nutrient-poor forests but not in nutrient-rich

95 forests (Fig. 2). The correlation between GPP and Re observed across nutrient-poor forests is
96 thus unlikely an artefact from the processing of eddy-covariance data for separating these
97 gross fluxes. We instead hypothesize that the positive relationship between Re and GPP only
98 in nutrient-poor forests is due to different patterns of ecosystem functioning in nutrient-poor
99 versus nutrient-rich forests.

100 Our statistical analyses using generalized linear models, including GPP, nutrient
101 availability and stand age, explained 74, 93 and 43% of the variance in NEP, Re (Table 1) and
102 CUEe across sites, respectively (Supplementary Table 2). Nutrient availability alone
103 explained 19% of the variance in NEP. When summed with its interactions with GPP (15%)
104 and age (1%), nutrient availability accounted for 35% of the variance in NEP. GPP alone
105 explained 18% of the cross-site variability in NEP. When additional interactions with nutrient
106 availability and age (9%) were included, GPP explained 42% of the variability in NEP. The
107 relationship between NEP and stand age, however, was only significant when GPP was
108 previously included in the models, which emphasises the smaller effect of stand age on NEP
109 as compared to GPP (Supplementary Figs. 3 and 4). Finally, MAT was positively correlated
110 with NEP and explained 9% of its variance. In contrast to NEP, GPP alone explained 64% of
111 the variance in Re, with nutrient availability and its interactions explaining 9% and age and its
112 interactions explaining only 5%. For CUEe, nutrient availability explained 12%, and GPP
113 14% of the variance in CUEe. Stand age also played an important role, interacting with GPP
114 (reducing the positive effect of GPP on CUEe as forests matured) and explaining 17% of the
115 variance in CUEe.

116 The relative contribution of explanatory variables thus differed among the NEP, Re and
117 CUEe models, but the key and robust result is that nutrient status was a key factor for NEP
118 and CUEe (Fig. 3, Table 1 and Supplementary Table 2), despite the use of nutrient status as a
119 binary variable (high vs. low nutrient availability). Other possible predictors such as
120 management and climate (MAP and WD), were not selected to enter in the general model by

121 the stepwise model selection procedure, i.e., they did not significantly affect neither NEP nor
122 Re (Table 1). Model-averaging techniques (see Supplementary Information) also indicated
123 little importance of climate or management on NEP and Re. In contrast to NEP and Re, GPP
124 was clearly climatically driven, being positively correlated with MAT and negatively
125 correlated with WD, which accounted for 65% and 10%, respectively, of the variance in GPP.

126 The significant positive effect of nutrient availability on NEP proved to be robust in
127 weighted models (Supplementary Fig. 5) and when controlling for effects of potentially
128 confounding factors, for example: i) when using only data derived from eddy covariance
129 measurements (Table 1), ii) when excluding forests with GPPs $> 2500 \text{ gC m}^{-2} \text{ year}^{-1}$ (i.e.
130 mostly tropical forests) from the analyses (no nutrient-rich forests were available for
131 comparison at GPP higher than this threshold, Figs. 1 and 2), iii) when using only managed
132 forests (Supplementary Figs. 6 and 7), iv) when using an alternative classification of nutrient
133 status to analyse sensitivity to possible classification errors (Tables 1 and Supplementary
134 Table 2) and v) when using the first factor of the factor analysis for nutrient classification as a
135 nutrient richness covariate (Table 1, *nutrient richness factor*). Furthermore, when including
136 the moderate nutrient availability forests, this group showed an intermediate behaviour
137 between the nutrient-rich and the nutrient-poor forests (Supplementary Fig. 8). On the other
138 hand, when nutrient status was excluded from the analyses, management played the role of
139 nutrients in our models, albeit the models explained less of the variance than did the models
140 containing nutrient availability (Table 1), and the second-order Akaike information criterion
141 (AICc) increased considerably (by 18.6 and 17.2 points for NEP and Re, respectively). These
142 results were expected because managed forests are mostly nutrient-rich forests
143 (Supplementary Fig. 7) for the generation of profits from fertile lands.

144 The positive effect of nutrient availability on a more efficient use of photosynthates and a
145 larger sequestration of carbon at the ecosystem level is likely not driven by a single
146 mechanism or a single compartment of the ecosystem but rather by a combination of

147 autotrophic and heterotrophic processes. Autotrophic processes are mainly related to different
148 patterns of carbon allocation in nutrient-rich and nutrient-poor forests ^{2,14}, whereas
149 mechanisms related to heterotrophic processes involve primarily changes in substrate quality
150 and the composition of the community of decomposers (mainly fungal and bacterial) ^{3,15}.

151 For the autotrophic compartment, we detected two differences in the distribution of
152 biomass across different organs between the different nutrient classes, despite also
153 considering other factors such as climate and management. 1) Although only marginally
154 significant, the ratio of fine-root biomass to total biomass was almost three times higher in
155 nutrient-poor forests than in nutrient-rich forests ($P = 0.06$, $N = 17$; Supplementary Fig. 9A),
156 indicating a higher proportional investment of GPP into fine roots for increasing access to
157 nutrients ^{16,17}. 2) The leaf area index per unit of fine-root biomass was twice as large in
158 nutrient-rich forests ($P = 0.013$, $N = 19$; Supplementary Fig. 9B), indicating a shift in carbon
159 allocation towards photosynthetic tissues when nutrients are not limiting growth and trees
160 need to invest less in nutrient-acquiring structures. Accordingly, an earlier study, using a
161 subset of our database, pointed out that nutrient-rich forests allocate larger proportions of their
162 photosynthates to wood production compared to nutrient-poor forests at the cost of producing
163 less root biomass ². These changes in allocation patterns thus suggest enhanced carbon
164 fixation in nutrient-rich forests.

165 An increase in the production of leaves in nutrient-rich forests, at the expense of
166 producing less fine roots, could decrease the benefit of increasing aboveground allocation in
167 terms of CUEe if that aboveground carbon is not stabilised. On the other hand, although some
168 studies have reported higher root respiration per unit mass at high root nutrient concentrations
169 ^{18,19}, a substantial decrease in root biomass may counterbalance this increase in autotrophic
170 respiration and even reduce it at the ecosystem level ³. In addition, when soil nutrients are
171 poorly available, plants engage in active nutrient transport through the cell to increase nutrient

172 uptake, spending energy for nutrient acquisition and therefore reducing energy available for
173 plant growth²⁰. The net effect of root physiological adjustments to nutrient supply is unclear.

174 Changes in patterns of photosynthate allocation are also relevant for the heterotrophic
175 compartment. For example, the higher proportion of GPP in nutrient-rich forests partitioned to
176 tissues with long turnover times such as wood^{2,14} may decrease heterotrophic respiration,
177 because wood is generally composed of rather recalcitrant molecules that decompose slowly
178²¹. Furthermore, numerous studies suggest that under high nutrient availability, forests
179 allocate less C to fungal root symbionts², and to exudation that stimulates heterotrophic
180 respiration in the rhizosphere³. Together, these nutrient effects would reduce microbial
181 biomass and respiration, relative to nutrient-poor forests. In addition, communities of
182 microbes and detritivores that consume nutrient-rich organic matter have higher growth
183 efficiencies (less respiration per unit of organic matter decomposed) than do communities that
184 decompose nutrient-poor organic matter^{15,22}. This difference could reduce heterotrophic
185 respiration in nutrient-rich forests^{3,15} and potentially enhance carbon sequestration and
186 accumulation in nutrient-rich forests.

187 Our results indicate a key effect of nutrient availability on forest carbon balance and
188 particularly on the capacity of forests to sequester carbon. Only when nutrient availability is
189 high can forests sequester large amounts of carbon. This knowledge is crucial, especially
190 given the human-induced alterations of nutrient availability and stoichiometry in many
191 regions of the planet^{23,24}. Earth system models should evolve from considering only the
192 effects of nitrogen on plant growth^{25,26} to considering the interactions of nitrogen as well as
193 other nutrients with the entire carbon cycle²⁷. The relationship between GPP and NEP appears
194 to be strongly controlled by the nutrient status of the forest, which implies that Earth system
195 models will be unable to accurately predict the carbon balance of forest ecosystems without
196 information on both background (pre-industrial) and regional changes in nutrient availability
197²⁸ resulting from direct human activities (e.g. nitrogen deposition) and from indirect human

198 activities (e.g. climate change and elevated CO₂ altering soil and plant nutrient cycling).
199 Moreover, because GPP and surrogates are widely available from remotely sensed data, the
200 assessment of nutrient status could allow estimation of NEP with remote sensing of GPP and
201 ground based measurements of CUEe. This way, estimates of global terrestrial carbon
202 sequestration could be improved, and guidance for improved management of forest carbon
203 could be provided. Finally, experimental research and environmental monitoring would
204 benefit substantially by considering nutrient availability as carefully as climate.

205

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295

296 **Figure captions**

297 **Fig. 1. Only nutrient-rich forests substantially increase carbon sequestration with**
298 **increasing carbon uptake.** The bar chart inside the main graph shows that CUEe (NEP to
299 GPP ratio) in nutrient-rich forests is more than five times higher than in nutrient-poor forests.
300 We also present results for forests with $GPP < 2500 \text{ gC m}^{-2} \text{ year}^{-1}$, because values of $GPP >$
301 $2500 \text{ gC m}^{-2} \text{ year}^{-1}$ were only available for nutrient-poor forests. When considering only
302 forests with $GPP < 2500 \text{ gC m}^{-2} \text{ year}^{-1}$, the Nutrients*GPP (where Nutrients = nutrient
303 availability) interaction was significant at the 0.006 level.

304 **Fig. 2. The coupling between Re and GPP is weak in nutrient-rich forests and very**
305 **strong in nutrient-poor forests.** Nutrient-rich forests decouple Re from GPP, resulting in an
306 increase in carbon accumulation with increasing GPP. When considering only forests with
307 $GPP < 2500 \text{ gC m}^{-2} \text{ year}^{-1}$, the Nutrients*GPP (where Nutrients = nutrient availability)
308 interaction is significant at the 0.005 level. Error bars indicate the uncertainty of the estimate
309 on both the x- and y-axes (SE).

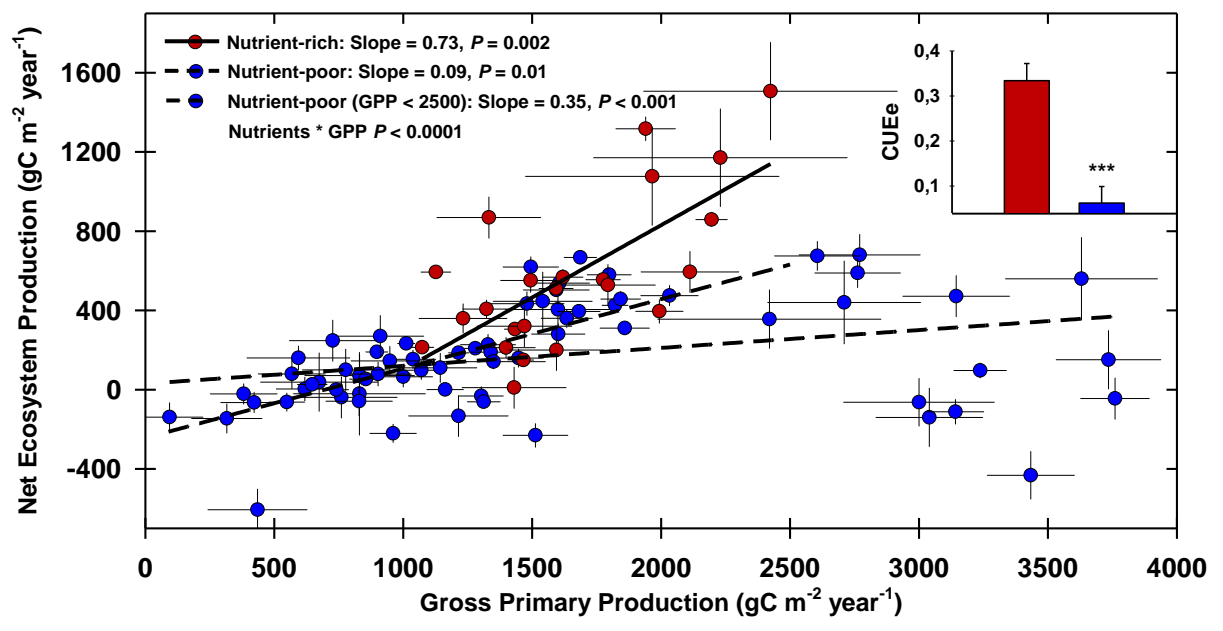
310 **Fig. 3. Relative contribution of predictor variables in the model explaining variability in**
311 **NEP.** Letters indicate significant differences according to the bootstrapped confidence
312 intervals computed for the differences among variables [relaimpo R package (23)]. Nutrients
313 = nutrient availability. All variables and interactions shown were statistically significant ($P <$
314 0.05).

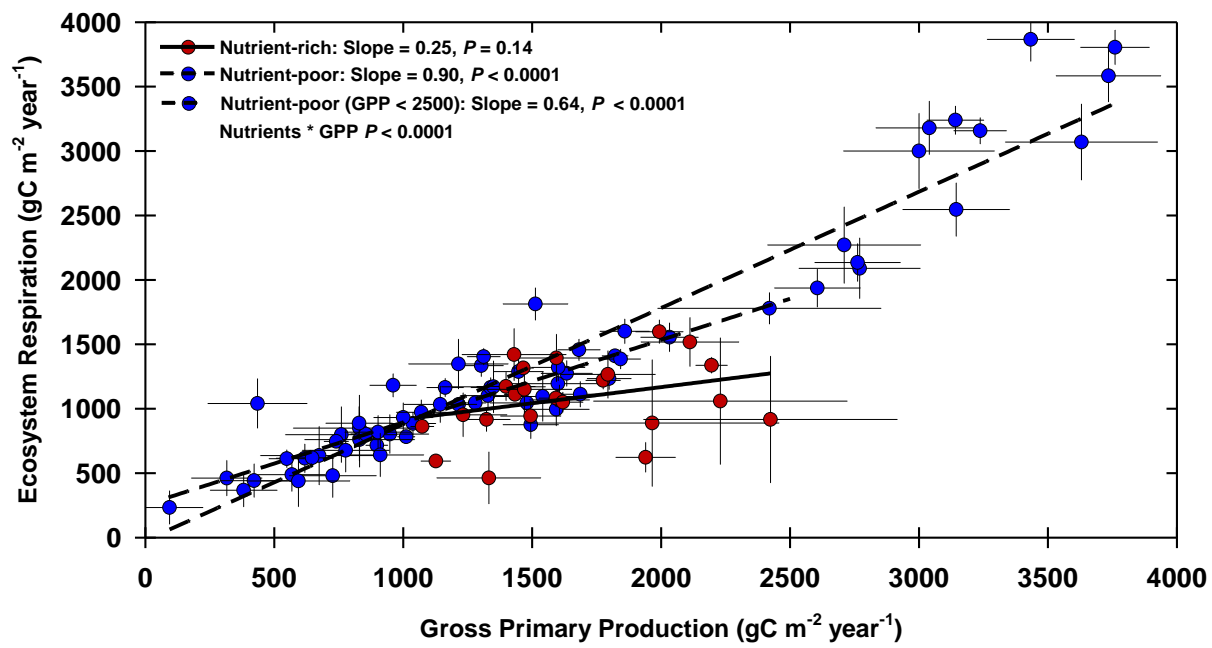
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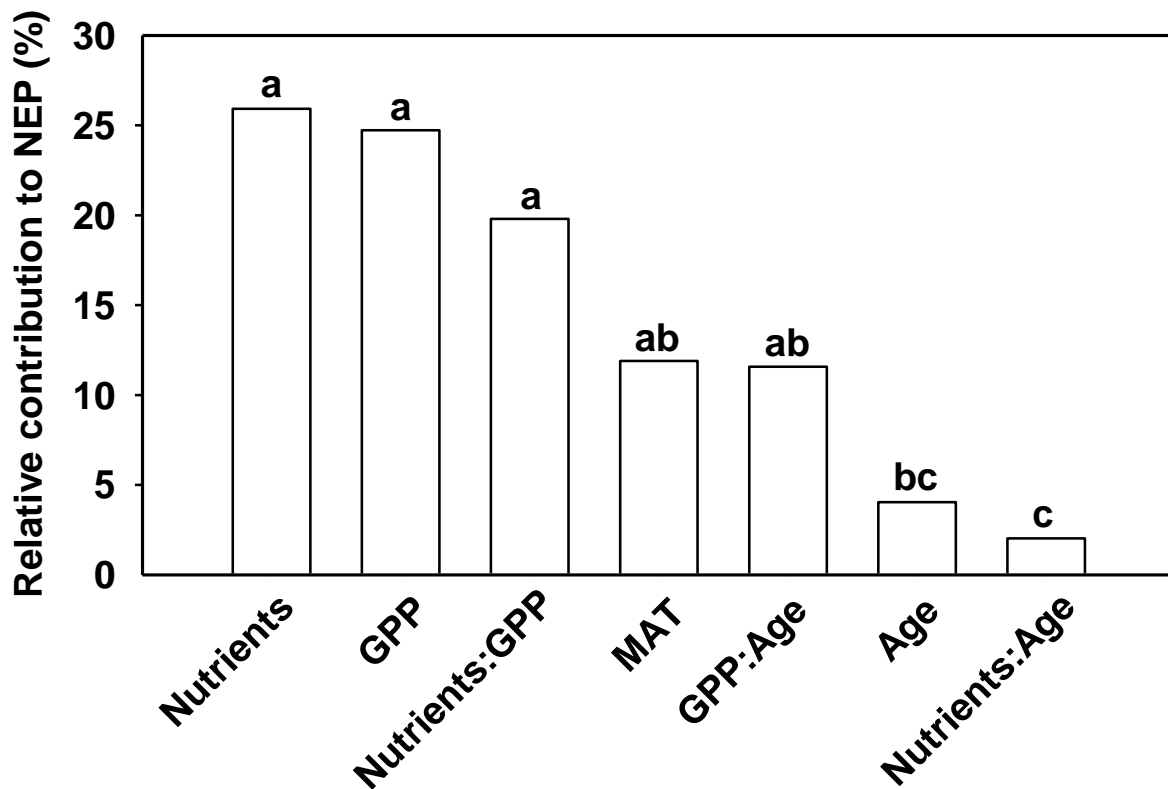
316 **Table 1. Summary of the percentage of variance explained by the significant variables of**
317 **the models relating NEP and Re with GPP, nutrient availability (NA), management**
318 **(MNG) and stand age and their second-order interactions.** The β coefficients of the
319 models are shown in brackets. For NA, MNG or their interactions with covariates, the β
320 coefficients of the factors and the interactions indicate differences from the reference level
321 (e.g. the slope of nutrient-rich forests of the general model is 1.8, and the slope, β , of the
322 nutrient-poor forests is $1.8 - 1.9 = -0.1$). The model “Nutrient richness factor” shows the
323 model including the factors used in the nutrient classification (see Methods, *information on*
324 *nutrient availability*, and Fig. S2) as a nutrient richness covariate instead of the binary
325 variable nutrient availability. For this model, NA indicates the effect of the first factor
326 extracted.

