

1 **Leaf habit drives leaf nutrient resorption globally alongside nutrient**
2 **availability and climate**

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9
10 **Abstract**

11 Nutrient resorption from senescing leaves can significantly affect ecosystem nutrient cycling,
12 making it an essential process to better understand long-term plant productivity under
13 environmental change that affects the balance between nutrient availability and demand.
14 Although it is known that nutrient resorption rates vary strongly between different species and
15 across environmental gradients, the underlying driving factors are insufficiently quantified.
16 Here, we present an analysis of globally distributed observations of leaf nutrient resorption to
17 investigate the factors driving resorption efficiencies for nitrogen (NRE) and phosphorus
18 (PRE). Our results show that leaf structure and habit, together with indicators of nutrient
19 availability, are the two most important factors driving spatial variation in NRE. Overall, we
20 found higher NRE in deciduous plants ($65.2\% \pm 12.4\%$, $n=400$) than in evergreen plants
21 ($57.9\% \pm 11.4\%$, $n=551$), likely associated with a higher share of metabolic N in leaves of
22 deciduous plants. Tropical regions show the lowest resorption for N (NRE: $52.4\% \pm 12.1\%$)
23 and tundra ecosystems in polar regions show the highest (NRE: $69.6\% \pm 12.8\%$), while the
24 PRE is lowest in temperate regions ($57.8\% \pm 13.6\%$) and highest in boreal regions ($67.3\% \pm$
25 13.6%). Soil clay content, N and P atmospheric deposition - globally available proxies for soil
26 fertility - and MAP played an important role in this pattern. The statistical relationships
27 developed in this analysis indicate an important role of leaf habit and type for nutrient cycling
28 and guide improved representations of plant-internal nutrient re-cycling and nutrient
29 conservation strategies in vegetation models.

30 **Keywords:** Leaf nutrient content; Leaf structure; Nitrogen and phosphorus resorption
31 efficiency; Plant ecophysiology; Plant functional traits; Plant nutrient limitation.

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40 1. Introduction

41 Nutrient cycling plays an important role in shaping the global distribution of terrestrial primary
42 productivity (Le Bauer et al., 2008; Zaehle, 2013; Du et al., 2020). Nitrogen (N) and
43 phosphorus (P) are the main limiting nutrients for plant growth. N is needed to maintain and
44 produce essential proteins for the biosynthesis; while P is an element of genetic material and
45 plays a major role in the regeneration of the main receptor of carbon (C) assimilation, and in
46 the production of energy that conducts many processes in living cells (Chapin, 1980; Güsewell,
47 2004). The anthropogenic increase in atmospheric CO₂ since the beginning of industrialization
48 has the potential to enhance the terrestrial carbon sink through increasing plant photosynthetic
49 rates, a process known as CO₂ fertilization (Bazzaz, 1990). A potential limitation to the
50 fertilization effect is progressive nutrient limitation to growth (Luo et al., 2004) and associated
51 plant strategies to deal with such limitations. Thus, understanding the ways in which nutrients
52 circulate in ecosystems and are acquired, lost, and conserved by plants, is essential for
53 simulating plant response to global changes.

54 Nutrient resorption - defined here as the translocation of nutrients from senescing leaves to
55 temporary storage tissues - is a plant strategy for nutrient conservation (Killingbeck, 1996;
56 Kobe et al., 2005). It allows plants to directly reuse nutrients, decreasing the dependence on
57 soil nutrient availability and the competition for these nutrients with other plants and microbes,
58 especially in nutrient-limited environments (Aerts, 1996; Aerts and Chapin, 1999). The
59 question that arises is then why do plants not all resorb the entirety of leaf nutrients for being
60 more efficient? The fact that they do not achieve their maximum resorption capacity implies
61 the existence of costs and limitations to resorption. A quantitative understanding of nutrient
62 resorption can yield insights into plant strategies to cope with nutrient limitation (Aerts and
63 Chapin, 1999; Chapin et al., 2011). This is because the resorption process influences most other
64 ecosystem processes that determine plant growth, as it directly affects litter quality and
65 therefore soil organic matter decomposition and has indirect consequences for plant nutrient
66 uptake, carbon cycling and finally plant competition (Killingbeck, 1996; Berg and
67 McClaugherty, 2008). The average fraction of leaf nutrients resorbed before abscission is
68 estimated to be ~62% for N and ~65% for P (Vergutz et al., 2013). Cleveland et al. (2013)

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70 estimated that this corresponds to 31% of a plant's annual demand for N and 40% of the annual
71 demand for P, but with large geographical and species variations.

72 However, despite advances in recent years, the drivers behind nutrient resorption and its
73 variation are still unclear: First, soil fertility has long been assumed to be a key driver for
74 variations in nutrient resorption, with increased resorption in infertile soils as the plant's main
75 strategy for nutrient conservation (Aerts and Chapin, 1999). This interpretation has also
76 provided a basis for modeling dynamic resorption efficiency by accounting for nutrient
77 availability in global vegetation models (Fisher et al., 2010; Lawrence et al., 2019).

78 Nonetheless, there is diverging evidence established at different geographic scales, showing
79 positive correlations (Aerts and Chapin, 1999), negative correlations (Yuan and Chen, 2015;
80 Xu et al., 2021), and even a lack of correlation between soil fertility and resorption efficiency
81 (Vergutz et al., 2013). Second, climate factors are also considered to be important drivers for
82 resorption, but the evidence is equally conflicting: On the one hand, Yuan and Chen (2009)
83 and Yan et al. (2017) suggested NRE is decreasing with mean annual temperature (MAT) and
84 precipitation (MAP), with the opposite trend for PRE, arguing that colder regions tend to be
85 more N-limited, while P-limitation is observed more commonly in warmer environments. From
86 low to high latitudes globally, the role of N in limiting productivity tends to increase as the
87 availability of N is mainly determined by temperature-limited processes such as biological N
88 fixation and mineralization of soil organic matter (Cleveland et al., 2013; Fay et al., 2015; Deng
89 et al., 2018), but the presence of N fixers in tropical forests introduces complexity to the pattern
90 of nutrient limitation between tropical and temperate zones (Hedin et al., 2009). Nevertheless,
91 the limited availability of P in the tropics due to highly weathered soils distinguishes low- to
92 mid-latitude environments (Elser et al., 2007). On the other hand, Vergutz et al. (2013) and Xu
93 et al., 2021 showed that NRE and PRE are both increasing with decreasing MAT and MAP
94 toward higher latitudes.

95 A third set of studies suggests plant functional types, leaf stoichiometry and plant nutrient
96 demand as drivers for nutrient resorption (Reed et al., 2012; Han et al., 2013; Tang et al., 2013;
97 Brant and Chen, 2015; Du et al., 2020; Chen et al., 2021a; Sun et al., 2023). When found greater
98 nutrient resorption in evergreen species, it is assumed to be a conservation strategy given their
99 comparatively low leaf nutrient content and slow growth rate and predominant occurrence in
100 nutrient-limited biomes (Killingbeck, 1996; Yan et al., 2017; Xu et al., 2021). The same
101 argument has been used for interpreting differences between broad-leaves and needle-leaves,

102 in which nutrient resorption is generally observed to be higher in needles as a strategy to
103 acclimatize and survive in resource-limited environments (Aerts and Chapin, 1999; Yuan et
104 al., 2005; Yan et al., 2017; Xu et al., 2021). Previous studies have suggested that shrub species
105 generally display higher nutrient resorption rates compared to trees, due to their smaller leaves
106 with shorter life cycles and for the need to optimize nutrient use in resource-limited
107 environments (Killingbeck, 1996; Yuan and Chen, 2009; Yan et al., 2017; Xu et al., 2021).
108 However, Brant and Chen (2015) suggest that deciduous plants are more dependent on nutrient
109 resorption as their investment in green leaf nutrients is higher to maintain their fast growth
110 through high physiological activity during the growing season. Plants with a slow growth
111 strategy, such as evergreens and needle-leaves, have lower photosynthetic nutrient use
112 efficiency due to a higher allocation of C and N to leaf structural rather than metabolic
113 compounds (Reich et al., 2017). Onoda et al. (2017) empirically supports this by showing that
114 a greater allocation of nutrients to structural compounds is associated with decreased specific
115 leaf area (SLA) and increased diffusive limitation to photosynthesis. Thus, variations in leaf
116 traits and construction costs could contribute to differences in resorption between plant
117 functional types (PFTs). Nevertheless, Drenovsky et al. (2010; 2019) suggested that resorption
118 variability is influenced by an interplay of the discussed drivers, that includes soil properties,
119 climatic conditions, and plant characteristics. Estiarte et al. (2023) support that leaf
120 biochemistry of plants determine the first limitation to nutrient resorption, with a secondary
121 regulation in resorption by environmental conditions, while the costs of leaf aging remain
122 consistent.

123 The divergence of observed patterns highlights the need for further investigation into the main
124 drivers of variations in nutrient resorption, distinguishing the influence of plant types, soil and
125 climatic conditions. In this study, we present a meta-analysis that combines the version 5.0 of
126 TRY Plant Trait database (Kattge et al., 2020) with different ancillary datasets for climate and
127 soil factors to investigate global patterns of resorption efficiencies for nitrogen (NRE) and
128 phosphorus (PRE). We aim to extend woody species observations for nutrient resorption and
129 investigate the factors that explain observed patterns along three main axes: climate, soil
130 fertility and leaf properties.

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134 2. Methods

135 2.1 Data collection

136 We assembled the dataset from the TRY Plant Trait database (<https://www.try-db.org>, Kattge
137 et al., 2020, version 5.0) containing field measurements of paired leaf and litter mass-based
138 tissue N and P concentrations ($N_{\text{mass, leaf}}$, $P_{\text{mass, leaf}}$, $N_{\text{mass, litter}}$, $P_{\text{mass, litter}}$) to derive the fractional
139 nutrient resorption (described in Sect. 2.2), and plant functional traits recorded in parallel from
140 the same species and same location to consider as biological predictors variables (Table 1). As
141 additional predictors for nutrient resorption, we combined it with climate and soil input data
142 (Table 2). We processed the data using R statistical software (version 4.0.4), keeping the data
143 at species-level. To manipulate the extracted functional traits, we used the package {rtry} (Lam
144 et al., 2022) developed to support the preprocessing of TRY Database (version 1.0.0), and
145 {tidyverse} package (Wickham et al., 2019) with its dependencies (version 1.3.2). The data
146 processing followed the quality control according to the published protocol of TRY (Kattge et
147 al., 2011; 2020).

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149 **Table 1.** Traits extracted from TRY database to derive nutrient resorption.

Plant traits	Variable name	Unit
$N_{\text{mass, leaf}}$	Leaf nitrogen (N) content per leaf dry mass	mg g
$P_{\text{mass, leaf}}$	Leaf phosphorus (P) content per leaf dry mass	mg g
$N_{\text{mass, litter}}$	Litter nitrogen (N) content per litter dry mass	mg g
$P_{\text{mass, litter}}$	Litter phosphorus (P) content per litter dry mass	mg g
SLA	Leaf area per leaf dry mass: petiole, rhachis and midrib excluded	mm ² mg ⁻¹
SLA	Leaf area per leaf dry mass: petiole excluded	mm ² mg ⁻¹
SLA	Leaf area per leaf dry mass: petiole included	mm ² mg ⁻¹
SLA	Leaf area per leaf dry mass: undefined if petiole is in- or excluded	mm ² mg ⁻¹
	Leaf dry mass	mg
	Leaf senescent dry mass	mg
LML	Leaf Mass Loss	unitless
PFT	Plant functional type / growth form	unitless
KGC	Köppen Climate Classification	unitless