327

328







335 **Table 1.**

Models	GPP	NA	GPP:NA	MAT	GPP:Age	Age	Age:NA	MNG	WD	GPP:MNG	Model R^2 (%)
General											
NEP (Fig. 1)	18 (1.8)	19 (1.3)	15 (-1.9)	9 (0.5)	9 (-1.0)	3 (1.1)	1 (-0.4)				74
Re (Fig. 2)	64 (0.1)	3 (-0.7)	5 (1.1)	16 (-0.2)	3 (0.5)	1 (-0.6)	1 (0.2)				93
CUEe	14 (0.9)	12 (-0.3)			17 (-1.2)	0 (1.1)					43
Weighted (Supl. Fig. 2)											
NEP	20 (1.6)	14 (1.0)	8 (-1.4)	8 (0.4)	6 (-1.0)	2 (1.2)	3 (-0.5)				61
Re	65 (0.3)	2 (-0.5)	3 (0.8)	15 (-0.2)	2 (0.5)	0 (-0.6)	1 (0.3)				88
CUEe	1 (0.5)	16 (-0.1)			9 (-0.8)	3 (0.9)	5 (-0.4)				34
Eddy covariance data only											
NEP	18 (1.5)	11 (0.8)	6 (-1.5)	9 (0.5)				4 (0.6)		11 (-0.8)	59
Re	67 (0.4)	1 (-0.4)	1 (0.7)	19 (-0.2)				1 (-0.2)		2 (0.4)	92
CUEe	12 (0.9)	9 (-0.3)			15 (-1.2)	2 (1.2)					38
Without nutrient availability											
NEP	31 (1.1)							8 (0.6)	5 (0.3)	15 (-1.8)	59
Re	70 (0.6)							2 (-0.3)	11 (-0.2)	4 (0.5)	87
CUEe	15 (0.9)							0 (0.8)		2 (-1.1)	46
GPP < 2500 gC m⁻² year⁻¹											
NEP (Fig. 1)	44 (1.2)	17 (0.6)	6 (-0.9)						5 (0.2)		72
Re (Fig. 2)	55 (0.3)	3 (-0.6)	6 (0.8)						10 (-0.2)		74
CUEe	38 (0.8)				7 (-0.8)	1 (0.9)					46
GPP < 2500 gC m⁻² year⁻¹ weighted (Supl. Fig. 2)											
NEP	34 (0.9)	11 (0.7)	5 (-0.9)	12 (0.3)							62
Re	58 (0.9)	3 (0.2)							11 (-0.2)		72
CUEe		15 (-0.2)		19 (0.3)							34
Managed Forests (Supl. Fig. 6)											
NEP	52 (1.1)	14 (0.3)	4 (-0.7)						9 (0.3)		79
Re	57 (0.4)	3 (-0.4)	5 (0.7)						17 (-0.3)		82
CUEe	37 (0.7)	9 (-0.3)			5 (-0.6)	3 (0.8)					54
Alternative classification											
NEP	25 (1.6)	12 (1.2)	11 (-1.5)	11 (0.5)	1 (-1.1)	4 (1.2)	2 (-0.4)				75
Re	67 (0.3)	2 (-0.8)	4 (0.9)	13 (-0.3)	4 (0.6)	1 (-0.7)	1 (0.2)				92
CUEe	12 (0.6)	7 (-0.3)		6 (0.4)	18 (-1.2)	0 (1.2)					43
Nutrient richness factor											
NEP	25 (0.9)	23 (-0.4)	5 (0.8)					5 (0.4)		9 (-0.7)	67
Re	79 (0.7)	4 (-0.2)						1 (-0.3)		3 (0.4)	87
CUEe	14 (0.8)	10 (0.2)						0 (0.8)		17 (-1.0)	41

336 Methods

337 *Sources of data*

338 We used data of mean annual carbon flux from a global forest database⁹. This data set
339 contains complete measurements of carbon balance and uncertainties of gross primary
340 production (GPP), ecosystem respiration (Re) and net ecosystem production (NEP) of forests
341 around the world. The WorldClim database¹⁰ (resolution ~ 1km at the equator) and MODIS
342 evapotranspiration time series (MOD15A2 product) provided climatic data [mean annual
343 temperature (MAT) and mean annual precipitation (MAP) from WorldClim and potential and
344 actual evapotranspiration (PET, AET) from MODIS]. The reliability of the data from the
345 WorldClim database was tested with the available observed climatic values from the forests
346 (N=123). Results indicated a strong correlation between observed and WorldClim values for
347 annual temperature and precipitation ($R^2 = 0.96$, $P < 0.001$ and $R^2 = 0.84$, $P < 0.001$
348 respectively).

349 All continents were represented in our analyses (Supplementary Fig. 1), although most
350 of the forests were located in Europe and North America. Boreal (N = 31) and especially
351 temperate (N = 68) sites outnumbered Mediterranean (N = 14) and tropical (N = 16) sites. 61
352 forests were coniferous, 57 were broadleaved and 11 were mixed.

353 *Information on nutrient availability*

354 For each forest, we compiled all available information from the published literature (carbon,
355 nitrogen and phosphorus concentrations of soil and/or leaves, soil type, soil texture, soil C:N
356 ratio, soil pH, measures of nutrients, etc.) related to nutrient availability. Then we followed
357 the criteria shown in Supplementary Table 3 to code these variables as three-level factors
358 indicating high, medium or low nutrient availability. Next, we transformed these factors into
359 dummy variables and performed a factor analysis. The first factor extracted explained 14.8%
360 of the variance in the dataset and was related to nutrient-rich dummy variables whereas the

361 second factor explained 8.7% of the variance and was related to nutrient-poor dummy
362 variables (Supplementary Fig. 2A). Then, based on the aggregations across the two main
363 factors extracted (Supplementary Fig. 2B) we classified the forests as having clearly high or
364 clearly low nutrient availabilities. The remaining forests, for which empirical evidence was
365 insufficient to classify them as nutrient-rich or nutrient-poor or indicated moderate nutrient
366 availability were classified as medium nutrient availability. To maximize robustness, we
367 included only the forests with clearly high (N = 23) and clearly low (N = 69) nutrient
368 availabilities in the main analysis, discarding data from the 37 remaining forests with medium
369 nutrient availability. We also present the analysis with all the available data (including the
370 medium nutrient availability category) in Supplementary Fig. 8 and in the Supplementary
371 Models.

372 *Statistical analyses*

373 We ran generalized linear models (GLM) to test for differences in CUEe, NEP, Re and GPP
374 between forests of high and low nutrient availability, accounting for the possible effects of
375 GPP, mean stand age, management (as a binary variable: managed or unmanaged) and climate
376 [MAT, MAP and water deficit (WD) = $1 - (\text{AET}/\text{PET}) * 100$]. That is, $\text{NEP} \sim \text{GPP} + \text{nutrient}$
377 $\text{availability} + \text{Age} + \text{Management} + \text{MAT} + \text{MAP} + \text{WD}$. We tested for interactions up to the
378 second order among GPP, nutrient availability, age and management. The significant
379 variables of the final model (minimum adequate model) were selected using stepwise
380 backward variable selection and the AIC of the respective regression models. To evaluate the
381 variance explained by each predictor variable, we used the *averaged over orderings* method
382 (the *lmg* metric, similar to hierarchical partitioning) to decompose R^2 from R^{29} with the
383 package *relaimpo* [Relative Importance for Linear Regression ³⁰]. Finally, we tested whether
384 nutrient status, management, age and climatic variables could lead to changes in patterns of
385 biomass allocation with stepwise forward regressions. Model residuals met the assumptions
386 required in all analyses (i.e., normality and homoscedasticity).

387 The robustness of our analyses was tested by five different methods: i) running
388 weighted models using the inverse of the uncertainty of the estimates as a weighting factor, ii)
389 using only data derived from eddy covariance towers, iii) restricting comparison of nutrient-
390 rich and nutrient-poor forests to a common rank of GPP ($GPP < 2500 \text{ gC m}^{-2} \text{ year}^{-1}$ in Figs. 1
391 and 2, thus excluding most of the tropical forests and using forests presenting GPPs above
392 1000 and below $2500 \text{ gC m}^{-2} \text{ year}^{-1}$ in Supplementary Fig. 10), iv) using an alternative
393 classification of nutrient availability (the second most plausible classification) as an analysis
394 of sensitivity and v) using the factors extracted for the classification of nutrients as nutrient
395 richness covariates instead of using the binary factor nutrient availability. Detailed
396 information about the methods used in this paper is presented in Supplementary Information.
397

398 **Supplementary Information:**

399 **Detailed and extended information on methods**

400 *Sources of data*

401 We used data of mean annual carbon flux from a global forest database⁹. This data set
402 contains complete measurements of carbon balance and uncertainties of gross primary
403 production (GPP), ecosystem respiration (Re) and net ecosystem production (NEP) of forests
404 around the world. Of these forests, we excluded those that had been disturbed less than one
405 year before measurement and those for which we found no information on nutrient
406 availability. The carbon balance of the remaining 129 forests was estimated by eddy
407 covariance (N = 124) or by modelling with site-specific parameterization (N = 5). During the
408 processing of eddy covariance data, any error in estimating Re from nighttime measurements
409 would be translated into biased GPP, and a spurious correlation between Re and GPP would
410 then be the consequence. However, problems related to the calculation of Re and GPP were
411 previously shown important at shorter timescales, but irrelevant at annual time scale¹³.
412 Carbon fluxes not captured by net ecosystem exchange (NEE), such as fluxes of volatile
413 organic compounds, dissolved carbon or lateral fluxes (exportations), were assumed to be
414 similar (and negligible) across forest sites.

415 The WorldClim database¹⁰ (resolution ~ 1km at the equator) and MODIS
416 evapotranspiration time series (MOD15A2 product) provided climatic data [mean annual
417 temperature (MAT) and mean annual precipitation (MAP) from WorldClim and potential and
418 actual evapotranspiration (PET, AET) from MODIS]. The reliability of the data from the
419 WorldClim database was tested with the available observed climatic values from the forests.
420 Results indicated a strong correlation between observed and WorldClim values for annual
421 temperature and precipitation ($R = 0.98$, $P < 0.001$ and $R = 0.91$, $P < 0.001$ respectively).

422 All continents were represented in our analyses (Supplementary Fig. 1), although most
423 of the forests studied were in Europe and North America. Boreal (N = 31) and especially
424 temperate (N = 68) sites outnumbered Mediterranean (N = 14) and tropical (N = 16) sites, and
425 61 forests were coniferous, 57 were broadleaved and 11 were mixed.

426 *Information on nutrient availability*

427 For each forest, we compiled all available information from the published literature (carbon,
428 nitrogen and phosphorus concentrations of soil and/or leaves, soil type, soil texture, soil C:N
429 ratio, soil pH, measures of nutrients, see Supplementary Table 1) related to nutrient
430 availability. Then we followed the criteria shown in Supplementary Table 3 to code these
431 variables as three-level factors indicating high, medium or low nutrient availability. Next, we
432 transformed these factors into dummy variables (e.g. 3 binary variables for pH indicating
433 high, medium or low nutrient availability) and performed a factor analysis in which we only
434 included those dummy variables indicating high and low nutrient availability. Those
435 indicating medium nutrient availability were excluded from the factor analysis (as well as
436 from all other analyses) to reduce the number of variables in the multivariate analysis and to
437 ensure a clear separation into two groups. The first factor extracted explained 14.8% of the
438 variance in the dataset and was related to nutrient-rich dummy variables whereas the second
439 factor explained 8.7% of the variance and was related to nutrient-poor dummy variables
440 (Supplementary Fig. 2A). Then, based on the aggregations across the two main factors
441 extracted (Supplementary Fig. 2B) we classified the forests as having clearly high or clearly
442 low nutrient availabilities. Those forests located near the threshold nutrient-rich/poor were
443 further analyzed, checking in detail all the information available for classification. The
444 remaining forests whose empirical evidence was not strong enough to be clearly classified
445 into the high or the low nutrient availability groups (due to lack of data, contradictory
446 information or simply presenting data indicating moderate nutrient availability) were
447 classified as medium nutrient availability.

448 To maximize robustness, we included only the forests with clearly high (N = 23) and
449 clearly low (N = 69) nutrient availabilities for the main analysis, discarding data from the 37
450 remaining forests of medium nutrient availability from the main analyses. In a second
451 analysis, those forests whose nutrient status was not completely certain were assigned an
452 alternative nutrient classification (the second most plausible nutrient availability level, e.g. if
453 a nutrient-rich forest did not present very strong evidence of belonging to the high category,
454 we assigned it to the medium category: the nutrient status changed in the direction that would
455 go against our main finding; thus potentially offsetting the observed increase of CUEe with
456 increasing nutrient availability), to perform a sensitivity analysis to test the robustness of our
457 results to possible misclassifications (Supplementary Table 2). This sensitivity analysis
458 supported the robustness of our results.

459 We further tested the objectiveness of our nutrient classification using logit models, in
460 which the response variable was the nutrient status of the forests (high or low availability),
461 and the predictor variables were those contained in Supplementary Table 1). Given the lack of
462 data for all variables for all forests, we categorized the predictor variables into four-level
463 factors (following the criteria shown in Supplementary Table 3), where na indicated that data
464 was not available, and high, medium and low indicated values or indications that suggested
465 high, medium or low nutrient availability.

466 From the saturated model (i.e. nutrient status [high or low] ~ all variables in
467 Supplementary Table S1), we constructed the minimum adequate model selecting the
468 predictor variables using stepwise backward selection and the Akaike information criterion
469 (AIC). We then cross-validated the saturated and the minimum adequate models using the
470 repeated random sub-sampling validation technique: 78 forests were randomly selected as the
471 training set for our nutrient classification models and were tested by predicting the 14
472 remaining forests for which the models were not previously fitted. This procedure was
473 repeated 1000 times. Both the saturated and stepwise-selected models performed well in the

474 classification of the nutrient status with the available data (100% and 99% of the cases were
475 correctly classified in the saturated and the stepwise model, respectively; see Supplementary
476 Table 4). To further test our classification, we tested the reports on nutrient availability
477 (“Report” column in Supplementary Table 1) available in the literature, considering them the
478 most objective classification, with the other predictor variables, except for the assessments by
479 the principal investigators because these assessments would mostly agree with those in the
480 publications. We applied the same model selection and cross-validation procedures to these
481 models predicting the reports from literature as to the models predicting our nutrient
482 classification. With all the available data, the saturated and stepwise models correctly
483 classified 95% and 93% of the forests, respectively (Supplementary Table 4).

484 *Statistical analyses*

485 We ran generalized linear models (GLM) to test for differences in CUEe, NEP, Re and GPP
486 between forests of high and low nutrient availability, accounting for the possible effects of
487 GPP, mean age of the stand (as a covariate), management (as a binary variable: managed or
488 unmanaged) and climate [MAT, MAP and water deficit (WD) = $1 - (\text{AET}/\text{PET}) * 100$]. In
489 addition, we tested for interactions up to the second order among GPP, nutrient availability,
490 age and management. Thus, the saturated model (e.g. for NEP) was: $\text{NEP} \sim (\text{GPP} + \text{nutrient}$
491 $\text{availability} + \text{Age} + \text{Management}) + \text{MAT} + \text{MAP} + \text{WD}$, where variables between brackets
492 where those for which we tested for interactions up to the second order. The significant
493 variables of the final model (minimum adequate model, all terms significant at the 0.05 level)
494 were selected using stepwise backward variable selection and the AIC of the respective
495 regression models. To evaluate the variance explained by each predictor variable, we used the
496 *averaged over orderings* method (the *lmg* metric, similar to hierarchical partitioning³¹) to
497 decompose R^2 from the R ²⁹ package *relaimpo* [Relative Importance for Linear Regression³⁰].
498 We further tested our results with model averaging [MuMIn R Package³²]. Model averaging
499 is a procedure based on multimodel inference techniques that computes an average model

500 from the estimates of the best models predicting the data and weighting their relative
501 importance according to the difference of the second-order AIC between each model and the
502 best model ³³. Finally, we tested whether nutrient status, management, age and climatic
503 variables could lead to changes in patterns of biomass allocation with stepwise forward
504 regressions. Model residuals met the assumptions required in all analyses.

505 The robustness of our analyses was tested by five different methods: i) running
506 weighted models using the inverse of the uncertainty of the estimates as a weighting factor, ii)
507 using only data derived from eddy covariance towers, iii) restricting comparison of nutrient-
508 rich and nutrient-poor forests to a common rank of GPP ($GPP < 2500 \text{ gC m}^{-2} \text{ year}^{-1}$, thus
509 excluding most of the tropical forests), iv) using an alternative classification of nutrient
510 availability (the second most plausible classification) as an analysis of sensitivity and v) using
511 the factors extracted for the classification of nutrients as nutrient richness covariates instead of
512 using the binary factor nutrient availability. We also present the analysis with all the data
513 available (including the medium nutrient availability category) in Supplementary Fig. 8 and in
514 the Supplementary Models. All analyses revealed very similar results.

515

516 **Captions**

517 **Fig. S1. Global map of the forests used in this study.** Forests have been coded according to
518 their nutrient status: red indicates nutrient-rich forests whereas blue indicates nutrient-poor
519 forests.

520

521 **Fig. S2. Summary of the factor analysis performed to evaluate nutrient availability.**

522 Graph A shows the factor loadings of the variables used in the analysis following the criteria
523 presented in Supplementary Table S3. A clear separation can be seen between those
524 indicating high (correlated with Factor 1, F1) and low (correlated with Factor 2, F2) nutrient
525 availability. Graph B shows the factor scores of the studied forests aggregated according to
526 the nutrient status. Note that in graph A FP is missing because no forest presented high values
527 of FP. Note also that in graph B some forests might present equal factor scores, resulting in
528 fewer points than expected. Abbreviations: ASI (additional soil information), CEC (cation
529 exchange capacity), CN (soil C:N ratio), FN (foliar nitrogen concentration), FP (foliar
530 phosphorus concentration), H (history of the stand), NDM (nitrogen deposition or
531 mineralization), ST (soil type), ON (other soil nutrients), PI (assessment by the principal
532 investigator of the forest), R (report about nutrient availability), SN (soil nitrogen
533 concentration).

534

535 **Fig. S3. Influence of stand age and nutrient availability on NEP.** Nutrient availability
536 clearly influences NEP ($P < 0.0001$), but stand age has no significant effect ($P = 0.14$) when
537 GPP is not considered. Neither interaction between nutrient availability and stand age is
538 significant ($P = 0.50$).

539

540 **Fig. S4. Relationships of NEP (A) and Re (B) with GPP in nutrient-rich and nutrient-**
541 **poor forests indicating the age category of each stand.** The age of the stand did not affect

542 the relationships of NEP (graphs **A, C, E**) and Re (graphs **B, D, F**) with GPP. The bar charts
543 inside the NEP graphs show the average CUEe of nutrient-rich and nutrient-poor forests.
544 Graphs **C** and **D** show forests older than 50 years old and graphs **E** and **F** show forests
545 younger than 50 years old. Red-like points indicate nutrient-rich forests and blue-like points
546 represent the nutrient-poor ones.

547

548 **Fig. S5. Relationships of NEP (A) and Re (B) with GPP in nutrient-rich and nutrient-**
549 **poor forests weighted using the inverse of the uncertainty as a weighting factor.** The
550 uncertainty of the estimates did not change the results. Thus, as in Fig. 1, nutrient-poor forests
551 do not increase NEP when rates of carbon uptake increase. The bar chart inside graph **A**
552 shows the average CUEe of nutrient-rich and nutrient-poor forests. Error bars indicate the
553 uncertainty of the estimate on both the x- and y-axes (SE). In forests with $GPP < 2500$,
554 $Nutrients * GPP$ (where Nutrients = nutrient availability) interactions are not significant at the
555 0.05 level.

556

557 **Fig. S6. Relationships of NEP (A) and Re (B) with GPP in nutrient-rich and nutrient-**
558 **poor managed forests.** The general pattern for NEP and Re versus GPP shown for nutrient-
559 rich forests was also evident here. Nutrients = nutrient availability.

560

561 **Fig. S7. NEP to GPP ratio (CUEe) is influenced by nutrient availability but not by**
562 **management.** Different letters indicate significant differences between groups (Tukey's
563 HSD). The numbers beside the letters indicate the number of forest sites in the data base.

564

565 **Fig. S8. Relationships of NEP (A) and Re (B) with GPP showing also the medium**
566 **nutrient availability category.** The general pattern for NEP and Re versus GPP in medium

567 nutrient availability forests fits between the patterns shown by the nutrient-rich and the
568 nutrient-poor forests. Nutrients = nutrient availability.

569

570 **Fig. S9. Nutrient-rich forests have a lower fine-root to total biomass ratio and a higher**
571 **ratio of leaf area index (LAI) per unit of fine-root biomass.** Error bars indicate standard
572 errors. The numbers above the bars indicate the number of forest sites in the data base.
573 Significance was tested with ANOVA.

574

575 **Fig. S10. Relationships of NEP (A) and Re (B) with GPP showing only forests presenting**
576 **1000 < GPP < 2500.** The results for this range of GPP indicate that the interaction between
577 GPP*nutrient availability is not significant neither for NEP nor for Re. However, nutrient
578 availability significantly increases the mean in NEP and reduces Re ($P = 0.0026$ and $P =$
579 0.0036 respectively). On the other hand, differences in CUEe between nutrient-rich and
580 nutrient-poor forests remained significant at the < 0.001 level (CUEe nutrient-rich = 0.33,
581 nutrient-poor = 0.17). Nutrients = nutrient availability.

582

583 **Table S1: Information on the nutrient availability of the forests studied.** The term id
584 indicates the number of the site, referenced at the bottom of the table. NA indicates our
585 classification of nutrient status according to the provided information [high (H), medium (M)
586 or low (L) nutrient availability]. PI indicates the nutrient status suggested by the principal
587 investigators of the forests. The other columns provide information on nutrient availability as
588 follows: soil type, additional soil information, soil pH, soil carbon content (kg m^{-2}) or
589 concentration (per dry mass %), soil nitrogen content or concentration, carbon-to-nitrogen
590 ratio (C:N), information on other soil nutrients, cation exchange capacity (CEC), nitrogen
591 deposition (D) or mineralisation (M), foliar nutrient concentration (N: nitrogen, P:
592 phosphorus), history of the forest and reports in the published literature on soil or forest

593 nutrient availability. Units: Carbon (C) and nitrogen (N) in percentage of dry mass (when
594 indicated by %) or in kg m^{-2} ; CEC in $\text{meq } 100 \text{ g}^{-1}$; nitrogen deposition and mineralization in
595 $\text{kg ha}^{-1} \text{ year}^{-1}$; foliar nutrient concentration in percentage of dry mass. Additional
596 abbreviations: L (lower soil horizons), Lt (litterfall), U (upper soil horizons).