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153 As predictors, we used a set of climate variables, N and P deposition, vegetation type-related
 154 variables, and soil data (Table 2) with a spatial resolution of $0.5^\circ \times 0.5^\circ$ to match that of the
 155 lowest resolution dataset (P deposition). [Soil fertility was represented here by N and P](#)
 156 [deposition and other soil characteristics that globally correlate with nutrient availability, such](#)
 157 [as total soil P and soil texture.](#) Mean annual temperature (MAT), mean annual precipitation
 158 (MAP) and the seasonal temperature amplitude were derived from the global climate database
 159 WorldClim (Fick and Hijmans, 2017). We extracted the Köppen climate classification to
 160 represent different climate zones from the TRY database and filled data gaps using the {Kgc}
 161 R package (Bryant et al., 2017), which provides the Köppen climate classification for each
 162 latitude and longitude. We calculated mean annual evapotranspiration (ET) and growing season
 163 length (GSL) from FLUXCOM (Jung et al., 2011), in which GSL was based on the seasonal
 164 phasing of gross primary productivity (GPP) considering the time period between 20% and
 165 80% of maximum GPP in an average year for the period 2002-2015. Total soil P concentrations
 166 were derived from Yang et al. 2013; soil clay content and soil pH were extracted from the
 167 Harmonized World Soil Database (HWSD; Wieder et al., 2014). We used atmospheric N
 168 deposition values from CESM-CMIP6 (Hegglin; Kinnison and Lamarque, 2016) taking the
 169 year 2010 as a reference considering that the fields are relatively smooth, summing the
 170 emissions and making the annual mean, and P deposition was extracted from Brahney et al.
 171 (2015) and Chien et al. (2016). All variables used as predictors of global N and P resorption
 172 are described in table 2.

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174 **Table 2.** All possible predictors for nutrient resorption.

	Variable name	Unit	Reference
MAT	Mean Temperature	Annual °C	Fick and Hijmans, 2017
MAP	Mean Annual Precipitation	mm	Fick and Hijmans, 2017
AmplT	Temperature amplitude	°C	Fick and Hijmans, 2017
ET	Evapotranspiration	mm	Jung et al., 2011
N_dep2010	Nitrogen deposition	kgN ha yr	Hegglin; Kinnison and Lamarque, 2016
P_dep	Phosphorus deposition	kgN ha yr	Brahney et al., 2015; Chien et al., 2016
soilP_tot	Total soil P	g P/m ²	Yang et al., 2013
Clay	Top soil clay content	% weight	Wieder et al., 2014
pH	Top soil pH	-log(H ⁺)	Wieder et al., 2014
GSL	Growing season length	days	Jung et al., 2011
SLA	Specific leaf area	mm ² mg ⁻¹	Kattge et al., 2020

LLS	Leaf Longevity	month	Kattge et al., 2020
Leaf habit(phenology)	Deciduous/Evergreen	-	Kattge et al., 2020
Leaf Type	Broadleaves/Needles	-	Kattge et al., 2020

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176 2.2 Data derivation

177 We define nutrient resorption efficiency (NuRE) as the amount of nutrient resorbed during leaf
178 senescence calculated as:

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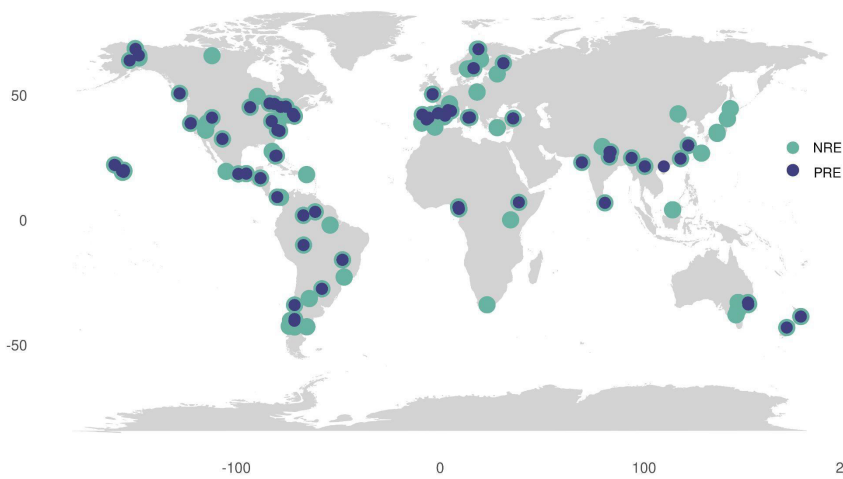
$$180 \quad NuRE = \left(1 - \frac{Nu_{senesced}}{Nu} MLCF\right) \times 100 \quad (1)$$

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181 where Nu_{green} and $Nu_{senesced}$ are nutrient (N or P) concentrations in dry green and senesced
182 leaves (mg g), respectively; MLCF (unitless) is the mass loss correction factor during
183 senescence to account for the loss of leaf mass when senescence occurs. Omitting MLCF
184 overestimates nutrient concentration in senescent leaves and underestimates resorption values
185 (Zhang et al., 2022). Zhang et al. (2022) showed a significant overall improvement when
186 considering MLCF, where both average of N and P resorption increased by ~9%, particularly
187 for cases with low resorption efficiencies. In the present study, not considering the MLCF also
188 underestimates the actual nutrient resorption efficiency when comparing the fraction of
189 resorption of four sub datasets from the final global dataset (Appendix A).

190 We calculated MLCF as the ratio between the dry mass of senesced and green leaves (van
191 Heerwaarden et al., 2003a), where it was not directly available as percentage leaf mass loss
192 (LML) in the data. We derived average values of MLCF per plant type from nutrient resorption
193 dataset to fill missing values: 0.712 for deciduous, 0.766 for evergreen, 0.69 for conifers, and
194 0.75 for woody lianas, respectively. To fill in MLCF values for the remaining leaf nutrient and
195 litter data from TRY, we associated these means of MLCF with leaf habit, leaf type and growth
196 form information available on each species. For that, trees with needle evergreen leaves were
197 associated with conifers MLCF; deciduous trees/shrubs with deciduous woody MLCF, and
198 evergreen trees/shrubs with evergreen woody MLCF, respectively. We grouped climbers and
199 lianas with shrubs. Initially, 107 observations for NRE and 76 observations for PRE were
200 derived from site-level MLCF data. We increased these numbers by 847 for NRE and 378 for
201 PRE when applying the mean MLCF per PFT. In total we extracted data from 131 sites for
202 NRE and 74 for PRE (Fig. 1), with more than one entry per site giving a total of 954 and 454
203 data points for NRE and PRE species-level, respectively. Temperate biomes were most

205 strongly represented in the dataset (518 entries), followed by tropical (180), boreal (103), polar
206 (102) and dry ecosystems (65).

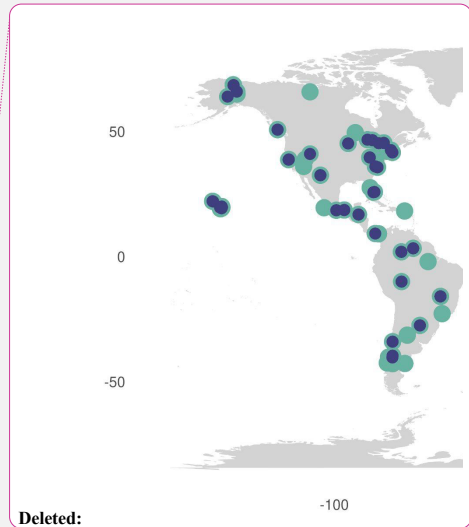


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208 **Figure 1:** Global distribution of data used for nitrogen resorption efficiency (NRE) and phosphorus resorption
209 efficiency (PRE).

212 2.3 Statistical analysis

213 As the nutrient resorption data did not conform to a normal distribution (Shapiro–Wilk test),
214 we used the nonparametric Kruskal–Wallis one-way ANOVA test of variance to examine
215 differences of NRE and PRE among different climate zones, and Mann–Whitney Wilcoxon test
216 to evaluate differences between leaf habit, leaf type and growth form (deciduous vs evergreen
217 plants, broad-leaves vs needle-leaves, shrubs vs trees), using the {ggstatsplot} R package (Patil,
218 2021). We applied Pearson correlation and linear regression to analyze the relationship between
219 nutrient resorption and the predictors described in Table 2. For MAP and N deposition, we
220 performed a log transformation prior to conducting the analysis to have the distribution close
221 to the normal. To find the best set of predictors for the variance in NRE and PRE, we used
222 multimodel inference (MMI; Burnham and Anderson, 2002) using the Akaike’s information
223 criterion (AIC) and estimated the relative importance of each explanatory variable. Different
224 from setting only a single model based on AIC, multimodel inference accounts for uncertainties
225 in the model performance and in the considered parameters. This approach involves modeling

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227 and evaluating all possible combinations of a predetermined set of predictors. The evaluation
228 is typically conducted using a criterion, such as AIC or Bayesian information criterion (BIC),
229 which favors simpler models and allows for a comprehensive examination of all possible
230 models and their respective performances. By synthesizing the estimated coefficients of
231 predictors across these models, MMI enables inference regarding the overall importance of
232 specific predictors. Before applying MMI, we used generalized linear mixed effect models
233 (GLMER) to fit different models after removing drivers described in Table 2 that showed: (1)
234 high collinearity between them ($R \geq 0.7$; Fig. S5); (2) non-significant correlation with NRE
235 (soil P) and PRE (MAP and SLA) (Fig. S5); (3) a threshold of Variance Inflation Factor (VIF)
236 higher than 10 (James et al. 2013). Specifically, temperature amplitude, GSL and ET were not
237 considered due to their high correlation with MAT and MAP and due to high VIF. Based on
238 ecological interactions, we fitted the model considering interactions between climate variables
239 MAT and MAP, as well as between plant characteristics such as leaf structure, leaf habit and
240 leaf type (SLA:LeafPhenology:LeafType). We are accounting for species identity as a random
241 factor in the mixed effect models to test if intrinsic intra-specific variability plays a role.
242 Environmental and biotic factors have strong shared effects in linear mixed models and
243 therefore are not assessed separately in this study. If the ratio between the sample size and the
244 number of parameters considered was higher than 40, we fitted the model using Restricted
245 Maximum Likelihood REML and AICc (corrected for small sample sizes) to avoid bias. We
246 selected the model with lowest AIC and applied it into the 'dredge' function implemented in
247 the multimodal inference package {MuMIn} (Bartoń K, 2023) which generated a full submodel
248 set. A set of best-performing models for NRE and PRE was selected using a cut-off of ΔAIC
249 < 2 , and based on these top models, the best model parameters were generated. Using {MuMIn}
250 package, we also calculated the relative importance of each predictor through the sum of the
251 Akaike weights across all models in which the respective parameter was being considered, with
252 a cut-off of 0.8 to distinguish between important and unimportant predictors (Terrer et al.,
253 2016). The marginal and conditional R^2 values for the fitted mixed models were 0.23 and 0.98
254 for NRE, and 0.29 and 0.48 for PRE respectively, therefore, fixed and random effects explain
255 98% of the variance in NRE and 48% in PRE, with fixed effects alone explaining 23% for NRE
256 and 29% for PRE. We performed all statistical analysis using p-value < 0.05 as statistically
257 significant.

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3. Results

261

3.1 Global patterns of nutrient resorption between different climate zones

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The global median of nutrient resorption for nitrogen (NRE) and phosphorus (PRE) is 60.0%

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± 12.3% of standard deviation (n=954) and 61.2% ± 13.6% (n=454), respectively. We find

264

differences for both NRE and PRE between the climate zones (Fig. 2). Tropical regions show

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the lowest resorption for N (NRE: 52.4% ± 12.1%) and tundra ecosystems in polar regions

266

show the highest (NRE: 69.6% ± 12.8%) (Fig. 2a). PRE in temperate regions shows the lowest

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values (57.8% ± 13.6%). PRE increases towards the higher latitude with significant difference

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of P resorption from temperate to boreal regions (67.3% ± 13.6%) (Fig. 2b). In contrast to NRE,

269

the difference of PRE between tropical and other climate zones, as well as polar regions, is not

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statistically significant (P > 0.05). NRE in dry regions (61.6% ± 9.7%) is statistically different

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from tropical and polar regions, while for PRE, the difference is not significant between climate