597

598

599 **Table S2. Analysis of sensitivity to a possible misclassification of nutrient availability.**

600 The table contains those forests for which information assessing nutrient status could lead to a
601 wrong classification. Each shows its values for CUEe, the uncertainty of this estimate (SE),
602 the original and most plausible classification of nutrient status and an alternative nutrient
603 classification. The *P*-values of the significant variables and the β weights of the covariates,
604 using the original and the alternative nutrient classification with stepwise backward
605 regressions, are shown at the bottom of the table. Possible predictors were GPP, nutrient
606 availability, stand age and management, including their interactions up to the second order,
607 MAT, MAP and WD. Significance levels: * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$. H high, M
608 medium and L low nutrient availability.

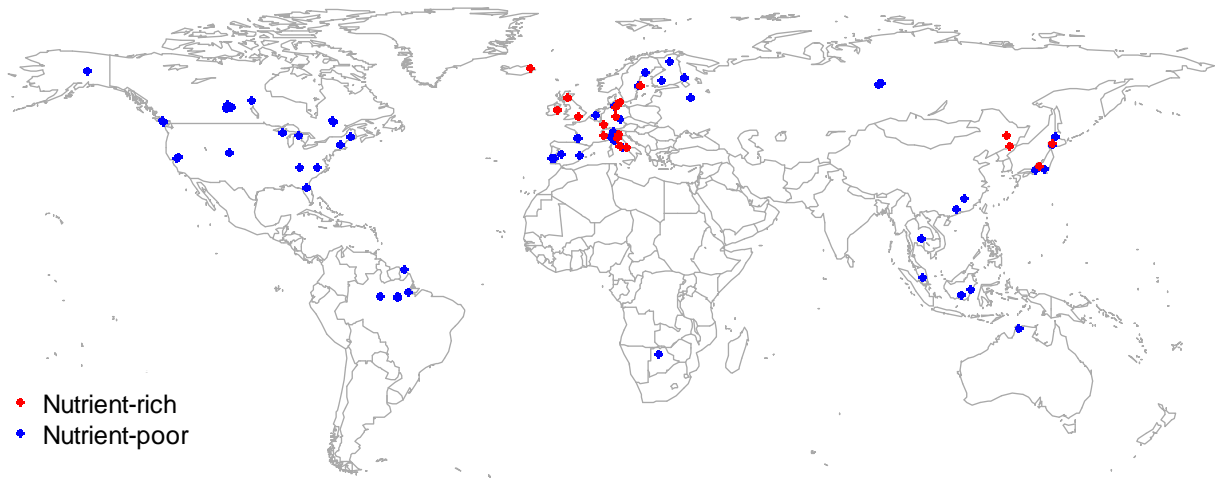
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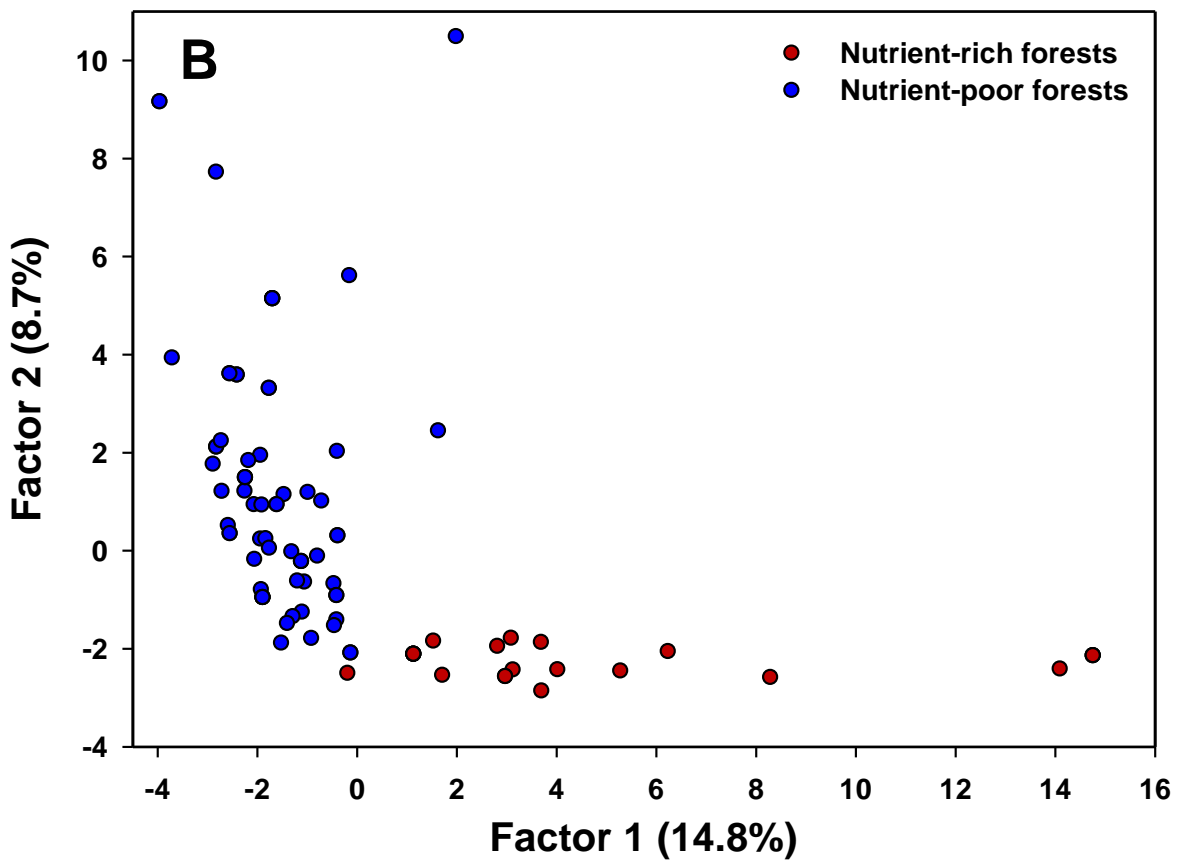
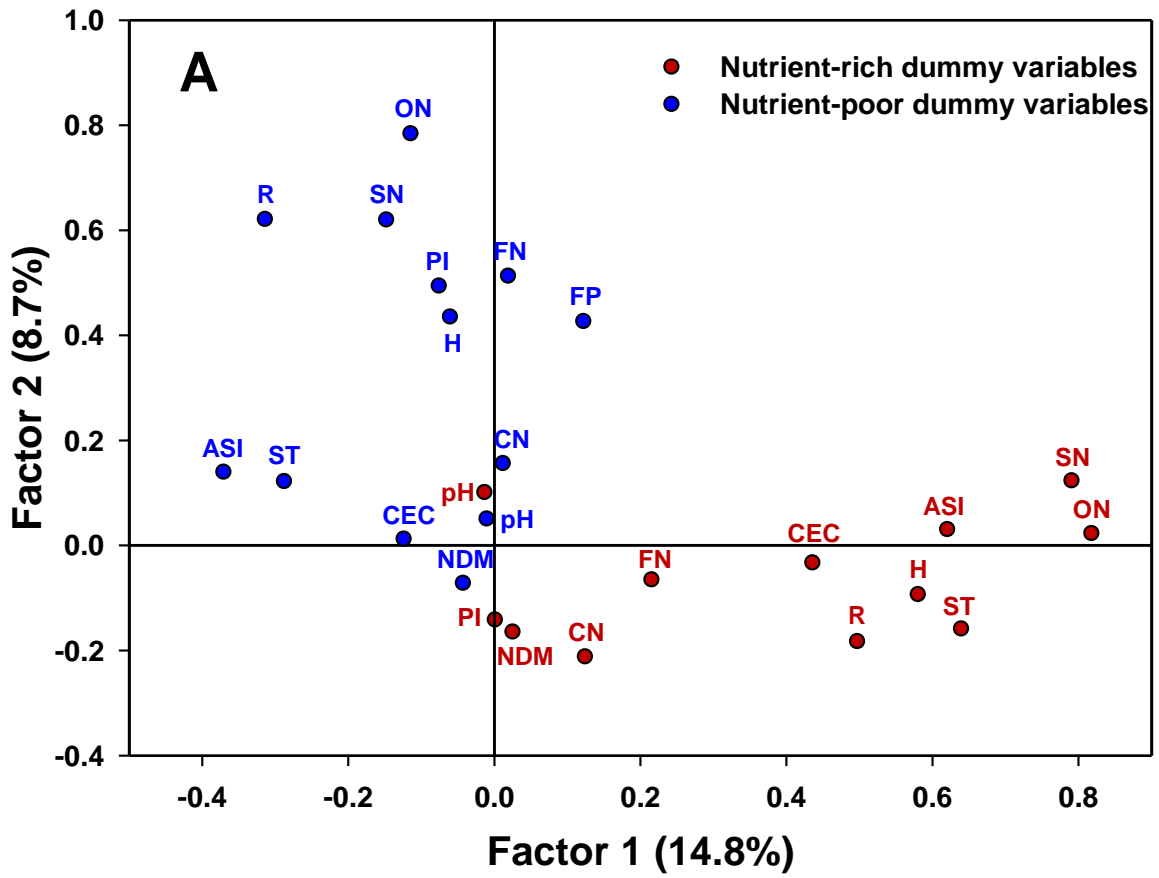
610 **Table S3: Followed criteria for evaluating nutrient availability.** The table shows the code
611 assigned to the forests according to the values of the variables used for the nutrient
612 availability assessment.

613

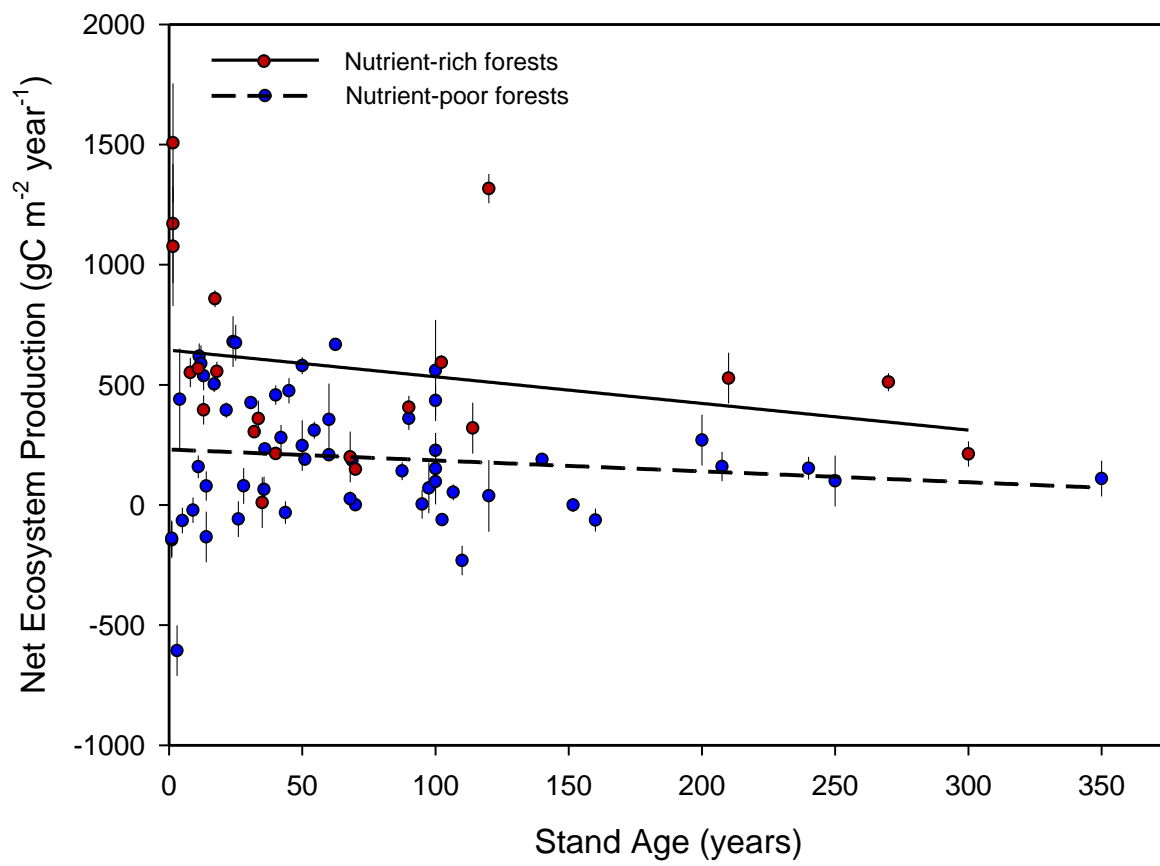
614 **Table S4. Validation of the nutrient classification.** Summary of the percentage of
615 successfully classified forests of the different logit models used to validate the nutrient
616 classification. In general terms, our nutrient classification was successfully predicted with the
617 available data for nutrient status that, in turn, achieved a good percentage of successful
618 predictions of the reports found in the literature on the nutrient status of the forests.