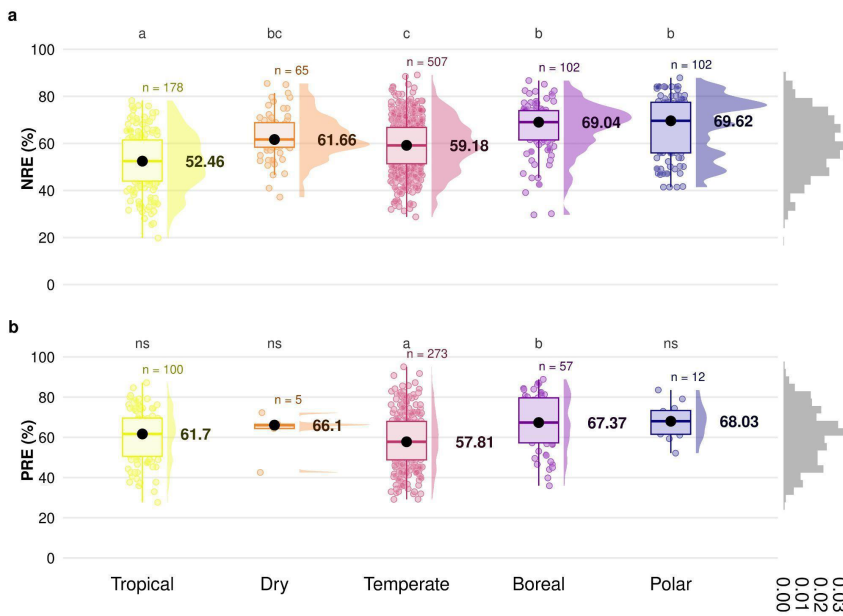
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zones. However, the sample for this zone is substantially smaller. Details of minimum,

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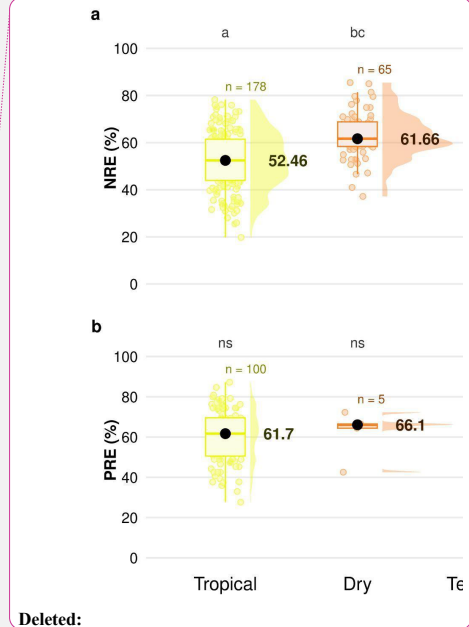
maximum, and median values can be found in Table B1.

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277 **Figure 2:** Difference in the resorption efficiency of nitrogen (NRE; a) and phosphorus (PRE; b) between climate
 278 zones by Köppen climate classification. Different letters indicate the significant differences in nutrient resorption
 279 between the climate zones, 'ns' means non significant, and 'n' represents the number of observations.

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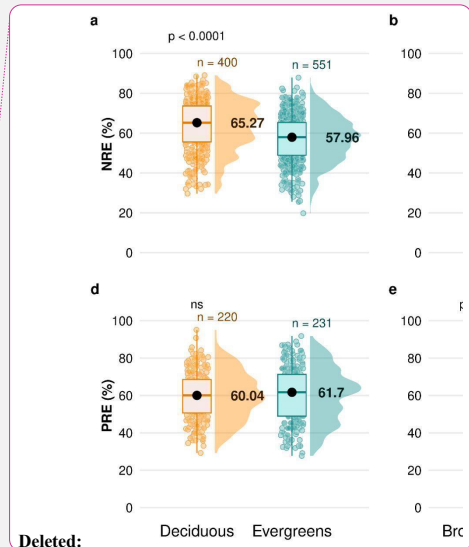
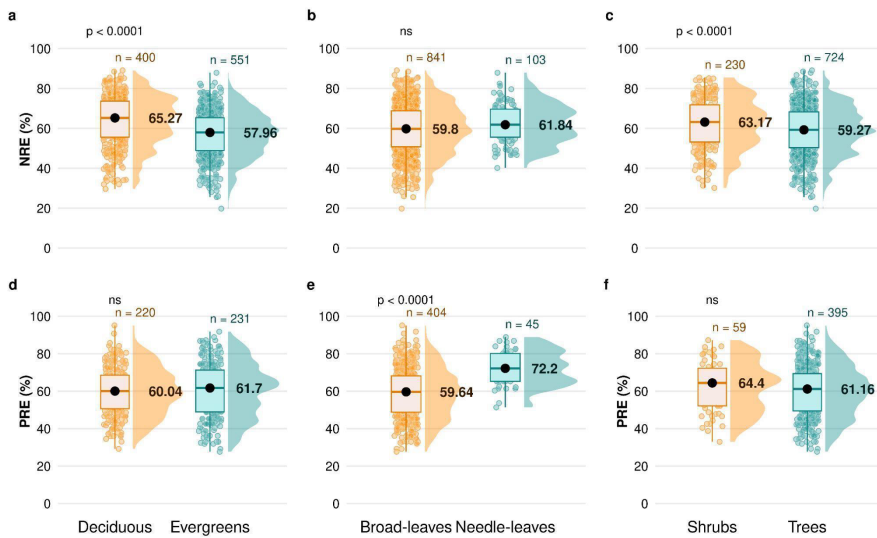
282 3.2 Patterns of nutrient resorption between plant functional types

283 We explore the variation of nutrient resorption between plant functional groups. Deciduous
 284 woody plants have a significantly higher NRE ($65.2\% \pm 12.4\%$, $n=400$) than evergreens ($57.9\% \pm 11.4\%$,
 285 $n=551$) ($P < 0.001$) (Fig. 3a), and shrubs have a significantly higher NRE ($63.1\% \pm 12.4\%$,
 286 $n=230$) than trees ($59.2\% \pm 12.1\%$, $n=724$) ($P < 0.001$) (Fig. 3c). Conversely, there is
 287 no significant difference in NRE between broad- (59.8% \pm 12.5%, $n=841$) and needle-leaved
 288 plants (61.8% \pm 9.9%, $n=103$) ($P > 0.05$) (Fig. 3b). PRE does neither differ significantly
 289 between deciduous (60.0% \pm 12.8%, $n=220$) and evergreen plants (61.7% \pm 14.4%, $n=231$) (P
 290 $= 0.4$) (Fig. 3d) nor between shrubs (64.4% \pm 13.5%, $n=59$) and trees (61.1% \pm 13.6%, $n=395$)
 291 ($P = 0.2$) (Fig. 3f). However, PRE differs significantly between leaf types, with needle-leaved
 292 showing higher resorption ($72.2\% \pm 9.2\%$, $n=45$) than broad-leaved plants ($59.6\% \pm 13.5\%$,
 293 $n=404$) ($P < 0.001$) (Fig. 3e). Details of minimum, maximum and median values can be found
 294 in Table B2.