619 **Fig. S1.**

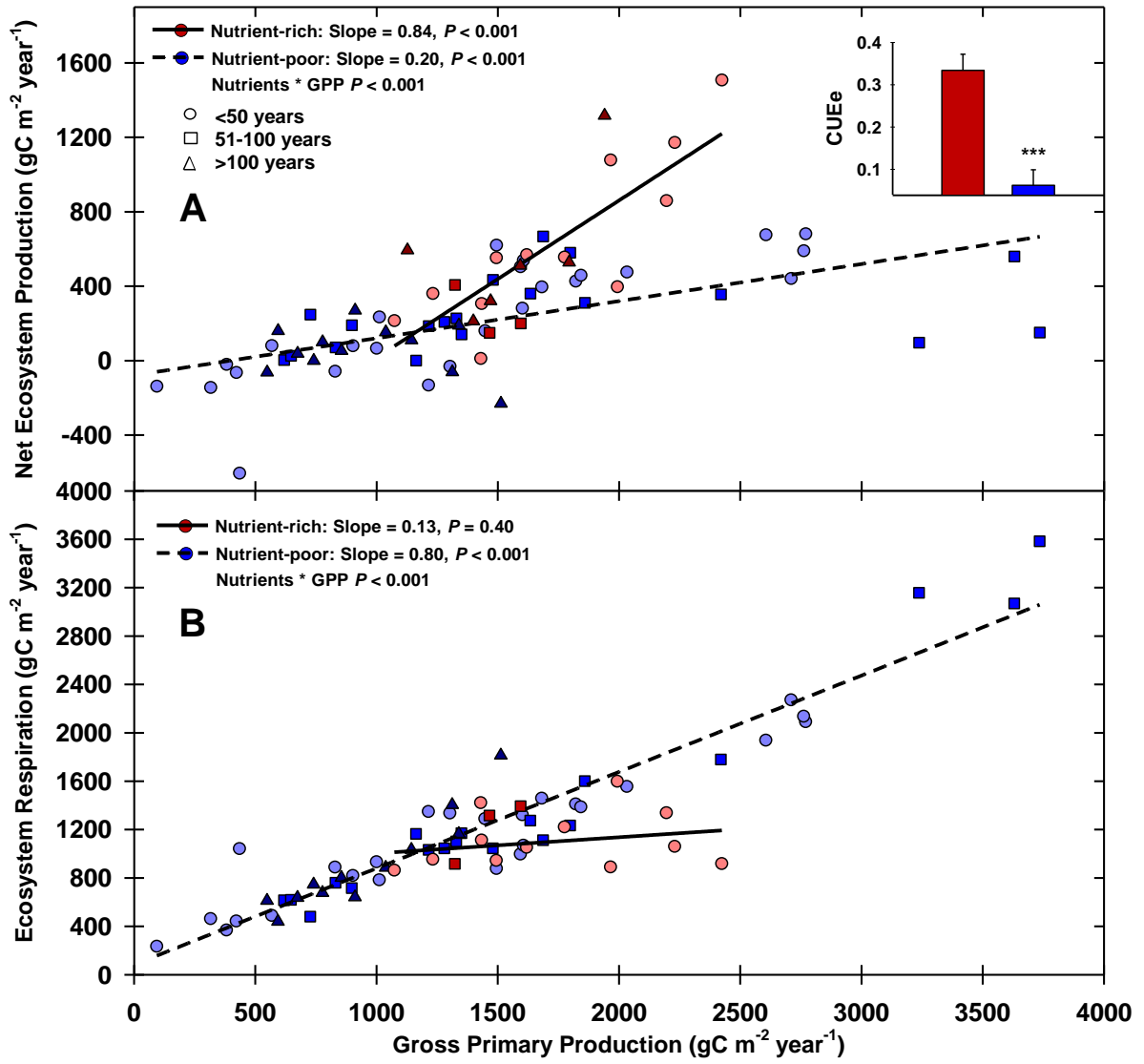


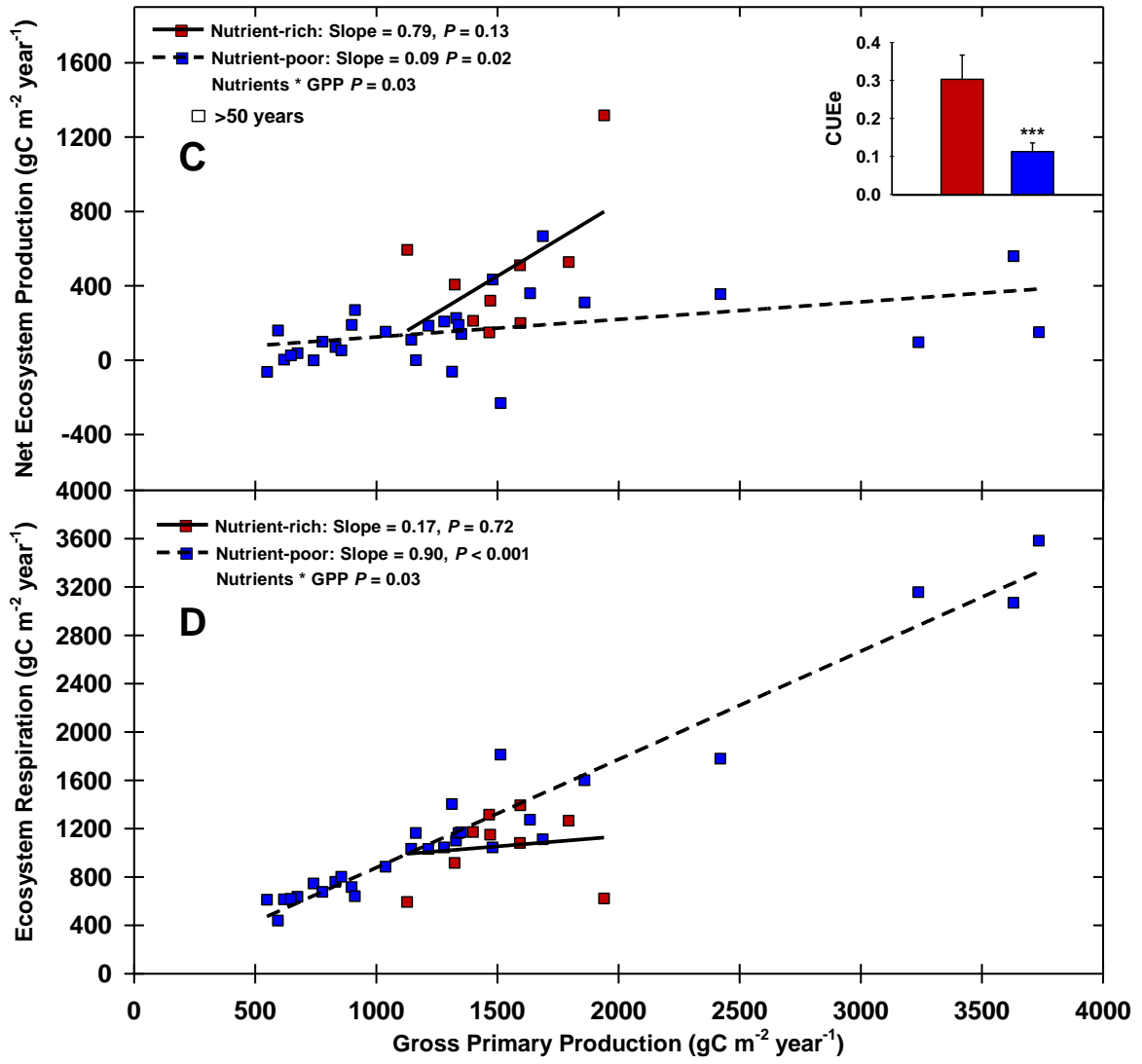


623 **Fig. S3.**



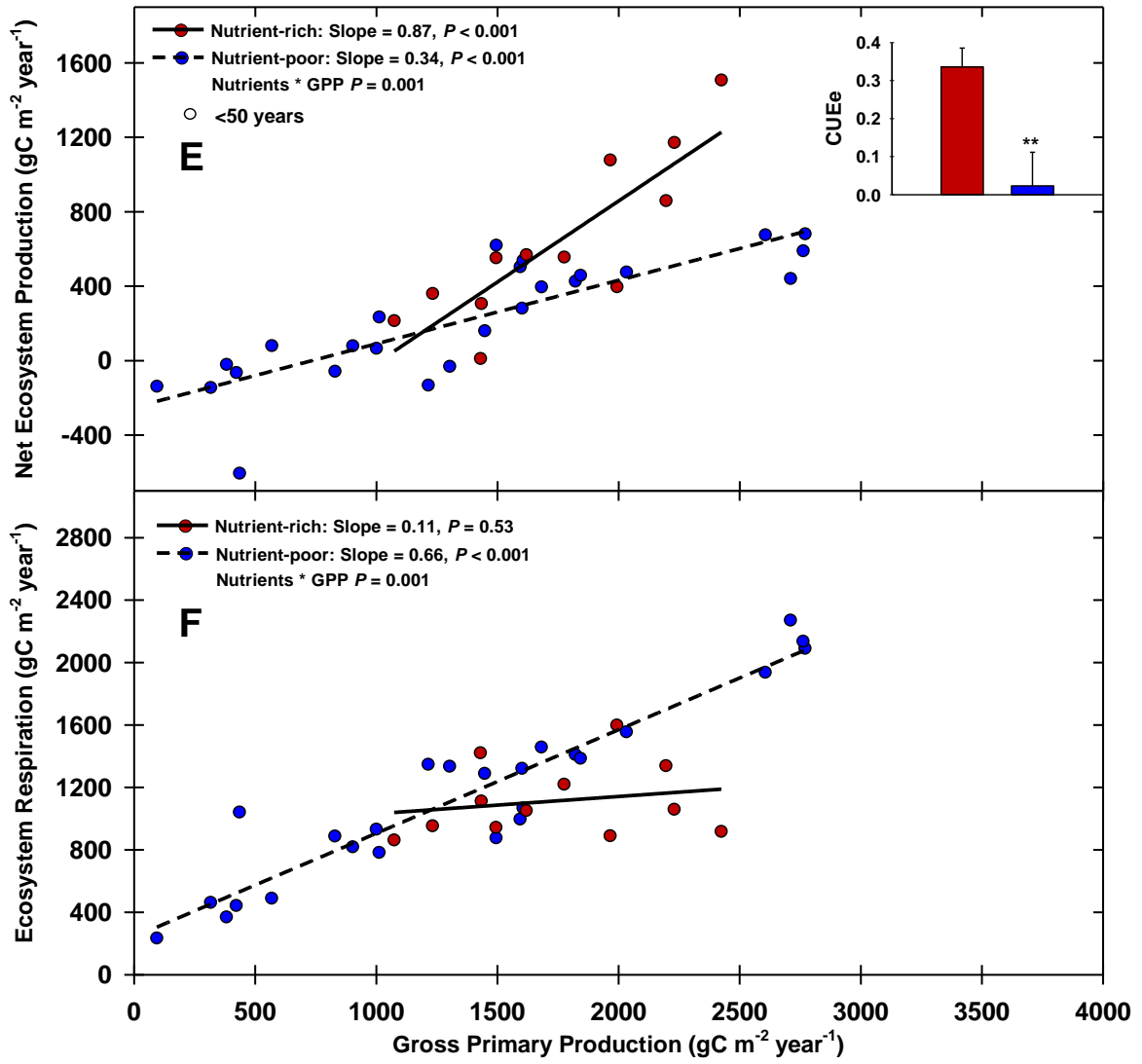
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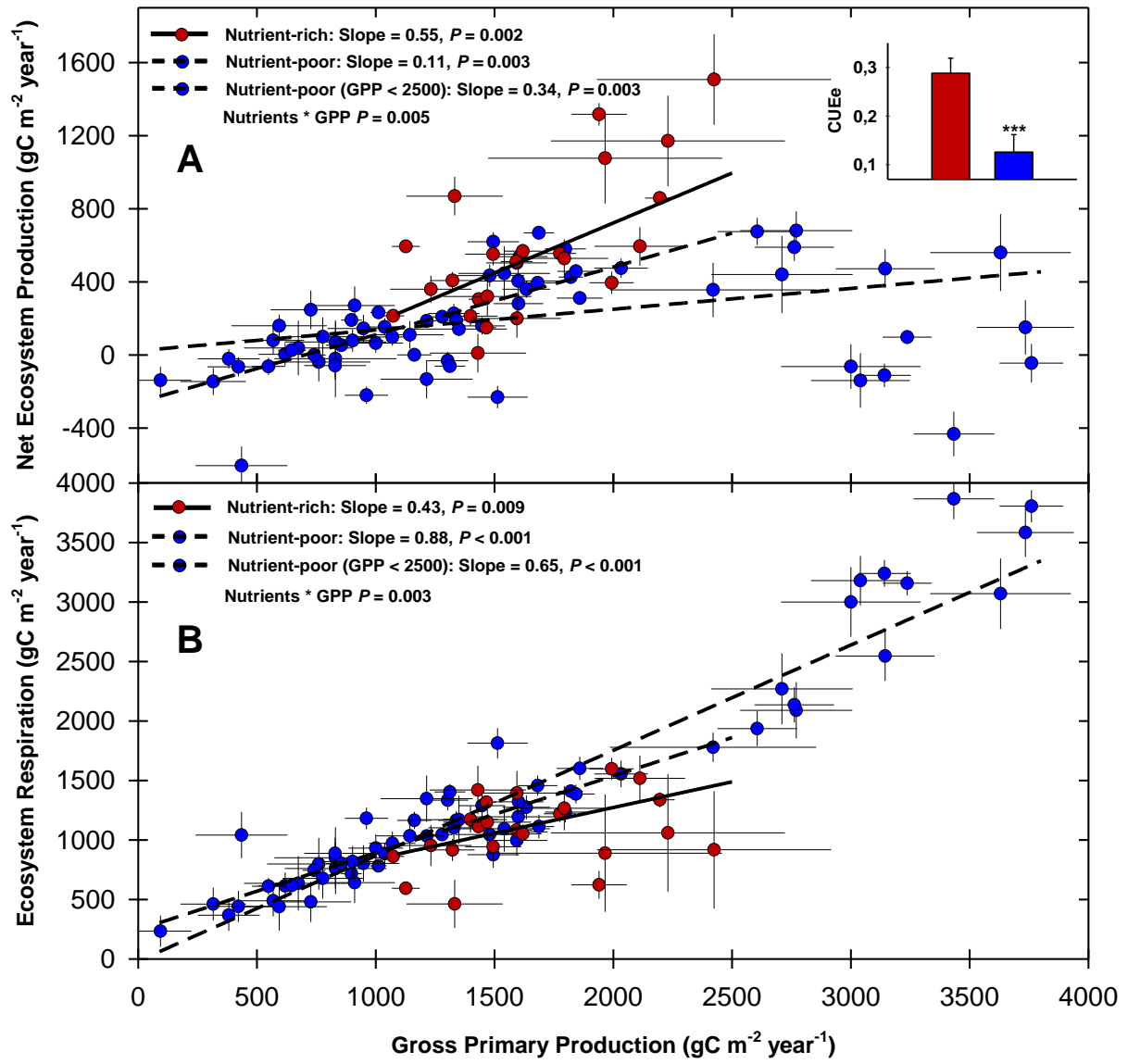


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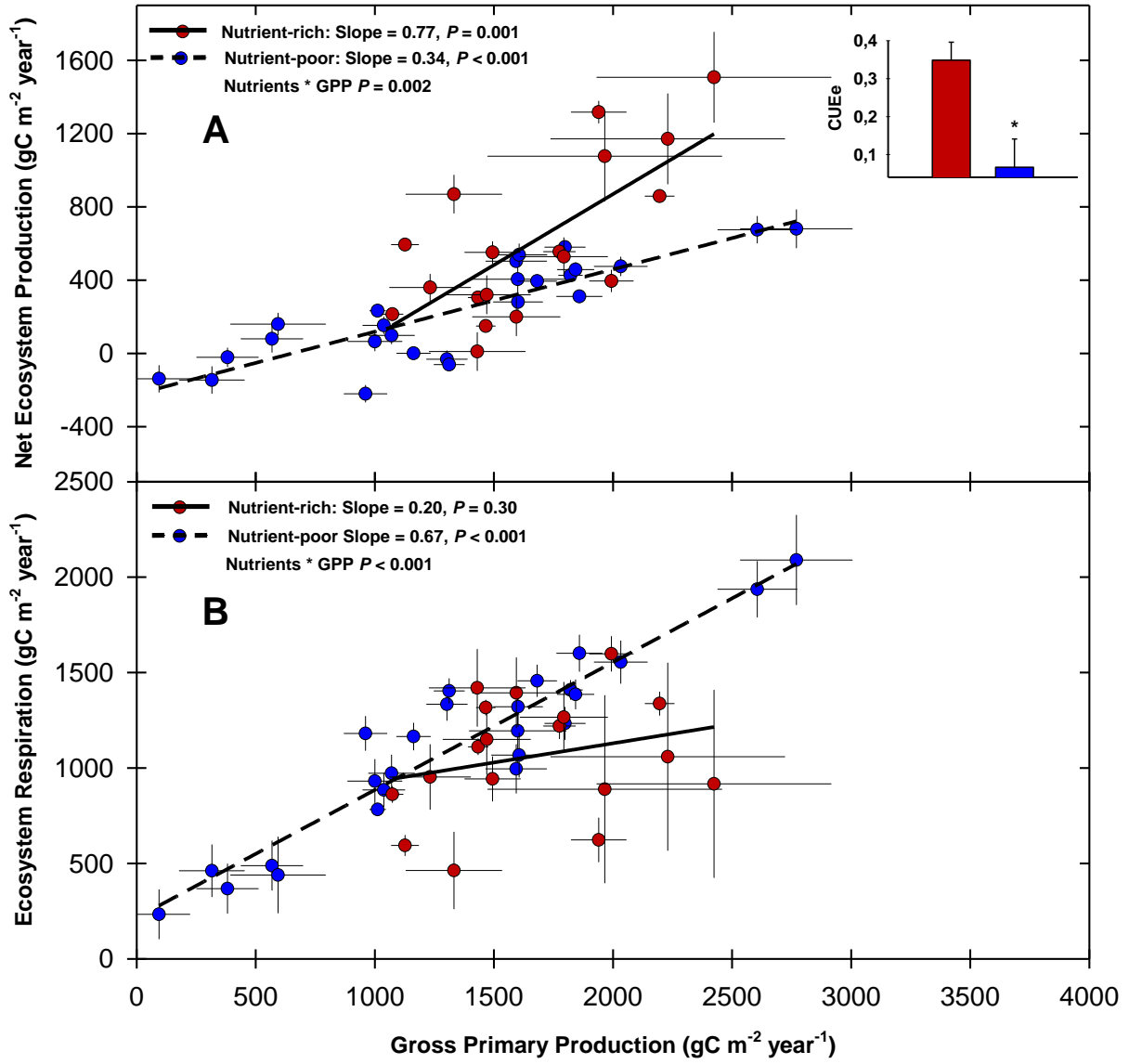


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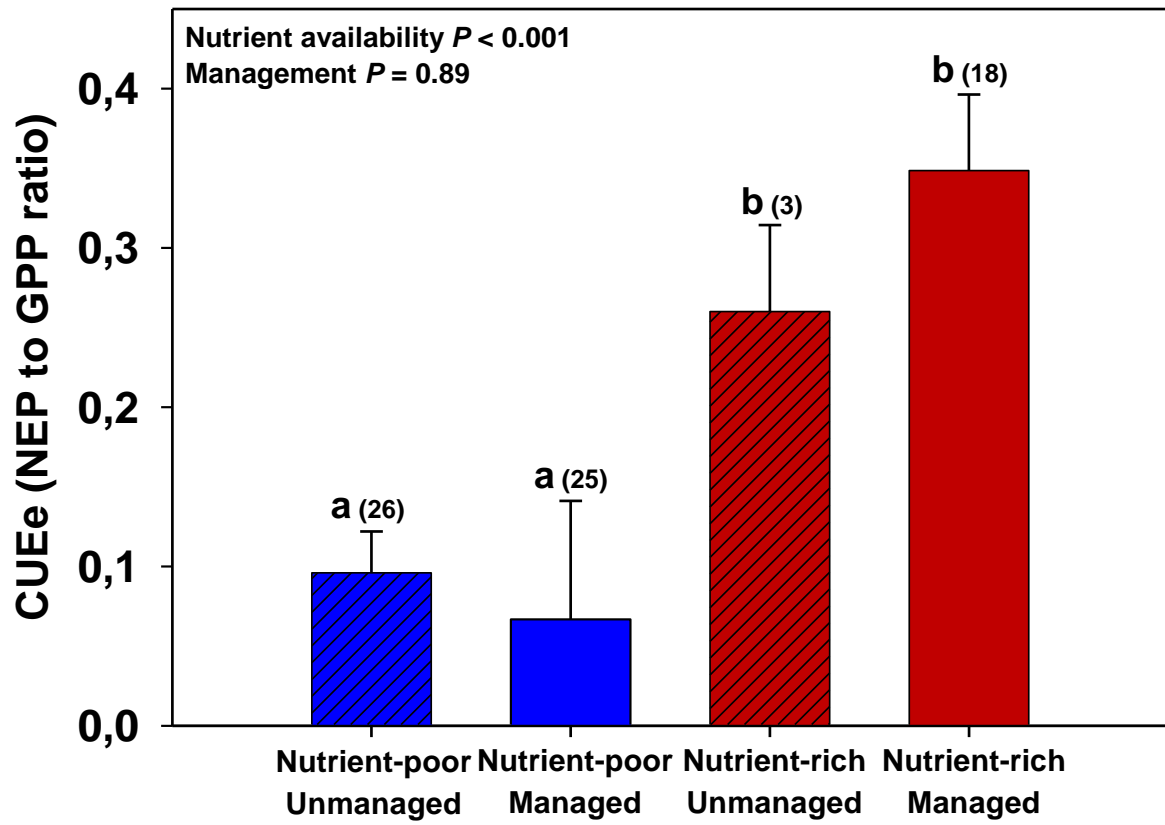
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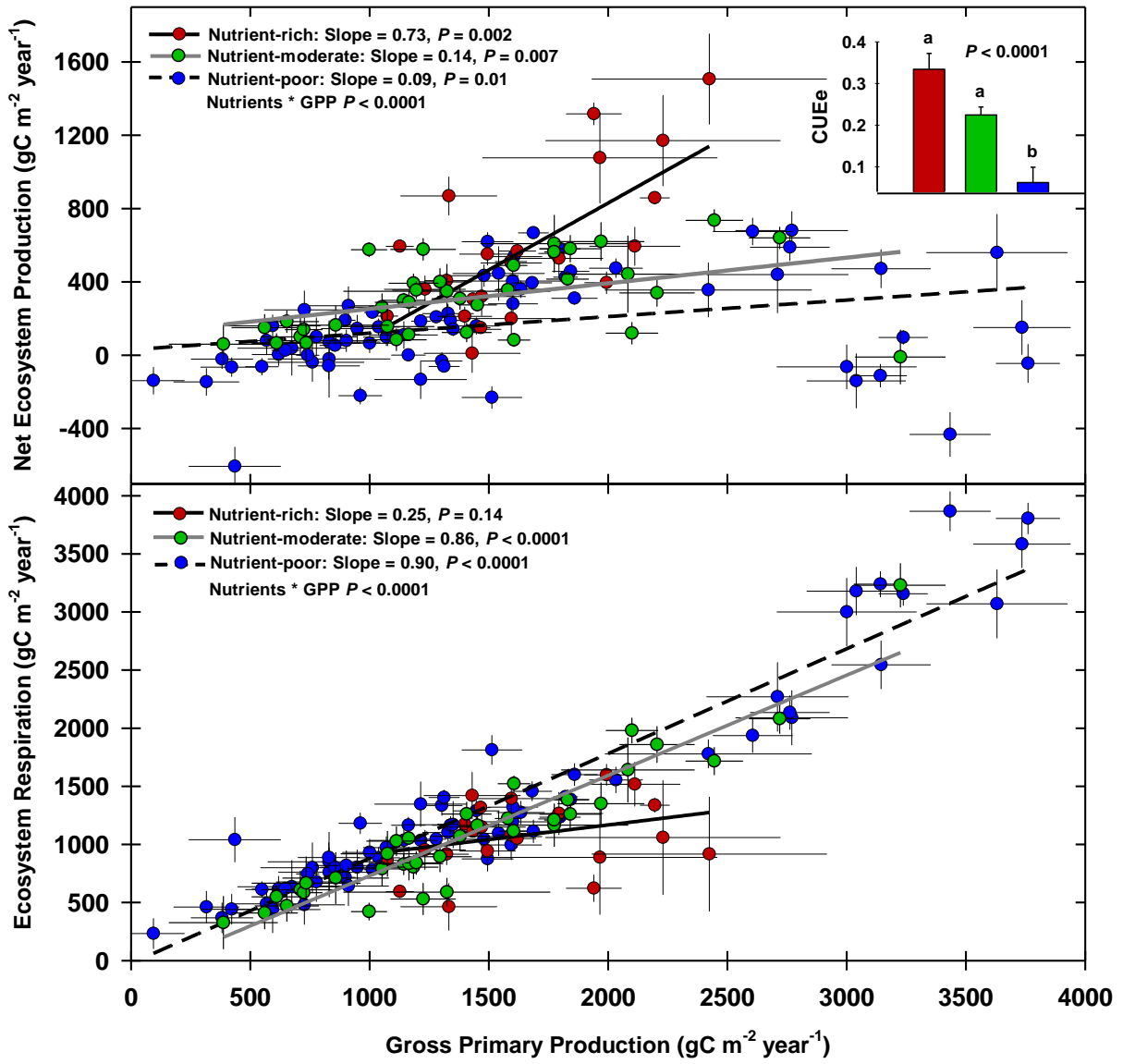


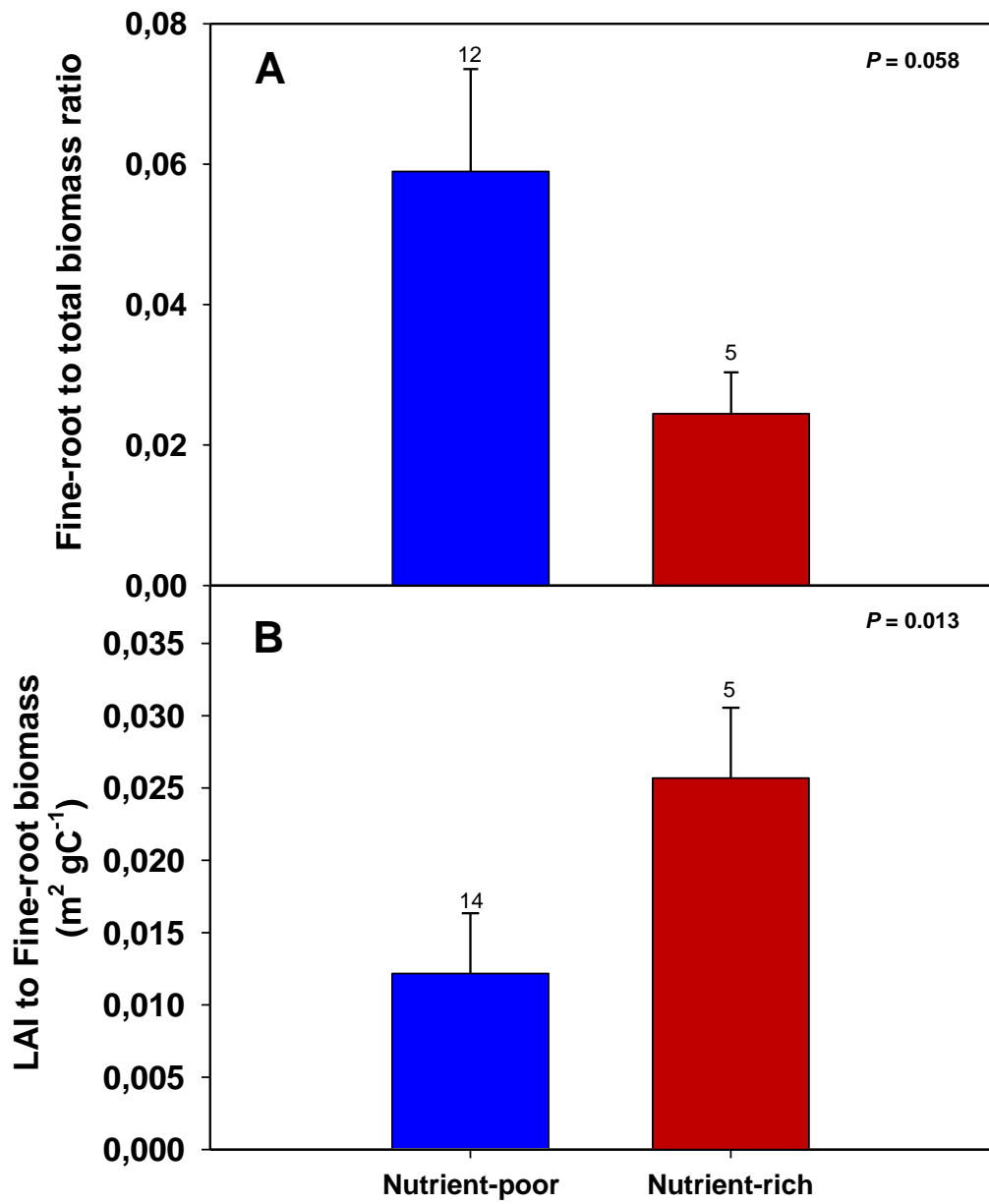
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635