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297 **Figure 3:** Difference in the nitrogen resorption efficiency (NRE) and phosphorus resorption efficiency (PRE)
 298 between plant functional types (PFTs) on a global scale, comparing deciduous versus evergreens (a d),

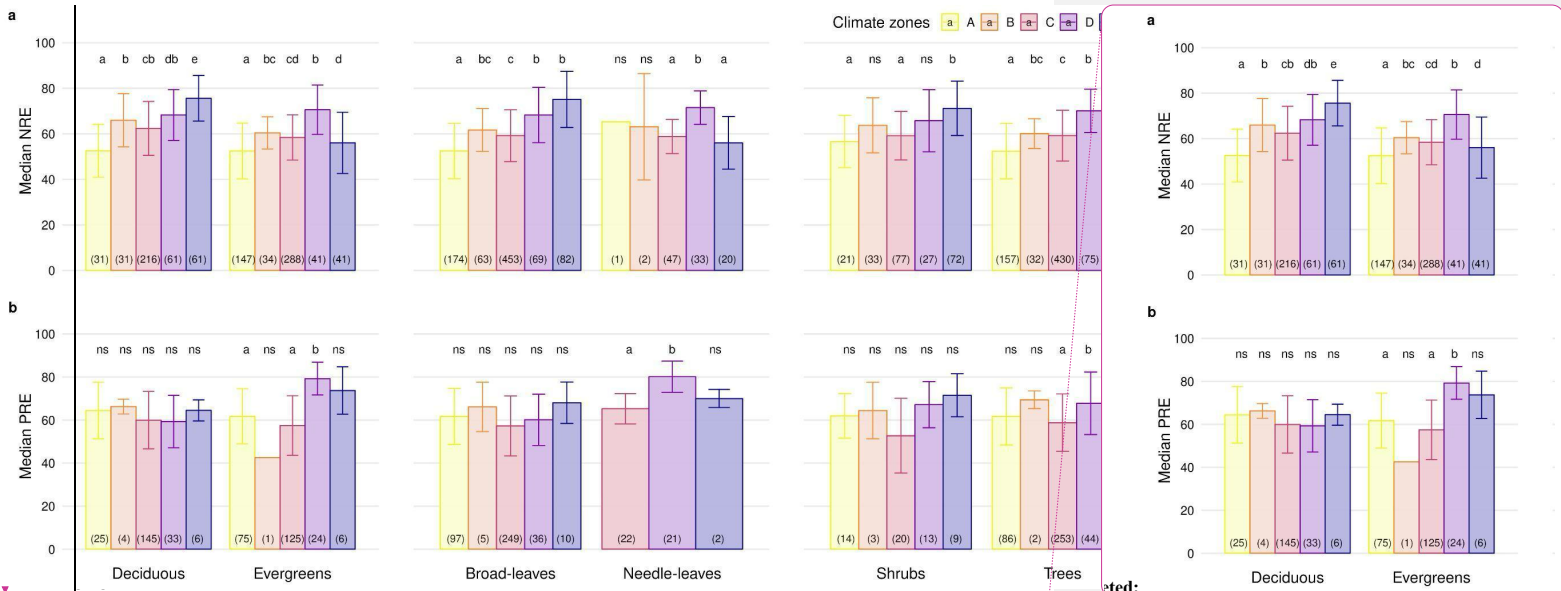


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300 broadleaved species versus needle leaves (b e), and shrubs versus trees (c f). 'n' represents the number of
 301 observations, and 'p' indicates the significant difference of nutrient resorption between each PFT.
 302

303 We next explore how climate zones affect NRE and PRE within plant functional groups. NRE
 304 tends to increase from tropical to boreal climates (Fig. 4a) – a pattern seen among deciduous
 305 and evergreen woody plants, among shrubs and trees, and among broadleaved, but not needle-
 306 leaved plants. Also PRE increases from temperate to boreal and polar climates, but declines
 307 from the tropics to temperate climates in evergreens (Fig. 4b). Apart from the overall tendency,
 308 we observe a few statistical deviations from the general pattern that emerged across all plants
 309 pooled: NRE is significantly lower in polar regions compared to boreal forests for evergreens
 310 (NRE: 56.0% ± 13.4%; NRE: 70.5% ± 10.8%) and compared to needle leaved plants (NRE:
 311 56.0% ± 11.5%; NRE: 51.5% ± 7.3%) (P < 0.001); PRE shows the same pattern deviation
 312 between these regions, but the pattern is not statistically significant (P > 0.05). Also, we did
 313 not observe lower NRE for tropical regions in needle leaved plants because the only
 314 observation of this plant type is in this climate zone. Details of minimum, maximum and
 315 median values can be found in Table B3.

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 317



319 **Figure 4:** Median of nitrogen resorption efficiency (NRE; a) and phosphorus resorption efficiency (PRE; b)
 320 between deciduous versus evergreens, broad- versus needle-leaves and shrubs versus trees in different climate

322 zones. Error bars are the standard deviations of the medians. Different letters indicate the significant differences
 323 in nutrient resorption between the climate zones. Numbers in parentheses represent the number of observations.
 324 Climate zones (A Tropical; B Dry; C Temperate; D Boreal; E Polar).

325
 326 **3.3 Main drivers of nutrient resorption**

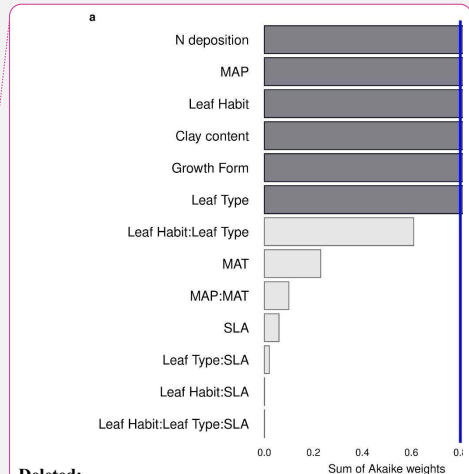
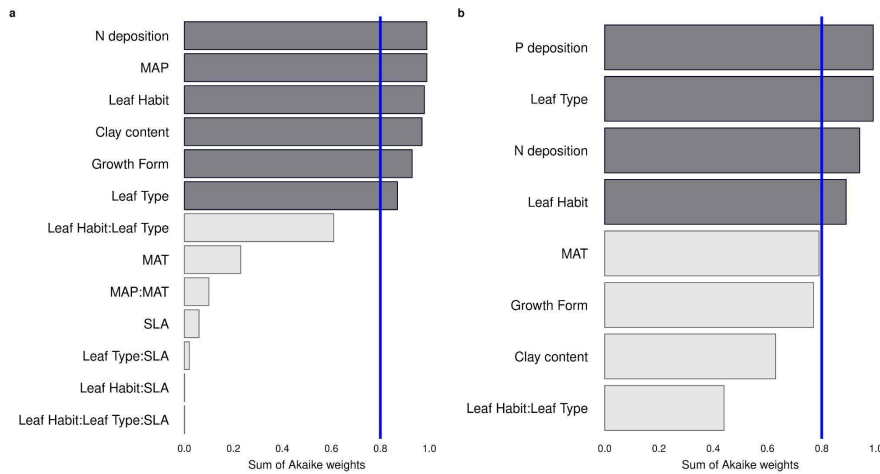
327 We investigate the main drivers for variation in nutrient resorption, considering biological,
 328 climatic, and soil factors and using data from all PFTs and climate zones pooled. Dredge model
 329 averaging based on a set of best-performing models with corrected AIC (see Methods 2.3)
 330 shows that the best model for NRE includes soil clay content, N deposition, MAP and growth
 331 form (Table 3). The best combination of predictors for the PRE model includes N deposition,
 332 leaf type, and MAT (Table 3). Sums of Akaike weights indicate that the order of importance
 333 of predictors for NRE is N deposition (RI 0.99), MAP (RI 0.99), leaf habit (RI 0.98), followed
 334 by soil clay content (RI 0.97), growth form (RI 0.93) and leaf type (RI 0.87) (Fig. 5a); while
 335 for PRE, the order is P deposition (RI 0.99), leaf type (RI 0.99), N deposition (RI 0.94) followed
 336 by leaf habit (RI 0.89) (Fig. 5b). The criteria to fit the model selecting and/or excluding
 337 predictors and interactions for the multimodel inference can be found in Sect. 2.3. Correlations
 338 between all variables, as well as linear relationships with the regression slope between nutrient
 339 resorption and all possible predictors can be found in Figs. C1 and C2.

340
 341 **Table 3** | Summarized results of dredge model averaging for nitrogen resorption efficiency (NRE) and phosphorus
 342 resorption efficiency (PRE). Significant codes: 0 ****' 0.001 ***' 0.01 **' 0.05 '.' 0.1 ' ' 1. SE means standard
 343 error.

NRE	Estimate	SE	Adjusted SE	z value	Pr(> z)
(Intercept)	63.24	2.86	2.87	21.96	<0.001 ***
Clay content	-0.33	0.09	0.09	3.54	<0.001 ***
Growth Form	2.57	1.11	1.12	2.30	0.02 *
Leaf habit	2.02	2.32	2.33	0.86	0.38
Leaf type	0.66	2.51	2.52	0.26	0.79
MAP	-5.07	1.58	1.58	3.19	0.001 **
N deposition	0.57	0.11	0.11	5.07	<0.001 ***
Leaf habit:Leaf type	-0.51	2.69	2.70	0.19	0.84
PRE	Estimate	SE	Adjusted SE	z value	Pr(> z)
(Intercept)	78.28	9.45	9.56	8.18	<0.001 ***
Clay content	-0.44	0.24	0.24	1.81	0.06 .
Growth Form	-1.35	2.99	3.03	0.44	0.65
Leaf habit	2.72	1.75	1.77	1.53	0.12
Leaf type	-10.34	4.29	4.35	2.37	0.01 *
MAT	1.08	0.49	0.49	2.18	0.02 *
N deposition	-1.77	0.54	0.54	3.23	0.001 **
P deposition	-97.13	65.80	66.75	1.45	0.14

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346 **Figure 5:** Importance of the abiotic and biotic predictors on nitrogen resorption efficiency (NRE; a) and
 347 phosphorus resorption efficiency (PRE; b). The relative importance (RI) of each predictor is calculated through
 348 the sum of the Akaike weights derived from multimodal inference selection, using corrected Akaike's information
 349 criteria. The blue line distinguishes between important and unimportant predictors. Mean Annual Precipitation
 350 (MAP); Mean Annual Temperature (MAT); SLA (Specific Leaf Area). Colon means interaction between
 351 predictors. Leaf habit is represented as 'Leaf Phenology'.
 352

353

354 4. Discussion

355 Through an extensive global dataset of leaf nutrient resorption and a multifactorial analysis,
 356 we show that leaf habit and type are a strong driver of the spatial variation in nutrient resorption,
 357 with thicker, longer-lived leaves having lower resorption efficiencies. Climate, and soil-
 358 availability-related factors also emerge as strong drivers, in which we discuss a secondary
 359 regulation related to environmental conditions in space and time. Our study covers significantly
 360 more woody species observations for nutrient resorption, especially for N, than previous
 361 studies (Yuan and Chen, 2009; Yan et al., 2017; Xu et al., 2021). We also account for variations
 362 in the mass loss of senescing leaves by deriving the MLCF when leaf mass loss or leaf dry
 363 mass were available, and then apply the calculated average MLCF to the missing data, rather
 364 than using a single average of MLCF from the literature per PFT (Yan et al., 2017; Xu et al.,
 365 2021), which may lead to a more correct estimate of nutrient resorption (see Methods 2.2).
 366

367 4.1 Nutrient resorption limited by leaf structure

369 The structural properties of leaves limit the efficiency of resorption along geographic and
370 climatic ranges. We find that the global mean for NRE is significantly higher in deciduous than
371 evergreen plants, and is higher in shrubs than trees (discussed at the end of this section) (Fig.
372 3a; 3c). This finding is in contrast to previous global studies that found decreasing nutrient
373 resorption with increasing green leaf nutrient content, implying that deciduous species, which
374 generally have higher leaf N content than evergreen species, have higher resorption (Yan et al.,
375 2017; Xu et al., 2021). Nevertheless, our finding is in agreement with Vergutz et al (2013),
376 who reported that deciduous woody species had higher NRE than evergreen woody species and
377 who found no significant differences for PRE.