636 Fig. S7.







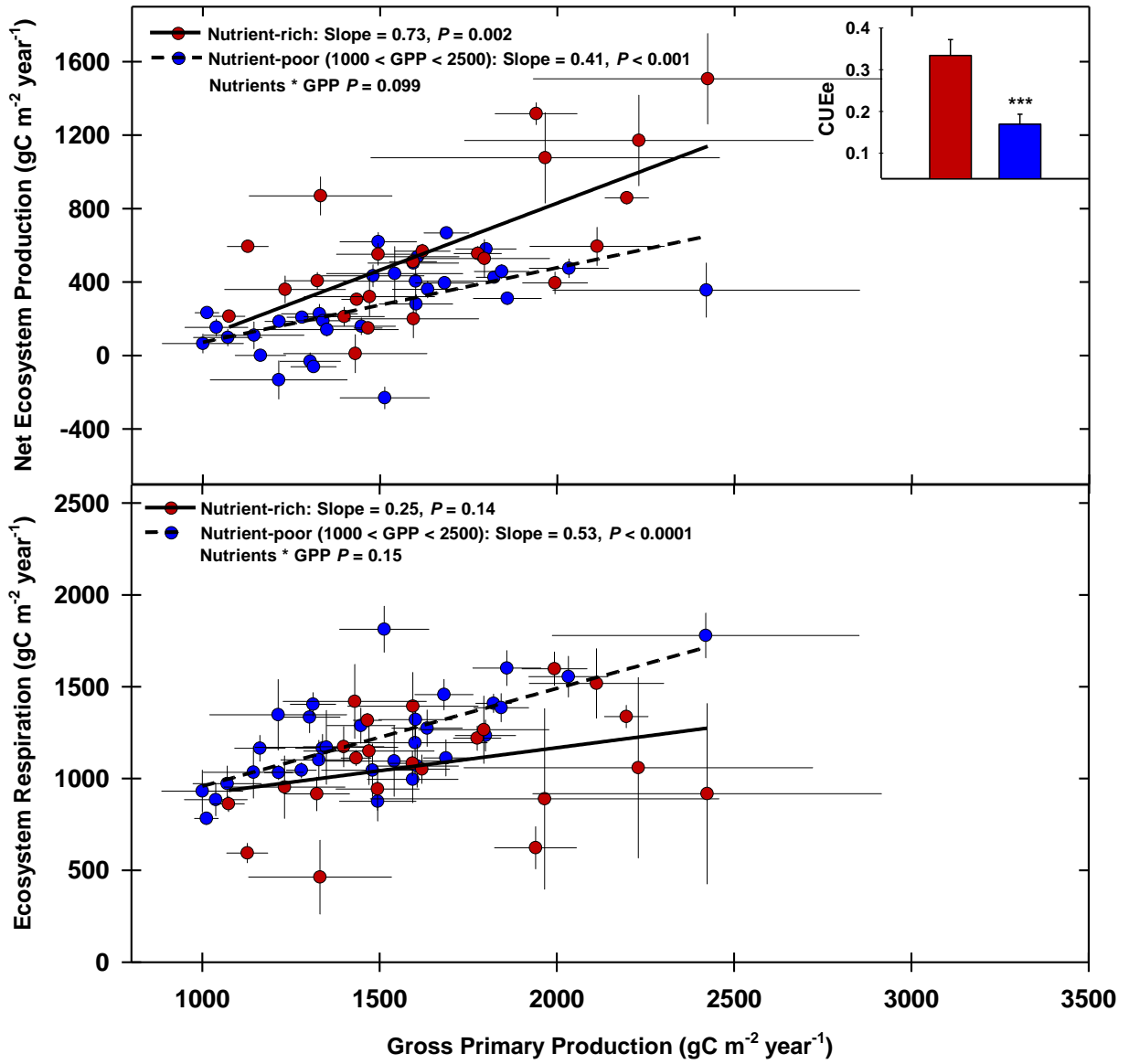


Table S1.

Site id	NA	PI	Soil type	Additional soil info	pH	C	N	C:N	Other Nutrients	CEC	N D/M	Fol N	History	Report
1	H										D:10		Fertilized with 350 kg urea ha ⁻¹ , 46% N	
2	L	L	Spodosol (ultic alaquods)	Poorly drained, argilic horizon										Nutrient limited
3	M			Stony sandy loam										Adequate nutrient supply
4	M							24			M:65			
5	L		Dystric, podzolic brown soils or Gleysols	Sandy to loamy sandy texture, organic layer mod/moder	3 to 5					Low (Ca, Mg)	D: high			
6	L		Hydromorphic podzol	Sandy, surface water table in winter										
7	M	M	Haplic and Entic podzols				U: 1.53% L: 0.13%	U: 30 L: 21						
8	L		Mixed, mesic, ultic haploxeralf (Cohasset series)	Fine-loamy, clay-loam	5.5	U: 6.9%	U: 0.17%	U: 41						
9	L		Fibric Histosol	Very wet, waterlogged										Nutrient-poor
10	M		Dystri-cambic Arenosol, near id 10	Not waterlogged							D: high			
11	L		Haplic podzol	wet sandy soil with humus and/or iron B horizon (Al buffer region).	4					Low	D: 35			Poor in Mg and P foliar concentrations. Good N foliar concentration.
12	L		Ultisol											
13	M	M	Brown podzolic	well drained, stone free, fine sandy loam materials										Good potato production when fertilized.
14	L			Sandy, hummus rich in calcium carbonate	5.8	U: 1.9% L: 0.7%		U: 66 L: 100						
15	L								Low P	Low				Extremely nutrient limited
16	H		Brown forest earth	Deep and nutrient-rich soil layer										
17	L		Ferro-humic or humic podzols	Good drainage			0.01%	135				N:0.79%		
18	L													Similar to id 17

19	M		Histosol (Belhaven series)	Loamy mixed dysis thermic terric Haplosaprists (peat soils)	<4.5										Previously farmed; F at planting: 28–50 kg ha ⁻¹ (N and P); F mid-rotation: 140–195 kg ha ⁻¹ N and 28 kg ha ⁻¹ P	
20	H		Humic alfisol	Silty loam-silty clay	5.2				Very high				Very high	D: high		
21	L		Oxisol	80% clay, high porosity (50-80%), low water capacity, highly weathered	4.3										Low nutrient content	
22	L		Rustic podsol, Chromic cambisol	Reddish soils	4			U: 29						D: 13		
23	L		Lateritic red or yellow soil	63% clay, 19% silt	3.8											
24	H														Former agricultural land regularly fertilized	Nutrient rich
25	L		Ultic alfisol	Mixed clay mineralogy, poorly drained from fall to spring	5.8											
26	L		Arenosol	Dune system												
27	L		Dystric cambisols		4.8	0.35%	0.03%								N: 1.17% P: 0.07%	
28	L		Gelisol	Loamy sand to loam, thick organic horizon (30cm)				U: 40% L: 3%	U: 0.7% L: 0.17%	U: 50 L: 20					N: 0.84%	
29	L															Strongly nutrient limited
30	L								Low					D: 5.7	Immature and nutrient-rich lava soil (64% N deficit)	
31	L			Peat soil	<4.7											Nutrient limited
32	M		Orthic Gleysol												N: 0.7 - 2.1%	
33	M		Andosol	Silty loam	5.8	U: 2.1%	Low							19		Nitrogen limited
34	L	L	Acrisol and ultisols	Sandy												Nutrient-poor
35	M		Brown alfisol	Sandy loam or loam												
36	H		Cambisol	4% sand, 56% lime, 44% clay												Nutrient-rich
37	H	H	Gleysol						U: 1.3%	U: 19 L: 30						
38	M		Gleysol	Peaty, seasonally waterlogged, black organic horizon											Fertilized 40 ago.	N increased after clear cutting

39	M		Gleysol	Peaty, seasonally waterlogged, black organic horizon									Fertilized 40 ago.	N increased after clear cutting
40	L			well drained, acidic sandy loam with some poorly drained peat soils									M: 34	Nutrient-poor
41	H		Luvisol or Stagnic luvisol											Typically very nutrient-rich soils
42	L	L		Well drained lateritic red and yellow earth soils with highly weathered sands	5.5		0.10%							Nutrient-poor
43	L	L			3.5			35					N: 1.06%	
44	L	M L	Haplic podzol						Low				M: low D: low	>99.9% soil N is unavailable for plants. Nitrogen limitation.
45	L			Sandy loam with limited water capacity	acid				Low		Low P			Bogs and peatland poor in N and very P limited
46	L	L	Lithic haploxerepts	Very rocky silt loam		1.1%	0.11%	10						
47	L			Heavily leached						Low P		Low		Nutrient-poor
48	H													Very nutrient-rich soil
49	H													Very nutrient-rich soil
50	H													Very nutrient-rich soil
51	M		Spodosol (or cryosol)	Coarse texture, highly leached, gray		2.2%	0.50%	4.4						
52	L		Entisol											
53	L		Dystric cambisol	90 cm depth, low water capacity, rocky and sandy (80%)	5.6		2.6%	14						
54	H	M	Typic Fragiudalf (Alfisol)	fine-silty	U: 3.7 L: 6.7		U: 6.2%	U: 0.5%	U: 12.6					
55	M		Haplic cambisol and rendzic leptosols (rendzina)	Very shallow	4 to 7.5		6.5	0.47	U: 15				D: 26	
56	H		Alfisol	Dark-brown										
57	H	H	Humic Umbrisol		6.1				15.8					
58	L		Hydromorphic podzol	Sandy, waterlogged in winter					26					
59	M			Sand dunes.									D: high	Nutrient-poor under natural conditions

60	M		Kandiustalfs		6.5										Relatively nutrient rich
61	L	L M	Kalahari sands	Presents a calcrete duricrust									N: 1 to 3%		Nutrient-poor
62	M			Sandy soils					Low						N-fixing shrubs increase N availability
63	M			Sandy soils					Low						N-fixing shrubs increase N availability
64	L	L		83% sand, 9% silt and 8% clay	5.6	1.6%	0.12%	133							
65	M		Typic Dystrachrept										M: 122		
66	M	M	Mollic Eutroboralf and Typic Argiboroll	Loam	5.3	2.5%	0.14	17.9	High P						Although N might be limiting, P is highly available
67	L	M L											N: 0.95%		
68	H		Eutric Vertisol	60% clay		5.6%	3.80%	8.5	P: 98ppm	27			N: 3%	Former fertilized agricultural land	
69	L		Podzolic glacial till	Sandy											Nutrient-poor
70	L	L	Ombrotrophic peat dome		<3	39%	1.30%	30	Low				P: very low N: low		Low availability of essential nutrients
71	L	L		58% sand, 32% silt, 10% clay	U: 6.4 L: 6.3	U: 1.2 L: 1.6	U: 0.08 L: 0.08	U: 15 L: 20					N: 0.71%		
72	L		Durian Series	Band of laterite, highly leached	3.5 to 4.8				Low P		Low				
73	H		Xeric Alfisol	Loam texture					High					Former agricultural land	Characterized by its high nutrient availability
74	H		Xeric Alfisol	Loam texture					High					Former agricultural land	Characterized by its high nutrient availability
75	H		Xeric Alfisol	Loam texture					High					Former agricultural land	Characterized by its high nutrient availability
76	L			Waterlogged											Nutrient availability restricted by slow decomposition rates
77	L			Waterlogged											Nutrient availability restricted by slow decomposition rates

78	L			Waterlogged												Nutrient availability restricted by slow decomposition rates
79	M	H		75% rocks, stone-free fraction is silty-clay loam (39% clay, 35% silt, 26% sand)		7.40%	0.48%	U: 15 L: 11							N: 1.26%	
80	L		Red earth					Low		Low						Very poor nutrient status
81	M				U: 3.9 L: 4.1	U: 27% L: 9%	U: 1.3% L: 0.4%	U: 20 L: 24		U: 0.08% L: 0.03%					N Lt: 1% P It: 0.07%	
82	H		Luvisol	100 cm depth, 52% sand, 12% silt, 35% clay	5.7			12.6								
83	L		Utisol	Stony	5.1		Low			Low		Low				Nutrient-poor, especially P
84	L	L		93% sand, 3% silt, 4% clay	6.5 to >7.9	U: 0.9 L: 0.4	U: 0.03 L: 0.03	U: 30 L: 14		Low					N: 0.70%	Poor sandy soil
85	H			Loam, from volcanic ashes.											N: 2.30%	
86	M	M				U: 4.2%	U: 0.4%	10.5								
87	L			Sandy to sandy loam		3.1	0.14	22.0							N: 0.95%	
88	L			Sandy to sandy loam		2.3	0.19	12.1							N: 1.07%	
89	L			Sandy to sandy loam		3.3	0.17	19.4							N: 1.35%	
90	L			Sandy to sandy loam		1.7	0.08	21.3							N: 1.36%	
91	L			Sandy		1.8	0.1	18.0							N: 1.20%	HJP75 could be more nutrient limited due to higher tree competition
92	L			Sandy to sandy loam		1.4	0.1	14.0							N: 1.55%	
93	M	M														
94	M	M														
95	H															Fertilized
96	L	L	Ultic alaquods	Sandy, siliceous, thermic		Low	Low			Low					Trees responded drastically to fertilization experiment	Low in available nutrients
97	L	L	Ultic alaquods	Sandy, siliceous, thermic		Low	Low			Low					Trees responded drastically to fertilization experiment	Low in available nutrients
98	L		Haplic podzol				Low			Low						Nutrient-poor soil

99	M				Low					Low			Nutrients are sufficiently available in this forest	
100	H		Luvisol							High			Very nutrient rich	
101	L	M		57% sand, 36% silt and 6% clay						0.18%		M: 4.4		
102	H			Brown soil									Very nutrient rich	
103	M			Dystric Cambisol									Clay loam, from volcanic ash deposit	
104	L			Belterra clay Ferralsols						Low			Nutrient-poor	
105	L			Belterra clay Ferralsols						Low			Nutrient-poor	
106	L			Gleyic Cambisol								D: 5	Stream water chemistry revealed very low N concentrations	
107	M			Dystric Cambisol									Less nutrient rich than a eutric Cambisol	
108	L				Drained, peat-rich					Low			Severely nutrient limited	
109	L			Volcanogenous regosol						Low			Nutrient-poor	
110	M	M		Brunicollic grey brown luvisol	Sandy to loamy sand soil, low-to-moderate water-holding capacity	6.3	0.56%	U: 0.06%	L: 11.4			D: 7.5	Planted on former agricultural land	Have higher amounts of soil macronutrients (i.e. P, K, Ca, Mg) than id 111 and 112
111	M	M		Gleyed brunisolic luvisol	Sandy to loamy sand soil, low-to-moderate water-holding capacity	4.1	0.61%	U: 0.05%	L: 15.4			D: 7.5	Planted on cleared oak-savannah land	
112	M	M		Brunicollic grey brown luvisol	Sandy to loamy sand soil, low-to-moderate water-holding capacity	3.7	0.60%	U: 0.06%	L: 19.4			D: 7.5	Planted on cleared oak-savannah land	
113	M	M		Gleyed brunisolic luvisol	Sandy to loamy sand soil, low-to-moderate water-holding capacity	4.3	0.51%	U: 0.07%	L: 14.2			D: 7.5	Planted on former agricultural land	Same as id 110
114	L			Entic Haplothod	Sandy, well drained					Low				Nitrogen limited
115	H				Brown Andosol			U: 8.1% L: 3.0%	U: 0.4% L: 0.2%	U: 20 L: 15			Grazed heathland pasture prior to afforestation	
116	L	L M			Gravelly loamy sand, 19 cm depth			U: 39% L: 4.6%	U: 0.9% L: 0.3%	U: 43 L: 15				Presents low nitrogen availability

117	L	L M		Gravelly loamy sand to sand, 19 cm depth	U: 45% L: 6.9%	U: 1% L: 0.2%	U: 45 L: 35		
118	L	L M		Gravelly loamy sand, 19 cm depth	U: 46% L: 18%	U: 1% L: 0.8%	U: 46 L: 23		
119	M	M							Fertilization stimulated tree growth
120	L		Typic Paleudult	Highly weathered, acidic		Low		low P	Low
121	M		Podzols and Cambisols						
122	M		Enthic Haplorthod					M: > id 114	Nutrient-poor soil similar to id 114
123	M		Stagni-vertic Cambisol	Some areas of arenihaplic Luvisols and calcaric Cambisols					Vegetation is typical for relatively nutrient-rich soils
124	M		Rendzina	Above chalk and limestone			11		Poor soil conditions
125	M		Brown	Loam		Low		Low	Nutrient limitations
126	L		Cambisols	Sandy silt		Low		Low	see report
127	L		Cambisols	Sandy silt		Low		Low	Idem id 126
128	L		Cambisols	Sandy silt		Low		Low	Idem id 126
129	L		Cambisols	Sandy silt		Low		Low	Idem id 126

647 **Site id: 1.** Aberfeldy/Griffins; **2.** Austin; **3.** Balmoral; **4.** Barlett; **5.** Bayreuth/Weiden Brunnen; **6.** Bilos; **7.** Bily Kriz Forest; **8.** Blodgett Forest; **9.** Bornhoved Alder; **10.**
648 Bornhoved Beech; **11.** Brasschaat; **12.** Bukit Soeharto; **13.** Camp Borden; **14.** Castelporziano; **15.** Caxiuana; **16.** Changbai Mountains; **17.** Chibougamau EOBS; **18.**
649 Chibougamau HBS00; **19.** Coastal plain North Carolina; **20.** Collelongo; **21.** Cuieiras/C14; **22.** Davos; **23.** Dinghushan DHS; **24.** Dooary; **25.** Duke Forest; **26.** El Saler; **27.**
650 Espirra; **28.** Fairbanks; **29.** Flakaliden C; **30.** Fujiyoshida; **31.** Fyedorovskoye; **32.** Groundhog; **33.** Gunnarsholt; **34.** Guyaflux; **35.** Gwangneung; **36.** Hainich; **37.** Hampshire;
651 **38.** Hardwood; **39.** Hardwood_21; **40.** Harvard; **41.** Hesse; **42.** Howards spring; **43.** Howland; **44.** Hyytiala; **45.** Ilomantsi Mekrijärvi; **46.** Ione; **47.** Jacaranda/K34; **48.**
652 Kannenbruch Alder/Ash; **49.** Kannenbruch Beech; **50.** Kannenbruch Oak; **51.** Khentei Taiga; **52.** Kiryu; **53.** La Majadas del Tietar; **54.** La Mandria; **55.** Lägeren; **56.** Laoshan;

653 **57.** Lavarone; **58.** Le Bray; **59.** Loobos; **60.** Mae Klong; **61.** Maun Mopane; **62.** Metolius; **63.** Metolius young; **64.** Mitra; **65.** Morgan Monroe; **66.** NAU Centennial; **67.**
654 Niwot Ridge; **68.** Nonantola; **69.** Norunda; **70.** Palangkaraya; **71.** Parco Ticino; **72.** Pasoh; **73.** Popface alba; **74.** Popface euamericana; **75.** Popface nigra; **76.** Prince Albert
655 SSA (SOAS); **77.** Prince Albert SSA (SOBS); **78.** Prince Albert SSA (SOJP); **79.** Puechabon; **80.** Qianyanzhou Ecological Station; **81.** Renon; **82.** Roccarespampami 2; **83.**
656 Sakaerat; **84.** San Rossore; **85.** Sapporo; **86.** Sardinilla; **87.** Saskatchewan F77; **88.** Saskatchewan F89; **89.** Saskatchewan F98; **90.** Saskatchewan HJP02; **91.** Saskatchewan
657 HJP75; **92.** Saskatchewan HJP94; **93.** Sky Oaks old; **94.** Sky Oaks young; **95.** Skyttorp2; **96.** Slash pine Florida Mid; **97.** Slash pine Florida old; **98.** Sodankylä; **99.** Solling;
658 **100.** Soroe; **101.** Sylvania; **102.** Takayama; **103.** Takayama 2; **104.** Tapajos 67; **105.** Tapajos 83; **106.** Teshio CC-LaG; **107.** Tharandt; **108.** Thompson NSA (NOBS); **109.**
659 Tomakomai; **110.** Turkey Point TP02; **111.** Turkey Point TP39; **112.** Turkey Point TP74; **113.** Turkey Point TP89; **114.** University of Michigan; **115.** Vallanes; **116.**
660 Vancouver Island DF49; **117.** Vancouver Island HDF00; **118.** Vancouver Island HDF88; **119.** Vielsalm; **120.** Walker Branch; **121.** Wet-T-57; **122.** Willow Creek; **123.**
661 Wytham Woods; **124.** Yatir; **125.** Yellow River Xiaolangdi; **126.** Yenisey Abies; **127.** Yenisey Betula; **128.** Yenisey Mixed; **129.** Yenisey/Zotino.

Table S2.

Forest name	CUEe	SE	Original Classification	Alternative Classification		
Bayreuth/Weiden Brunnen	-0.02	0.04	L	M		
Bilos	0.25	0.07	L	M		
Blodgett Forest	0.11	0.03	L	M		
Bornhoved Alder	0.15	0.07	L	M		
Brasschaat	0.00	0.02	L	M		
Camp Borden	0.12	0.05	M	L		
Castelporziano	0.32	0.02	L	M		
Guyaflux	0.04	0.04	L	M		
Hampshire	0.28	0.06	H	M		
Hardwood	0.32	0.05	M	H		
Hardwood_21	0.31	0.06	M	H		
Lägeren	0.23	0.03	M	H		
Lavarone	0.68	0.05	H	M		
Loobos	0.23	0.02	M	L		
Maun Mopane	-0.03	0.25	L	M		
Prince Albert SSA (SOAS)	0.15	0.02	L	M		
Prince Albert SSA (SOBS)	0.06	0.06	L	M		
Prince Albert SSA (SOJP)	0.05	0.08	L	M		
Sylvania	0.10	0.07	L	M		
Teshio CC-LaG	0.05	0.08	L	M		
Vielsalm	0.31	0.02	M	L		
Wet-T-57	-0.03	0.04	M	H		
Willow Creek	0.25	0.06	M	H		
Yatir	0.28	0.11	M	L		
Yellow River Xiaolangdi	0.30	0.05	M	L		
			Effect (β)	R^2	Effect (β)	R^2
Nutrient availability			H>L; -0.32**	0.12	H>L; -0.29**	0.07
GPP			0.91***	0.14	0.59**	0.12
Age			1.13***	<0.01	1.22***	0.01
GPP*Age			-1.17***	0.17	-1.18***	0.18
MAT			-	-	0.39*	0.06
Adjusted R^2			0.40		0.39	

663 **NOTE:** Depending on the classification, the number of replicates varies (because the number of forests of medium
664 nutrient availability changes).

Table S3.

Variable	Code	Variable	Code
Soil Additional Info		Soil type	
Poorly drained, argilic horizon	Low	Acrisol and ultisols	Low
100 cm depth, 52% sand, 12% silt, 35% clay	Medium	Alfisol	High
4% sand, 56% lime, 44% clay	Medium	Andosol	Medium
57% sand, 36% silt and 6% clay	Low	Arenosol	Low
58% sand, 32% silt, 10% clay	Medium	Belterra clay Ferralsols	Low
60% clay	Medium	Brown Andosol	High
63% clay, 19% silt	Low	Brown podzolic	Low
75% rocks, stone free fraction is silty-clay loam (39% clay, 35% silt, 26% sand)	Medium	Brown soil	High
80% clay, high porosity (50-80%), low water capacity, highly weathered	Low	Brunicollic grey brown luvisol	High
83% sand, 9% silt and 8% clay	Low	Cambisol	Medium
90 cm depth, low water capacity, roky and sandy (80%)	Low	Dystric cambisol	Medium
93% sand, 3% silt, 4% clay	Low	Entic Haplorthod	Low
Above chalk and limestone	Low	Entisol	Low
Band of laterite, highly leached	Low	Eutric Vertisol	Low
Clay loam, from volcanic ash deposit	Medium	Fibric Histosol	Low
Coarse texture, highly leached, gray	Low	Gleyed brunisolic luvisol	High
Dark-brown	High	Gleyic Cambisol	Medium
Deep and fertile soil layer	High	Gleysol	Medium
Drained, peat-rich	Low	Haplic cambisol and rendzic leptosols	Medium
Dune system	Low	Histosol	Low
Fine-loamy, clay-loam	Medium	Humic umbrisol	Medium
Fine-silty	Medium	Kalahari sands	Low
Good drainage	High	Kandiustalfs	Medium
Gravelly loamy sand to sand, 19 cm depth	Medium	Lateritic red or yellow soil	Low
Gravelly loamy sand, 19 cm depth	Medium	Lithic haploxerepts	Low
Heavily leached	Low	Luvisols	High
Highly weathered, acidic	Low	Mixed mesic ultic haploxeralf	Low
Loam	High	Mollic Eutroboralf and Typic Argiboroll	Medium
Loam, from volcanic ashes.	High	Ombrotrophic peat dome	Low
Loamy mixed dysis thermic terric Haplosaprists (peat soils)	Low	Orthic Gleysol	Medium
Loamy sand to loam, thick organiz horizon (30cm)	Medium	Oxisol	Low
Mixed clay mineralogy, poorly drained from fall to spring	Low	Podzol	Low
Not waterlogged	Medium	Red earths	Low
Peat soil	Low	Spodosol	Low
Peaty, seasonally waterlogged, black organic horizon	Low	Stagni-vertic Cambisol	Medium
Peaty, seasonally waterlogged, black organic horizon	Low	Typic Dystrichrept	Medium
Presents a calcrete duricrust	Low	Typic Paleudult	Low
Sand dunes	Low	Ultic alaquods	Low
Sandy	Low	Ultic alfisol	Low
Sandy loam or loam	Medium	Ultisol	Low
Sandy loam with limited water capacity	Low	Volcanogenous regosol	Medium
Sandy silt	Medium		

Sandy to loamy sand soil, low-to-moderate water holding capacity	Medium	Other Nutrients (soil P)	
Sandy to loamy sandy texture, organic layer mod/moder	Medium	9 ppm	Low
Sandy to sandy loam	Medium	98 ppm	High
Sandy, hummus rich in calcium carbonate	Low	0.08-0.03%	Medium
Sandy, siliceous, thermic	Low		
Sandy, surface water table in winter	Low	C:N ratio	
Sandy, waterlogged in winter	Low	> 30	Low
Sandy, well drained	Low	30 - 20	Medium
Silty loam	Medium	<20	High
Silty loam-silty clay	Medium		
Some areas of arenihaplic Luvisols and calcareous Cambisols	Medium	CEC (meq L⁻¹)	
Stony	Low	>20	High
Stony sandy loam	Medium	>10	Medium
Very rocky silt loam	Low	<10	Low
Very shallow	Low		
Very wet, waterlogged	Low	N deposition (kg ha⁻¹ year⁻¹)	
Waterlogged	Low	>20	High
Well drained	Medium	20 - 10	Medium
Well drained lateritic red and yellow earth soils with highly weathered sands	Low	<10	Low
Well drained, acidic sandy loam with some poorly drained peat soils	Low		
Well drained, stonefree, fine sandy loam materials	Medium	N mineralization (kg ha⁻¹ year⁻¹)	
Wet sandy soil with humus and/or iron B horizon (Al buffer region).	Medium	4.4	Low
		34	Low
		65	Medium
Soil pH		122	High
0 - 5	Low		
5.1 - 6	Medium		
6.1 - 8	High	Foliar N%	
		>2%	High
Soil N%		2 - 1%	Medium
>0.8%	High	<1%	Low
>0.1%	Medium		
<0.1%	Low	Foliar P%	
		0.07%	Low

668 **Table S4.**

Dependent variable	Model selection	AIC	Correct cases	Failed cases	Success (%)
Nutrient status	Saturated	110	92	0	100%
Nutrient status	Stepwise	37	91	1	99%
Report	Saturated	130	55	3	95%
Report	Stepwise	37	54	4	93%

669

670

671 **List of Models**

672 Here, we present the minimum adequate models exposed in Table 1 followed by its homologous final model
 673 achieved by the model averaging procedure. Predictor variables were: GPP, Nutrient availability (NA), Age,
 674 Management (MNG), and its interactions up to second order, MAT, MAP and WD. Forests whose category
 675 of management was not managed or unmanaged were excluded. In model averaging summaries, R imp
 676 indicates the relative importance of the variables in the final model.

677 **General Model**

678 **NEP (Fig. 1)**

	Estimate	Std.Err	t value	Pr(> t)	
Intercept	-1056	219.8	-4.803	0.0000124	***
gpp	0.8679	0.1235	7.029	3.38E-09	***
age	4.76	1.319	3.609	0.000664	***
nutrient.classLOW	934.9	229.4	4.076	0.000149	***
mat	20.67	6.186	3.342	0.001502	**
gpp:age	-0.00293	0.0007656	-3.828	0.000333	***
gpp:nutrient.classLOW	-0.6802	0.1318	-5.162	0.00000346	***
age:nutrient.classLOW	-1.862	0.7679	-2.425	0.018614	*

$R^2 = 0.7356$ $adj R^2 = 0.702$

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	809163	1	23.0691	0.00001244	***	
gpp	1732864	1	49.4036	3.384E-09	***	0.18
age	456867	1	13.0252	0.0006645	***	0.03
nutrient.class	582787	1	16.6151	0.0001486	***	0.19
mat	391717	1	11.1678	0.0015015	**	0.09
gpp:age	513890	1	14.6509	0.0003332	***	0.09
gpp:nutrient.class	934745	1	26.6494	3.465E-06	***	0.15
age:nutrient.class	206289	1	5.8813	0.0186138	*	0.01
Residuals	1929161	55				

679 **NEP model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R Imp
(Intercept)	-935.8	239.8	244.1	3.833	0.00013	*** (Intercept)	1.00
age	3.947	2.058	2.075	1.902	0.05715	. gpp	1.00
gpp	0.7856	0.1379	0.1404	5.597	<0.00001	*** gpp:NA	1.00
mat	18.69	6.871	7.011	2.667	0.00766	** NA	1.00
NA.LOW	731.9	287.5	291.9	2.507	0.01217	* mat	0.97
age:gpp	-0.00284	0.00081	0.000824	3.445	0.00057	*** MNG	0.62
age:NA.LOW	-1.865	0.7762	0.7939	2.349	0.01881	* gpp:MNG	0.55
gpp:NA.LOW	-0.5897	0.164	0.1668	3.536	0.00041	*** age	0.53
MNG.UM	280.4	156.1	158.2	1.773	0.07628	. wd	0.50
wd	2.738	1.733	1.768	1.549	0.12146	age:gpp	0.45
gpp:MNG.UM	-0.2451	0.0736	0.07525	3.257	0.00112	** age:NA	0.42
MNG.UM:NA.LOW	-72.39	136	139.1	0.52	0.60276	map	0.15
map	-0.0281	0.09175	0.0938	0.3	0.76454	MNG:NA	0.08
						age:MNG	0.00

16 models $\Delta < 4$

680

681 **Re (Fig. 2)**

	Estimate	Std.Err	t value	Pr(> t)	
(Intercept)	1097	228.8	4.794	0.0000129	***
gpp	0.09329	0.1285	0.726	0.471097	
age	-4.788	1.373	-3.487	0.000968	***
nutrient.classLOW	-955.6	238.8	-4.002	0.00019	***
mat	-17.02	6.44	-2.643	0.010676	*
gpp:age	0.00294	0.000797	3.688	0.000519	***
gpp:nutrient.classLOW	0.6805	0.1372	4.961	0.00000712	***
age:nutrient.classLOW	1.967	0.7995	2.46	0.017077	*

$R^2 = 0.9108$ $adj R^2 = 0.8995$

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	873556	1	22.9785	0.00001286	***	
gpp	20021	1	0.5266	0.4710968		0.64
age	462225	1	12.1587	0.0009684	***	0.01
nutrient.class	608864	1	16.0159	0.0001896	***	0.03
mat	265614	1	6.9869	0.0106758	*	0.16
gpp:age	517154	1	13.6035	0.0005186	***	0.03
gpp:nutrient.class	935495	1	24.6078	7.125E-06	***	0.05
age:nutrient.class	230005	1	6.0502	0.0170767	*	0.01
Residuals	2090888	55				

682 **Re model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R Imp
(Intercept)	1028	252.1	256.7	4.004	6.2E-05	*** (Intercept)	1.00
age	-4.61	1.463	1.492	3.089	0.00201	** gpp	1.00
gpp	0.1505	0.1434	0.146	1.031	0.30247	NA	1.00
mat	-15.27	7.095	7.242	2.108	0.03502	* gpp:NA	1.00
NA.LOW	-765.2	303.2	307.8	2.486	0.01293	* mat	0.85
age:gpp	0.00283	0.00083	0.00085	3.332	0.00086	*** age	0.71
age:NA.LOW	1.971	0.8094	0.8277	2.382	0.01723	* age:gpp	0.71
gpp:NA.LOW	0.5838	0.1719	0.1747	3.342	0.00083	*** age:NA	0.68
wd	-3.12	1.809	1.845	1.691	0.09077	. wd	0.59
MNG.UM	-214.4	164.1	165.9	1.292	0.1963	MNG	0.39
gpp:MNG.UM	0.2253	0.07724	0.07896	2.853	0.00434	** gpp:MNG	0.29
map	0.05755	0.09505	0.09721	0.592	0.55382	map	0.15
MNG.UM:NA.LOW	76.51	142	145.3	0.527	0.59841	MNG:NA	0.03
						age:MNG	0.00

13 models $\Delta < 4$

683

684 **Models weighted by the uncertainty of the estimates (Supplementary Fig. 5)**

685 **NEP**

	Estimate	Std.Err	t value	Pr(> t)	
(Intercept)	-848.4	226.4	-3.747	0.000431	***
gpp	0.7368	0.1328	5.548	8.53E-07	***
age	5.099	1.522	3.349	0.001468	**
nutrient.classLOW	719.1	240.9	2.985	0.004221	**
mat	17.79	6.842	2.6	0.011953	*
gpp:age	-0.00308	0.0009198	-3.346	0.001484	**
gpp:nutrient.classLOW	-0.515	0.1536	-3.352	0.001457	**
age:nutrient.classLOW	-2.288	0.8235	-2.778	0.007462	**

R²= 0.614 adj R²= 0.5648

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R ²
(Intercept)	15401	1	14.0377	0.0004313	***	
gpp	33773	1	30.783	8.532E-07	***	0.20
age	12308	1	11.2187	0.0014678	**	0.02
nutrient.class	9778	1	8.9126	0.0042208	**	0.14
mat	7416	1	6.7591	0.011953	*	0.08
gpp:age	12281	1	11.1935	0.0014844	**	0.06
gpp:nutrient.class	12327	1	11.2351	0.001457	**	0.08
age:nutrient.class	8469	1	7.7187	0.0074616	**	0.03
Residuals	60343	55				

686

687 **NEP model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R Imp
(Intercept)	1028	252.1	256.7	4.004	6.2E-05	*** (Intercept)	1.00
age	-4.61	1.463	1.492	3.089	0.00201	** gpp	1.00
gpp	0.1505	0.1434	0.146	1.031	0.30247	NA	1.00
mat	-15.27	7.095	7.242	2.108	0.03502	* gpp:NA	1.00
NA.LOW	-765.2	303.2	307.8	2.486	0.01293	* mat	0.85
age:gpp	0.002829	0.00083	0.000849	3.332	0.00086	*** age	0.71
age:NA.LOW	1.971	0.8094	0.8277	2.382	0.01723	* age:gpp	0.71
gpp:NA.LOW	0.5838	0.1719	0.1747	3.342	0.00083	*** age:NA	0.68
wd	-3.12	1.809	1.845	1.691	0.09077	. wd	0.59
MNG.UM	-214.4	164.1	165.9	1.292	0.1963	MNG	0.39
gpp:MNG.UM	0.2253	0.07724	0.07896	2.853	0.00434	** gpp:MNG	0.29
map	0.05755	0.09505	0.09721	0.592	0.55382	map	0.15
MNG.UM:NA.LOW	76.51	142	145.3	0.527	0.59841	MNG:NA	0.03
						age:MNG	0.00

13 models $\Delta < 4$

688

689

690 **Re**

	Estimate	Std.Err	t value	Pr(> t)
(Intercept)	843.6	226	3.733	0.000451 ***
gpp	0.257	0.1309	1.963	0.054717 .
age	-4.752	1.544	-3.078	0.003249 **
nutrient.classLOW	-710.6	240.3	-2.957	0.004569 **
mat	-14.44	6.942	-2.08	0.042228 *
gpp:age	0.002832	0.0009312	3.041	0.003608 **
gpp:nutrient.classLOW	0.5055	0.1522	3.321	0.001596 **
age:nutrient.classLOW	2.252	0.8341	2.7	0.009199 **

$R^2 = 0.8781$ $\text{adj } R^2 = 0.8626$

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)	R^2
(Intercept)	10232	1	13.9334	0.0004507 ***	
gpp	2830	1	3.8532	0.0547171 .	0.65
age	6956	1	9.4726	0.0032495 **	0.00
nutrient.class	6421	1	8.7445	0.0045687 **	0.02
mat	3176	1	4.3251	0.0422277 *	0.15
gpp:age	6791	1	9.2477	0.0036078 **	0.02
gpp:nutrient.class	8101	1	11.032	0.0015956 **	0.03
age:nutrient.class	5353	1	7.2893	0.009199 **	0.01
Residuals	40389	55			

691

692 **Re model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R Imp
(Intercept)	787.1	271	275.3	2.858	0.00426 **	(Intercept)	1.00
age	-4.66	1.566	1.602	2.91	0.00362 **	gpp	1.00
gpp	0.2976	0.1511	0.1536	1.937	0.05273 .	NA	1.00
mat	-13.85	7.181	7.34	1.887	0.05921 .	gpp:NA	0.97
NA.LOW	-557	302.8	307	1.814	0.06964 .	mat	0.73
age:gpp	0.00279	0.00094	0.00097	2.889	0.00387 **	age	0.70
age:NA.LOW	2.252	0.8484	0.8675	2.596	0.00942 **	age:gpp	0.70
gpp:NA.LOW	0.4508	0.1705	0.1735	2.598	0.00938 **	age:NA	0.70
wd	-2.856	1.872	1.913	1.493	0.1354	wd	0.51
MNG.UM	-185.5	162	163.9	1.132	0.25761	MNG	0.30
gpp:MNG.UM	0.2135	0.09021	0.09213	2.317	0.02049 *	gpp:MNG	0.22
map	-0.03157	0.08994	0.09188	0.344	0.73117	map	0.11
						age:MNG	0.00
						MNG:NA	0.00

15 models $\Delta < 4$

693

694

695 **Models forests Eddy Covariance data**

696 **NEP**

	Estimate	Std.Err	t value	Pr(> t)	
(Intercept)	-575.607	257.70547	-2.234	0.029924	*
gpp	0.58016	0.1567	3.702	0.000525	***
nutrient.classLOW	468.7595	281.1306	1.667	0.101563	
managementUM	321.0978	119.82562	2.68	0.009896	**
mat	18.41545	7.09241	2.597	0.012274	*
gpp:nutrient.classLOW	-0.43306	0.18555	-2.334	0.02358	*
gpp:managementUM	-0.25613	0.07463	-3.432	0.001197	**

$R^2 = 0.58$ **adj $R^2 = 0.5306$**

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	181821	1	4.9889	0.029924	*	
gpp	499578	1	13.7077	0.000525	***	0.18
nutrient.class	101326	1	2.7803	0.101563		0.11
management	261706	1	7.1808	0.009896	**	0.04
mat	245706	1	6.7418	0.012274	*	0.09
gpp:nutrient.class	198516	1	5.447	0.02358	*	0.06
gpp:management	429267	1	11.7785	0.001197	**	0.11
Residuals	1858698	51				

697

698 **NEP model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R Imp
(Intercept)	-541.6	328.6	333.1	1.626	0.10396	(Intercept)	1.00
gpp	0.5573	0.1879	0.1907	2.922	0.00348	gpp	1.00
MNG.UM	328.7	130.2	133.2	2.467	0.01361	NA	1.00
mat	17.67	7.436	7.606	2.323	0.02018	MNG	0.91
NA.LOW	391.7	370.2	374.8	1.045	0.29596	gpp:MNG	0.91
gpp:MNG.UM	-0.2623	0.07625	0.07807	3.36	0.00078	mat	0.90
gpp:NA.LOW	-0.4468	0.1904	0.1948	2.293	0.02183	gpp:NA	0.83
wd	1.995	1.977	2.023	0.986	0.32403	age	0.18
MNG.UM:NA.LOW	-91.61	138.1	141.5	0.648	0.51729	wd	0.18
age	2.343	2.424	2.434	0.963	0.33564	MNG:NA	0.11
age:gpp	-0.00275	0.0008	0.000822	3.341	0.00083	age:gpp	0.09
age:NA.LOW	-1.928	0.799	0.8188	2.354	0.01855	age:NA	0.09
map	0.02251	0.09908	0.1015	0.222	0.82458	map	0.08
						age:MNG	0.00

9 models $\Delta < 4$

699

700

701 **Re**

	Estimate	Std.Err	t value	Pr(> t)
(Intercept)	627.57583	260.16476	2.412	0.01949 *
gpp	0.38836	0.1582	2.455	0.01754 *
nutrient.classLOW	-522.60114	283.81343	-1.841	0.07139 .
managementUM	-314.55694	120.96911	-2.6	0.01215 *
mat	-17.83373	7.16009	-2.491	0.01605 *
gpp:nutrient.classLOW	0.46899	0.18732	2.504	0.01554 *
gpp:managementUM	0.2495	0.07534	3.311	0.00171 **

$R^2 = 0.9163$ $\text{adj } R^2 = 0.9065$

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)	R^2
(Intercept)	216134	1	5.8188	0.01949 *	
gpp	223853	1	6.0266	0.01754 *	0.67
nutrient.class	125940	1	3.3906	0.07139 .	0.01
management	251153	1	6.7616	0.01215 *	0.01
mat	230428	1	6.2036	0.01605 *	0.19
gpp:nutrient.class	232822	1	6.2681	0.01554 *	0.01
gpp:management	407320	1	10.966	0.00171 **	0.02
Residuals	1894342	51			

702

703 **Re model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R Imp
(Intercept)	643	310.3	315.7	2.037	0.04166 *	(Intercept)	1.00
gpp	0.3806	0.1769	0.1803	2.111	0.03475 *	gpp	1.00
MNG.UM	-321.6	134.1	137.2	2.344	0.01908 *	NA	1.00
mat	-17.6	7.308	7.486	2.351	0.01871 *	gpp:NA	0.95
NA.LOW	-509.2	338.6	344.3	1.479	0.1391	mat	0.90
gpp:MNG.UM	0.2514	0.07647	0.07833	3.21	0.00133 **	MNG	0.89
gpp:NA.LOW	0.4727	0.1973	0.2017	2.344	0.01908 *	gpp:MNG	0.89
wd	-1.792	1.933	1.981	0.905	0.36569	age	0.20
MNG.UM:NA.LOW	109.1	139.1	142.6	0.765	0.44426	wd	0.14
age	-2.459	2.41	2.421	1.016	0.3098	MNG:NA	0.12
age:gpp	0.00268	0.00081	0.00083	3.236	0.00121 **	age:gpp	0.11
age:NA.LOW	1.953	0.8048	0.8247	2.367	0.01791 *	age:NA	0.11
map	-0.01641	0.1001	0.1025	0.16	0.87287	map	0.09
						age:MNG	0.00

8 models $\Delta < 4$

704

705

706 **Models without nutrient status**

707 **NEP**

	Estimate	Std.Err	t	Pr(> t)	
(Intercept)	-594.399	133.86874	-4.44	4.1E-05	***
gpp	0.511744	0.0616439	8.302	1.9E-11	***
managementUM	355.4655	131.84313	2.696	0.00917	**
wd	5.280222	1.6748899	3.153	0.00256	**
gpp:managementUM	-0.36777	0.0796442	-4.62	2.2E-05	***

$R^2 = 0.5974$ $adj R^2 = 0.5697$

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	998461	1	19.7151	4.09E-05	***	
gpp	3490265	1	68.9169	1.92E-11	***	0.31
management	368140	1	7.2691	0.009166	**	0.08
wd	503344	1	9.9388	0.002562	**	0.05
gpp:management	1079913	1	21.3234	2.20E-05	***	0.15
Residuals	2937383	58				

708

709 **NEP model averaging**

710

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R
(Intercept)	-571.522	154.13	157.1015	3.638	0.00028	*** (Intercept)	1.00
gpp	0.51726	0.06999	0.07143	7.241	2.0E-16	*** gpp	1.00
MNG.UM	331.4987	138.953	141.85	2.337	0.01944	* MNG	1.00
wd	5.23634	1.73593	1.7725	2.954	0.00314	** gpp:MNG	1.00
gpp:MNG.UM	-0.3526	0.08492	0.08666	4.069	4.7E-05	*** wd	1.00
map	-0.11618	0.09751	0.09959	1.167	0.24337	map	0.38
age	0.3439	0.45327	0.46312	0.743	0.45774	age	0.22
mat	3.80219	7.9414	8.10027	0.469	0.63879	mat	0.19
						age:gpp	0.00
						age:MNG	0.00

6 models $\Delta < 4$

711

712

713

714 **Re**

	Estimate	Std.Err	t	Pr(> t)	
(Intercept)	608.429056	137.84864	4.414	0.0000448	***
gpp	0.4893964	0.0634765	7.71	1.88E-10	***
managementUM	-348.463312	135.7628	-2.567	0.01287	*
wd	-5.4720214	1.7246841	-3.173	0.00242	**
gpp:managementUM	0.3532584	0.082012	4.307	0.0000646	***

R²= 0.8672 adj R²= 0.858

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R ²
(Intercept)	1046150	1	19.481	4.48E-05	***	
gpp	3192086	1	59.442	1.88E-10	***	0.70
management	353779	1	6.588	0.01287	*	0.02
wd	540575	1	10.066	0.002415	**	0.11
gpp:management	996345	1	18.554	6.46E-05	***	0.04
Residuals	3114635	58				

715

716 **Re model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R
(Intercept)	553.652	163.49	166.527	3.325	0.00089	*** (Intercept)	1.00
gpp	0.46987	0.07201	0.07349	6.393	2.0E-16	*** gpp	1.00
MNG.UM	-301.36	144.967	147.921	2.037	0.04162	* MNG	1.00
map	0.16497	0.09806	0.10018	1.647	0.09961	. gpp:MNG	1.00
wd	-5.33181	1.77344	1.811	2.944	0.00324	** wd	1.00
gpp:MNG.UM	0.31923	0.0905	0.09226	3.46	0.00054	*** map	0.57
mat	-1.60924	8.40043	8.56236	0.188	0.85092	mat	0.18
age	-0.27027	0.46671	0.47681	0.567	0.57084	age	0.20
						age:gpp	0.00
						age:MNG	0.00

6 models $\Delta < 4$

717

718

719 **Models excluding forests with GPP>2500**

720 **NEP (Fig. 1)**

	Estimate	Std.Err	t value	Pr(> t)	
Intercept)	-862.685	196.8156	-4.383	0.0000557	***
gpp	0.7604	0.1203	6.32	5.59E-08	***
nutrient.classLOW	441.8157	226.904	1.947	0.05682	.
wd	4.2971	1.5516	2.77	0.00772	**
gpp:nutrient.classLOW	-0.4184	0.1396	-2.998	0.00413	**

R²= 0.7179 adj R²= 0.6966

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R ²
(Intercept)	706098	1	19.2125	0.00005568	***	
gpp	1467744	1	39.9365	5.592E-08	***	0.44
nutrient.class	139341	1	3.7914	0.056824	.	0.17
wd	281899	1	7.6703	0.007721	**	0.05
gpp:nutrient.class	330378	1	8.9894	0.004128	**	0.06
Residuals	1947852	53				

721

722 **NEP model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)		Variables	R Imp
(Intercept)	-869.3	197.7	202.4	4.295	1.7E-05	***	(Intercept)	1.00
gpp	0.7416	0.1187	0.1215	6.105	<0.00001	***	gpp	1.00
mat	17.13	6.702	6.847	2.502	0.01233	*	NA	1.00
NA.LOW	700.2	250.3	255.2	2.744	0.00607	**	gpp:NA	1.00
wd	2.96	1.667	1.705	1.737	0.08247	.	mat	0.95
gpp:NA.LOW	-0.5919	0.1571	0.1602	3.696	0.00022	***	wd	0.63
age	0.4008	0.6631	0.6738	0.595	0.55191		age	0.20
MNG.UM	28.78	57.71	59.08	0.487	0.6262		MNG	0.15
map	0.003563	0.09553	0.09778	0.036	0.97093		map	0.13
age:gpp	-0.00076	0.00076	0.000778	0.982	0.32601		age:gpp	0.04
							age:MNG	0.00
							age:NA	0.00
							gpp:MNG	0.00
							MNG:NA	0.00

10 models $\Delta < 4$

723

724

725 **Re (Fig. 2)**

	Estimate	Std.Err	t value	Pr(> t)
(Intercept)	904.8063	195.6001	4.626	0.0000244 ***
gpp	0.2193	0.1196	1.834	0.07224 .
nutrient.classLOW	-460.8056	225.5027	-2.043	0.04599 *
wd	-4.3754	1.542	-2.838	0.00643 **
gpp:nutrient.classLOW	0.4221	0.1387	3.043	0.00364 **

R²= 0.7411 adj R²= 0.7215

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)	R ²
(Intercept)	776734	1	21.398	0.00002441 ***	
gpp	122124	1	3.3644	0.072238 .	0.55
nutrient.class	151576	1	4.1757	0.045992 *	0.03
wd	292264	1	8.0515	0.006429 **	0.10
gpp:nutrient.class	336102	1	9.2592	0.003641 **	0.06
Residuals	1923867	53			

726

727 **Re model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R Imp
(Intercept)	911.146	200.906	205.649	4.431	9.4E-06 ***	(Intercept)	1.00
gpp	0.22852	0.12099	0.12381	1.846	0.06494 .	gpp	1.00
mat	-12.4522	6.86698	7.01552	1.775	0.07591 .	NA	1.00
NA.LOW	-586.236	259.596	264.532	2.216	0.02668 *	gpp:NA	1.00
wd	-3.77785	1.69819	1.73473	2.178	0.02942 *	wd	0.86
gpp:NA.LOW	0.50671	0.16353	0.16657	3.042	0.00235 **	mat	0.63
age	-0.14644	0.34228	0.35019	0.418	0.67582	MNG	0.17
MNG.UM	-24.049	60.7591	62.0809	0.387	0.69847	age	0.14
map	-0.01268	0.09794	0.10008	0.127	0.89922	map	0.13
						age:gpp	0.00
						age:MNG	0.00
						age:NA	0.00
						gpp:MNG	0.00
						MNG:NA	0.00

10 models $\Delta < 4$

728

729

730 **Weighted models excluding forests with GPP>2500**

731 **NEP**

	Estimate	Std.Err	t value	Pr(> t)	
Intercept)	-567.832	201.3927	-2.82	0.00675	**
gpp	0.5898	0.1245	4.737	0.0000167	***
nutrient.classLOW	484.8521	235.3754	2.06	0.04433	*
mat	16.0388	6.577	2.439	0.01813	*
gpp:nutrient.classLOW	-0.4356	0.1585	-2.748	0.00818	**

R²= 0.6143 adj R²= 0.5852

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R ²
(Intercept)	8623	1	7.9497	0.00675	**	
gpp	24335	1	22.435	0.00001666	***	0.34
nutrient.class	4603	1	4.2432	0.044333	*	0.11
mat	6450	1	5.9468	0.018128	*	0.12
gpp:nutrient.class	8191	1	7.5515	0.008178	**	0.05
Residuals	57488	53				

732

733 **NEP model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)		Variables	R Imp
(Intercept)	-630.542	240.08	244.2723	2.581	0.00984	**	(Intercept)	1.00
gpp	0.58475	0.13469	0.13717	4.263	2E-05	***	gpp	1.00
mat	13.9113	7.15618	7.30633	1.904	0.05691	.	NA	1.00
NA.LOW	313.3486	302.626	306.4643	1.022	0.30656		gpp:NA	0.87
wd	3.69658	1.81166	1.85251	1.995	0.04599	*	wd	0.76
gpp:NA.LOW	-0.37807	0.17028	0.17373	2.176	0.02954	*	mat	0.75
map	0.07223	0.08776	0.08967	0.806	0.4205		map	0.19
MNG.UM	29.63878	54.6654	55.95706	0.53	0.59634		MNG	0.12
age	0.11882	0.35025	0.35868	0.331	0.74045		age	0.10
							age:gpp	0.00
							age:MNG	0.00
							age:NA	0.00
							gpp:MNG	0.00
							MNG:NA	0.00

12 models $\Delta < 4$

734

735 **Re**

	Estimate	Std.Err	t value	Pr(> t)
(Intercept)	330.71463	132.59705	2.494	0.01572 *
gpp	0.58081	0.05895	9.852	1.16E-13 ***
nutrient.classLOW	170.1716	56.38605	3.018	0.00388 **
wd	-3.91987	1.78531	-2.196	0.03243 *

$R^2 = 0.7128$ $adj R^2 = 0.6968$

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)	R^2
(Intercept)	4639	1	6.2207	0.01572 *	
gpp	72381	1	97.0636	1.156E-13 ***	0.58
nutrient.class	6792	1	9.1082	0.003878 **	0.03
wd	3595	1	4.8208	0.032435 *	0.11
Residuals	40268	54			

736

737 **Re model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R Imp
(Intercept)	614.725	234.124	238.326	2.579	0.0099 **	(Intercept)	1.00
gpp	0.40001	0.13299	0.13544	2.953	0.00314 **	gpp	1.00
mat	-11.4335	7.2117	7.36514	1.552	0.12057	NA	1.00
NA.LOW	-303.751	284.67	288.541	1.053	0.29247	gpp:NA	0.90
wd	-3.46331	1.80117	1.8424	1.88	0.06014 .	wd	0.72
gpp:NA.LOW	0.35391	0.16485	0.16807	2.106	0.03523 *	mat	0.56
map	-0.04307	0.08784	0.08976	0.48	0.63136	MNG	0.14
MNG.UM	-19.3384	58.1629	59.4065	0.326	0.74478	map	0.14
age	-0.05802	0.34906	0.35716	0.162	0.87094	age	0.12
						age:gpp	0.00
						age:MNG	0.00
						age:NA	0.00
						gpp:MNG	0.00
						MNG:NA	0.00

15 models $\Delta < 4$

738

739 **Models using only managed forests**

740 **NEP**

	Estimate	Std.Err	t value	Pr(> t)	
(Intercept)	-857.573	205.9132	-4.165	0.000201	***
gpp	0.7092	0.1253	5.661	0.00000237	***
nutrient.classLOW	257.9824	249.5965	1.034	0.308621	
wd	6.39	1.8149	3.521	0.001247	**
gpp:nutrient.classLOW	-0.2955	0.1474	-2.005	0.053009	.

$R^2 = 0.7857$ **adj $R^2 = 0.7605$**

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	619836	1	17.345	0.0002014	***	
gpp	1145367	1	32.0511	2.372E-06	***	0.52
nutrient.class	38177	1	1.0683	0.3086206		0.14
wd	443006	1	12.3967	0.0012471	**	0.09
gpp:nutrient.class	143617	1	4.0189	0.0530094	.	0.04
Residuals	1215014	34				

741

742 **NEP model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)		Variables	R Imp
(Intercept)	-872.4	254.7	261.1	3.341	0.00083	***	(Intercept)	1.00
gpp	0.6644	0.1388	0.1426	4.66	3.2E-06	***	gpp	1.00
mat	16.51	9.362	9.723	1.698	0.08957	.	NA.	1.00
NA.LOW	282.1	334.3	341	0.827	0.408		wd	1.00
wd	6.396	2.165	2.229	2.869	0.00412	**	gpp:NA	0.85
gpp:NA.LOW	-0.3741	0.172	0.1776	2.107	0.03516	*	mat	0.49
age	0.9862	0.8297	0.8554	1.153	0.24892		age	0.46
age:NA.LOW	-1.362	1.124	1.168	1.166	0.24349		map	0.13
map	-0.02869	0.118	0.1222	0.235	0.81435		age:NA	0.11
age:gpp	0.00027	0.00105	0.001097	0.246	0.80581		age:gpp	0.03

13 models $\Delta < 4$

743

744

745 **Re**

	Estimate	Std.Err	t value	Pr(> t)	
(Intercept)	909.3045	208.0546	4.371	0.000111	***
gpp	0.2617	0.1266	2.067	0.04639	*
nutrient.classLOW	-323.2086	252.1922	-1.282	0.208656	
wd	-6.2747	1.8337	-3.422	0.001636	**
gpp:nutrient.classLOW	0.3361	0.1489	2.257	0.03055	*

$R^2 = 0.8121$ $adj R^2 = 0.79$

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	696872	1	19.1014	0.0001107	***	
gpp	155911	1	4.2735	0.0463903	*	0.57
nutrient.class	59923	1	1.6425	0.2086559		0.03
wd	427173	1	11.7089	0.0016363	**	0.17
gpp:nutrient.class	185837	1	5.0938	0.0305504	*	0.05
Residuals	1240417	34				

746

747 **Re model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R Imp
(Intercept)	928.819	249.516	256.331	3.624	0.00029	*** (Intercept)	1.00
gpp	0.29454	0.14175	0.14572	2.021	0.04325	* gpp	1.00
NA.LOW	-353.056	325.228	332.658	1.061	0.28855	NA	1.00
wd	-6.27146	2.166	2.23117	2.811	0.00494	** wd	1.00
gpp:NA.LOW	0.3958	0.17112	0.17674	2.239	0.02513	* gpp:NA	0.90
mat	-15.2377	9.50801	9.87347	1.543	0.12276	mat	0.44
age	-1.00995	0.8149	0.83836	1.205	0.22833	age	0.41
age:NA.LOW	1.42601	1.14127	1.18605	1.202	0.22924	age:NA	0.12
map	0.03553	0.11456	0.11897	0.299	0.76523	map	0.10
						age:gpp	0.00

10 models $\Delta < 4$

748

749

750 **Models using an alternative nutrient availability classification**

751 **NEP**

	Estimate	Std.Err	t value	Pr(> t)	
Intercept)	-926.2	195.4	-4.74	0.0000165	***
gpp	0.7644	0.1093	6.994	4.6E-09	***
age	5.143	1.253	4.104	0.000141	***
alternutrLOW	769.5	203	3.79	0.000387	***
mat	20.21	5.225	3.869	0.000302	***
gpp:age	-0.00337	0.0007395	-4.557	0.0000309	***
gpp:alternutrLOW	-0.5263	0.1166	-4.515	0.0000357	***
age:alternutrLOW	-1.918	0.7773	-2.468	0.016854	*

$R^2 = 0.7553$ **adj $R^2 = 0.723$**

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
Intercept)	623153	1	22.4697	0.00001645	***	
gpp	1356752	1	48.9219	4.604E-09	***	0.25
age	467161	1	16.8449	0.0001407	***	0.04
alternutr	398366	1	14.3643	0.000387	***	0.12
mat	415043	1	14.9657	0.0003016	***	0.11
gpp:age	575924	1	20.7667	0.00003088	***	0.1
gpp:alternutr	565233	1	20.3812	0.0000357	***	0.11
age:alternutr	168904	1	6.0903	0.0168544	*	0.02
Residuals	1469850	53				

752

753 **NEP model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R
Intercept	-924.6	208.3	212.8	4.344	1.4E-05	*** (Intercept)	1.00
age	5	1.387	1.413	3.539	0.0004	*** age	1.00
alternutrLOW	761.1	213.8	218.6	3.482	0.0005	*** alternutr	1.00
gpp	0.7599	0.1127	0.1152	6.598	2E-16	*** gpp	1.00
mat	20.18	5.445	5.572	3.622	0.00029	*** mat	1.00
age:alternutrLOW	-1.943	0.7858	0.8042	2.416	0.01571	* age:gpp	1.00
age:gpp	-0.00331	0.0008	0.000812	4.077	4.6E-05	*** alternutr:gpp	1.00
alternutrLOW:gpp	-0.5283	0.1217	0.1245	4.244	2.2E-05	*** age:alternutr	0.93
map	0.05238	0.08533	0.08736	0.6	0.54879	map	0.15
MNG.UM	25.84	60.62	62.06	0.416	0.67716	MNG	0.14
wd	0.508	1.615	1.653	0.307	0.7586	wd	0.13
						age:MNG	0.00
						alternutr:MNG	0.00
						gpp:MNG	0.00

5 models $\Delta < 4$

754

755

756 **Re**

	Estimate	Std.Err	t value	Pr(> t)	
(Intercept)	977.7	198	4.939	0.00000824	***
gpp	0.2071	0.1107	1.87	0.067002	.
age	-5.106	1.27	-4.022	0.000184	***
alternutrLOW	-828.8	205.7	-4.029	0.00018	***
mat	-19.72	5.294	-3.725	0.000475	***
gpp:age	0.003305	0.0007492	4.41	0.0000508	***
gpp:alternutrLOW	0.5626	0.1181	4.763	0.0000152	***
age:alternutrLOW	1.975	0.7876	2.508	0.015246	*

$R^2 = 0.9122$ $adj R^2 = 0.9006$

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	694393	1	24.3888	8.243E-06	***	
gpp	99570	1	3.4971	0.0670024	.	0.67
age	460518	1	16.1745	0.0001841	***	0.01
alternutr	462143	1	16.2316	0.0001799	***	0.02
mat	395084	1	13.8763	0.0004749	***	0.13
gpp:age	553836	1	19.4521	0.0000508	***	0.04
gpp:alternutr	645866	1	22.6844	0.00001521	***	0.04
age:alternutr	179061	1	6.2891	0.0152462	*	0.01
Residuals	1509004	53				

757

758 **Re model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R Imp
(Intercept)	988.9	205.1	209.8	4.713	2.4E-06	*** (Intercept)	1.00
age	-5.131	1.284	1.314	3.905	9.4E-05	*** age	1.00
alternutrLOW	-830.8	212.8	217.7	3.815	0.00014	*** alternutr	1.00
gpp	0.2053	0.1117	0.1143	1.796	0.07251	. gpp	1.00
mat	-19.53	5.501	5.63	3.469	0.00052	*** mat	1.00
age:alternutrLOW	1.996	0.7959	0.8146	2.451	0.01425	* age:alternutr	1.00
age:gpp	0.00332	0.00076	0.00078	4.272	1.9E-05	*** age:gpp	1.00
alternutrLOW:gpp	0.5642	0.1231	0.126	4.479	7.5E-06	*** alternutr:gpp	1.00
map	-0.04651	0.08653	0.08859	0.525	0.59959	map	0.16
MNG.UM	-24.53	61.43	62.9	0.39	0.69654	MNG	0.15
wd	-0.5608	1.636	1.675	0.335	0.7377	wd	0.14
						age:MNG	0.00
						alternutr:MNG	0.00
						gpp:MNG	0.00

4 models $\Delta < 4$

759

760

761 **Models with the factors extracted from the nutrient classification**

762 **NEP**

	Estimate	Std.Err	β	β Std.Err	t value	Pr(> t)	
(Intercept)	-269.131	88.209304	0	0	-3.051	0.00346	**
f1	-27.8263	25.151078	-0.358	0.3235612	-1.106	0.27322	
gpp	0.414041	0.0556693	0.87959	0.1182636	7.438	<.0001	***
managementUM	269.0477	124.50198	0.38392	0.1776568	2.161	0.03491	*
f1:gpp	0.030442	0.0129536	0.7639	0.3250582	2.35	0.02226	*
gpp:managementUM	-0.2593	0.0770538	-0.6833	0.2030509	-3.365	0.00137	**
	R2= 0.6811		adj R2= 0.6532				

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R2
(Intercept)	379989	1	9.3089	0.003459	**	
f1	49966	1	1.224	0.273216		0.23008
gpp	2258026	1	55.3167	5.93E-10	***	0.25579
management	190625	1	4.6699	0.034912	*	0.05029
f1:gpp	225437	1	5.5227	0.022257	*	0.05242
gpp:management	462245	1	11.324	0.001374	**	0.09254
Residuals	2326737	57				

763

764 **NEP model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R Imp
(Intercept)	-283.9	117.3	119.3	2.38	0.01733	*	(Intercept) 1.00
f1	-23.95	29.63	30.08	0.796	0.42587		F1 1.00
gpp	0.3949	0.0736	0.07487	5.274	1.00E-07	***	gpp 1.00
managementUM	287.8	129	131.8	2.184	0.02897	*	MNG 1.00
f1:gpp	0.03079	0.01348	0.01376	2.236	0.02532	*	F1:GPP 0.91
gpp:managementUM	-0.2697	0.07942	0.08109	3.326	0.00088	***	gpp:MNG 1.00
mat	8.61	6.457	6.599	1.305	0.19198		mat 0.40
wd	1.836	1.88	1.917	0.958	0.33831		wd 0.23
f1:managementUM	10.99	24.14	24.68	0.445	0.65613		age 0.14
age	0.1778	0.4022	0.411	0.433	0.66526		f1:MNG 0.11
map	-0.00703	0.09706	0.09907	0.071	0.94347		map 0.11

13 models $\Delta < 4$

765

766

767 **Re**

	Estimate	Std.Err	β	β Std.Err	t value	Pr(> t)	
(Intercept)	262.962863	95.062739	0	0	2.766	0.007595	**
f1	-29.580566	6.7969963	-0.2122776	0.04877697	-4.352	5.54E-05	***
gpp	0.592046	0.0600396	0.7015992	0.0711494	9.861	5.20E-14	***
managementUM	-354.527459	127.54614	-0.2821977	0.10152452	-2.78	0.007325	**
gpp:managementUM	0.3044804	0.0785227	0.4475773	0.11542614	3.878	0.000272	***
	R2= 0.8825	adj R2= 0.8744					

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R2
(Intercept)	363520	1	7.6519	0.0075953	**	
f1	899786	1	18.94	5.54E-05	***	0.04064662
gpp	4619512	1	97.2379	5.20E-14	***	0.79499854
management	367050	1	7.7262	0.0073248	**	0.01205423
gpp:management	714312	1	15.0358	0.0002716	***	0.03479453
Residuals	2755424	58				

768

769 **Re model averaging**

	Estimate	SE	Adj SE	z val	Pr(> z)	Variables	R Imp
(Intercept)	304.659	129.075	131.275	2.321	0.0203	*	(Intercept) 1.00
f1	23.8269	30.8621	31.3221	0.761	0.4468		F1 1.00
gpp	0.5864	0.06759	0.06894	8.506	<2e-16	***	gpp 1.00
managementUM	-269.56	134.21	137.027	1.967	0.0492	*	MNG 1.00
f1:gpp	-0.03089	0.01409	0.01439	2.146	0.0319	*	F1:GPP 0.89
gpp:managementUM	0.24987	0.08332	0.08504	2.938	0.0033	**	gpp:MNG 1.00
wd	-2.08056	1.89952	1.93923	1.073	0.2833		wd 0.30
mat	-5.51703	6.9059	7.05402	0.782	0.4341		mat 0.18
map	0.05393	0.09743	0.09953	0.542	0.5879		map 0.15
f1:managementUM	-10.2502	25.1642	25.7219	0.398	0.6903		f1:MNG 0.11
age	-0.10723	0.41819	0.42727	0.251	0.8018		age 0.11

13 models $\Delta < 4$

770

771

772 **Models using the “medium” nutrient availability category**

773 **NEP**

	Estimate	Std.Err	β	β Std.Err	t value	Pr(> t)	
(Intercept)	-650.147	207.74185	0	0	-3.13	0.00221	**
gpp	0.689827	0.1239448	1.68764	0.30322786	5.566	1.66E-07	***
nutrient.classLOW	258.9967	227.36606	0.41185	0.36154805	1.139	0.25696	
nutrient.classMEDIUM	391.1855	238.17323	0.56405	0.34342186	1.642	0.10316	
managementOTHR	110.4697	116.18876	0.13705	0.14414666	0.951	0.34366	
managementUM	270.503	103.77753	0.38345	0.14710976	2.607	0.01032	*
wd	3.125687	1.1435189	0.20683	0.07566875	2.733	0.00723	**
gpp:nutrient.classLOW	-0.32062	0.1365047	-1.0328	0.43971008	-2.349	0.0205	*
gpp:nutrient.classMEDIUM	-0.37808	0.1422941	-0.8666	0.32615306	-2.657	0.00898	**
gpp:managementOTHR	-0.20223	0.0766118	-0.3909	0.14808735	-2.64	0.00942	**
gpp:managementUM	-0.3007	0.0626977	-0.8944	0.18649016	-4.796	4.77E-06	***

R2= 0.5834 **adj R2=** 0.548

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)	R2
(Intercept)	438923	1	9.7943	2.21E-03	**
gpp	1388151	1	30.9759	1.66E-07	***
nutrient.class	149973	2	1.6733	0.192051	
management	312383	2	3.4853	0.033835	*
wd	334825	1	7.4714	7.23E-03	**
gpp:nutrient.class	316390	2	3.53	0.032437	*
gpp:management	1030957	2	11.5026	2.73E-05	***
Residuals	5288049	118			

774

775

776

777 **Re**

	Estimate	Std.Err	β	β Std.Err	t	Pr(> t)	
(Intercept)	946.1472	225.7538	0	0	4.191	6.42E-05	***
gpp	0.1500605	0.1312338	0.17799832	0.15566652	1.143	0.255847	
nutrient.classLOW	-598.9845	238.7771	-	0.19726044	-2.509	0.013893	*
nutrient.classMEDIUM	-769.0284	254.6037	-	0.19182404	-3.02	0.003276	**
age	-2.345405	0.7963151	-	0.08718799	-2.945	0.004096	**
managementOTHR	112.3993	62.51324	0.06759027	0.03759176	1.798	0.075492	.
managementUM	171.6502	60.24119	0.12208751	0.04284699	2.849	0.005417	**
wd	-2.910387	1.324959	-	0.04379972	-2.197	0.030591	*
gpp:nutrient.classLOW	0.5007344	0.1411159	0.75653774	0.21320593	3.548	0.000615	***
gpp:nutrient.classMEDIUM	0.5897503	0.1492076	0.7248549	0.18338927	3.953	0.000153	***
gpp:age	0.00160319	0.0005973	0.24371494	0.09080813	2.684	0.008647	**

R2= 0.8971 **adj R2=** 0.8858

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R2
(Intercept)	741158	1	17.565	6.42E-05	***	
gpp	55170	1	1.3075	2.56E-01		0.71958764
nutrient.class	393809	2	4.6665	0.0117675	*	0.01904361
age	366040	1	8.6749	4.10E-03	**	0.00879914
management	397873	2	4.7147	1.13E-02	*	0.01802822
wd	203592	1	4.825	0.0305909	*	0.09880494
gpp:nutrient.class	659885	2	7.8194	0.0007349	***	0.02221301
gpp:age	303933	1	7.203	8.65E-03	**	0.01059682

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780 CUEe

	Estimate	Std.Err	β	β Std.Err	t value	Pr(> t)	
(Intercept)	-0.05665285	0.0929213	0	0	-0.61	0.5435	
gpp	0.00030991	5.251E-05	0.79007388	0.1338564	5.902	5.51E-08	***
nutrient.classLOW	-0.173781	0.064971	-0.3085533	0.1153579	-2.675	0.0088	**
nutrient.classMEDIUM	-0.02722514	0.0697433	-0.04408481	0.1129332	-0.39	0.6971	
age	0.00290722	0.0008546	0.68411616	0.2010993	3.402	0.001	***
map	-0.00016161	6.121E-05	-0.29530044	0.1118445	-2.64	0.0097	**
gpp:age	-1.9465E-06	6.354E-07	-0.63595917	0.2076081	-3.063	0.0028	**

R2= 0.3763 **adj R2=** 0.3369
ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R2
(Intercept)	0.0197	1	0.3717	0.5435249		
gpp	1.8473	1	34.8383	5.51E-08	***	0.1446
nutrient.class	0.5977	2	5.6359	0.0048644	**	0.1056
age	0.6137	1	11.5728	9.81E-04	***	0.0117
map	0.3696	1	6.9711	0.0096844	**	0.0468
gpp:age	0.4976	1	9.3836	0.0028486	**	0.0677
Residuals	5.0375	95				

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783 **GPP Models**

784 **General**

	Estimate	Std.Err	t value	Pr(> t)		R ²
(Intercept)	1306.23	137.051	9.531	1.28E-13 ***		
mat	74.397	6.163	12.072	2E-16 ***		0.65
wd	-8.874	2.581	-3.438	0.00107 **		0.1
	R ² = 0.7514		adj R ² = 0.7432			

785 **Weighted**

	Estimate	Std.Err	t value	Pr(> t)		R ²
(Intercept)	1379.807	140.646	9.811	4.39E-14 ***		
mat	63.475	6.473	9.805	4.47E-14 ***		0.56
wd	-10.171	2.751	-3.697	0.000474 ***		0.15
	R ² = 0.7056		adj R ² = 0.6958			

786 **GPP < 2500**

	Estimate	Std.Err	t value	Pr(> t)		R ²
(Intercept)	1406.357	135.555	10.375	1.83E-14 ***		
NA.LOW	-263.7	97.152	-2.714	0.0089 **		0.11
mat	56.63	7.272	7.787	2.18E-10 ***		0.47
wd	-5.408	2.517	-2.149	0.0362 *		0.04
	R ² = 0.6223		adj R ² = 0.6013			

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788 **GPP < 2500 Weighted**

	Estimate	Std.Err	t value	Pr(> t)		R ²
(Intercept)	1386.784	133.901	10.357	1.57E-14 ***		
mat	51.652	7.161	7.213	1.69E-09 ***		0.44
wd	-9.159	2.644	-3.464	0.00104 **		0.14
	R ² = 0.5799		adj R ² = 0.5646			

789 **Only Managed forests**

	Estimate	Std.Err	t value	Pr(> t)		R ²
(Intercept)	1048.172	119.347	8.783	1.77E-10 ***		
NA.LOW	-309.188	117.171	-2.639	0.0122 *		0.07
mat	74.979	9.498	7.894	2.29E-09 ***		0.59
	R ² = 0.6598		adj R ² = 0.6409			

790 **Only Eddy covariance data**

	Estimate	Std.Err	t value	Pr(> t)		R ²
(Intercept)	1223.0939	167.9484	7.283	1.43E-09 ***		
mat	51.4191	8.761	5.869	2.76E-07 ***		0.38
map	0.363	0.1423	2.551	0.0136 *		0.27
wd	-12.0537	2.6356	-4.573	0.0000284 ***		0.16
	R ² = 0.811		adj R ² = 0.8005			

791 **Alternative Classification**

	Estimate	Std.Err	t value	Pr(> t)		R ²
(Intercept)	1569.856	123.786	12.682	2E-16 ***		
alternutrLOW	-216.12	90.99	-2.375	0.0209 *		0.04
mat	67.954	5.944	11.433	2E-16 ***		0.58
wd	-11.626	2.252	-5.163	0.00000321 ***		0.13
	R ² = 0.7514		adj R ² = 0.7384			

792 CUE Models

793 General

	Estimate	Std.Err	t value	Pr(> t)	
(Intercept)	-0.2251	0.113	-1.993	0.050969	.
gpp	0.0003517	0.0000645	5.452	0.00000107	***
age	0.004071	0.0009644	4.221	0.0000866	***
NA.LOW	-0.1956	0.05992	-3.264	0.001843	**
gpp:age	-2.944E-06	7.065E-07	-4.168	0.000104	***
	R ² = 0.4349		adj R ² = 0.3959		

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R ²
(Intercept)	0.1901	1	3.9722	0.050969	.	
gpp	1.42266	1	29.7273	1.068E-06	***	0.14
age	0.85283	1	17.8204	0.00008656	***	0.004
NA.	0.50995	1	10.6556	0.0018432	**	0.12
gpp:age	0.83122	1	17.3688	0.0001038	***	0.17
Residuals	2.7757	58				

794 Weighted

	Estimate	Std.Err	t value	Pr(> t)	
(Intercept)	-0.03192	0.1037	-0.308	0.75943	
gpp	0.0001887	0.0000578	3.265	0.00185	**
age	0.003124	0.001041	3.001	0.00398	**
NA.LOW	-0.03051	0.05347	-0.571	0.57044	
gpp:age	-1.967E-06	6.16E-07	-3.193	0.0023	**
age:NA.LOW	-0.001373	0.0005272	-2.604	0.01173	*
	R ² = 0.3448		adj R ² = 0.2873		

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R ²
(Intercept)	0.043	1	0.0947	0.759431		
gpp	4.8367	1	10.6612	0.001854	**	0.01
age	4.087	1	9.0088	0.003982	**	0.03
NA.	0.1478	1	0.3257	0.570442		0.16
gpp:age	4.6239	1	10.1922	0.002296	**	0.09
age:NA.	3.0765	1	6.7813	0.011726	*	0.05
Residuals	25.8594	57				

795 GPP<2500

	Estimate	Std.Err	t value	Pr(> t)	
(Intercept)	-0.504	0.1096	-4.598	0.0000261	***
gpp	0.0004657	7.229E-05	6.442	3.31E-08	***
age	0.003238	0.001097	2.952	0.00466	**
gpp:age	-2.172E-06	8.525E-07	-2.548	0.01371	*
	R ² = 0.4552		adj R ² = 0.4249		

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R ²
(Intercept)	1.03712	1	21.1416	0.00002612	***	
gpp	2.03587	1	41.5013	3.308E-08	***	0.38
age	0.42758	1	8.7162	0.00466	**	0.01
gpp:age	0.31848	1	6.4922	0.01371	*	0.07
Residuals	2.64901	54				

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797 **GPP<2500 weighted**

	Estimate	Std.Err	t value	Pr(> t)		R ²
(Intercept)	0.187674	0.036618	5.125	0.00000396 ***		
NA.LOW	-0.126927	0.035287	-3.597	0.00069 ***		0.15
mat	0.012343	0.003086	4	0.000191 ***		0.19
	R ² = 0.3397		adj R ² = 0.3157			

798 **Only Managed**

	Estimate	Std.Err	t value	Pr(> t)		R ²
(Intercept)	-0.3887	0.1444	-2.693	0.0109 *		
gpp	0.0004172	7.783E-05	5.36	0.00000585 ***		0.37
age	0.00461	0.001737	2.655	0.012 *		0.03
NA.LOW	-0.171	0.08213	-2.082	0.0449 *		0.09
gpp:age	-2.712E-06	1.304E-06	-2.079	0.0452 *		0.05
	R ² = 0.5477		adj R ² = 0.4945			

799 **Eddy covariance**

	Estimate	Std.Err	t value	Pr(> t)		R ²
(Intercept)	-0.2325	0.1195	-1.945	0.057055 .		
gpp	0.0003537	7.426E-05	4.763	0.0000152 ***		0.12
age	0.004067	0.001055	3.857	0.000313 ***		0.02
NA.LOW	-0.1892	0.06651	-2.845	0.006295 **		0.09
gpp:age	-2.933E-06	8.006E-07	-3.663	0.000576 ***		0.15
	R ² = 0.3728		adj R ² = 0.3255			

800 **Alternative Classification**

	Estimate	Std.Err	t value	Pr(> t)		R ²
Intercept)	-0.2209	0.115	-1.921	0.05998 .		
gpp	0.0002462	7.852E-05	3.136	0.00275 **		0.12
age	0.004683	0.001057	4.43	0.0000453 ***		0.01
alternutrLOW	-0.1627	0.06088	-2.672	0.0099 **		0.07
mat	0.01454	0.006533	2.225	0.03017 *		0.06
gpp:age	-3.202E-06	7.429E-07	-4.31	0.000068 ***		0.18
	R ² = 0.4426		adj R ² = 0.392			

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803 **Using Factor 1 and 2 from the nutrient classification analysis**

	Estimate	Std.Err	t value	Pr(> t)	
(Intercept)	-0.09955499	0.0714464	-1.393	0.17	
f1	0.01556442	0.0053638	2.902	0.01	**
f2	0.04844199	0.0200583	2.415	0.02	*
gpp	0.00020052	4.541E-05	4.416	<0.0001	***
managementUM	0.1584173	0.0931077	1.701	0.09	.
f2:gpp	-2.6022E-05	1.143E-05	-2.277	0.03	*
gpp:managementUM	-0.0001458	5.589E-05	-2.609	0.01	*
	R2= 0.4812		adj R2= 0.4246		

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R ²
(Intercept)	0.03965	1	1.9416	0.169098		
f1	0.17194	1	8.4201	0.005328	**	0.18
f2	0.1191	1	5.8325	1.91E-02	*	0.02
gpp	0.39819	1	19.4996	4.76E-05	***	0.09
management	0.05912	1	2.8949	0.094507	.	0.04
f2:gpp	0.1059	1	5.186	0.02668	*	0.07
gpp:management	0.13899	1	6.8064	0.011675	*	0.09
Residuals	1.12313	55				

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