378 We find that leaf habit is a strong driver for variation in resorption for both nutrients (Table 3;
379 Fig. 5). Fig. 3a shows that leaf habit is associated with clearly different mean NRE values for
380 evergreen and deciduous species, while the relationship of the average resorption is less clear
381 for PRE (Fig. 3d). This is likely the consequence of a dominance of evergreen species in the
382 tropics in our data set, but we cannot conclude that the lower amount of data for PRE is also a
383 driver of this pattern. The inconsistencies of patterns and significance in P resorption can be
384 related to high biochemical divergence in leaf P fractions compared to N, leading to varied
385 mobilization paths (Estiarte et al., 2023). The breakdown of proteins is the main way N moves
386 around as 75-80% of N is allocated in proteins, while P mobilization involves many different
387 catabolic pathways that lead to wider variety in P dynamics in leaves during leaf development
388 (Estiarte et al., 2023).

389 We observe no statistical difference between leaf types for NRE (Fig. 3). The higher PRE in
390 needle- than broad-leaves (Fig. 3e) is likely a species effect since almost all needle observations
391 for PRE are plants of the same family, *Pinaceae*. Nevertheless, leaf type is also a strong driver
392 for variance in NRE and PRE (Table 3; Fig. 5). This finding goes together with the view of
393 thicker, longer-lived leaves - such as evergreens and needle-leaves - having lower resorption
394 efficiencies. One possible explanation for this global leaf habit and type pattern is that thicker
395 leaves from evergreens plants, i.e. those with low specific leaf area (SLA), have more N
396 allocated to structural leaf compartments, which means it is harder to break down and resorb
397 nutrients back, leading to less resorption. This is different to deciduous plants, in which leaves
398 are characterized by a higher SLA and a larger N investment into metabolic compounds (Onoda
399 et al., 2017). Although SLA was not directly selected in the statistical model, our results

400 [implicitly contain the effects of SLA on nutrient resorption through the strong and known](#)
401 [relationship between SLA and leaf type and habit \(Fig. C4\).](#)

402 The leaf economics spectrum (LES) distinguishes "fast" and "slow" economic strategies found
403 globally and existing independent of climate (Wright et al., 2004). A rapid return on
404 investments, or "fast" economic strategy, is typically associated with deciduous plants and
405 achieved through a combination of traits such as shorter leaf longevity, higher nutrient
406 concentrations, and thinner leaves (high specific leaf area SLA), resulting in higher gas
407 exchange rates per unit mass/area (Reich et al., 1992, 1997; Wright et al., 2004). Conversely,
408 a slow return on investments is associated with the opposite set of traits and typically found in
409 evergreen plants (Reich et al., 1992, 1997; Wright et al., 2004). The low SLA of long-lived
410 leaves is associated with low photosynthetic N-use efficiency, but with nutrient investment
411 spread over a longer period. The low photosynthetic N-use efficiency can be attributed to a
412 higher proportion of C and N being allocated to structural rather than metabolic components
413 of the leaf (Reich et al., 2017), which aligns with the theory on leaf carbon optimization
414 proposed by Kikuzawa (1995) and posits that shorter leaf longevity is associated with higher
415 photosynthetic rates or lower costs of leaf construction.

416 Here, we found that plants with a conservative nutrient resorption strategy are located at the
417 non-conservative end of the LES, that is, in the "fast" economic strategy. The discussion that
418 revolves around the LES is determined by a combination of trade-offs between investments in
419 structural and metabolic components, as well as trade-offs over time in the expected returns on
420 those investments (Reich et al., 2017). The non-transferable and possibly transferable nutrients
421 depend on where they are located in the cell and their biochemistry (Estiarte et al., 2023).
422 Metabolic fractions are considered to be fully accessible for resorption while structural
423 fractions have been considered non-degradable (Estiarte et al., 2023). Wang et al. (2023) brings
424 the worldwide pattern of high leaf lifespan (LLS) in plants with low SLA as a natural selection
425 response to maximize carbon gain during leaf development, with variations in SLA in
426 deciduous and evergreen species being determined by microclimate conditions. This pattern
427 scales up from the organ level to a broader perspective that encompasses the trade-off between
428 growth and survival at the plant level (Kikuzawa and Lechowicz, 2011). We found higher NRE
429 in shrubs than trees as observed in previous studies (Yuan and Chen, 2009; Yan et al., 2017;
430 Xu et al., 2021), which is also reflected in the identification of plant growth form as one of the
431 main driving factors for NRE in the multimodel inference analysis (Table 3; Fig. 5a).

432 Compared to trees, shrubs typically have smaller leaves and shorter leaf-lifespans. With that
433 they need to be more resourceful with the nutrients available and prioritize nutrient resorption
434 as a way to optimize nutrient usage for growth.

435 Resorption is an internal plant process that aims to maintain the balance of soil-plant
436 interactions in the acquisition and conservation of nutrients, considering which process is less
437 costly for the plant. The efficiency in nutrient-use by plants is determined mainly by the nutrient
438 residence time in the plant, in which they can access through the leaf longevity maintaining the
439 nutrients or through resorption before leaf abscission (Veneklaas, 2022). Our results support
440 the concept that nutrient resorption is mainly driven by the share of metabolic vs total leaf N
441 (P), which co-varies with SLA (proxy for construction costs).

442 Therefore, higher resorption in deciduous trees may be an important conservation strategy as
443 this process is less energetically costly than new growth. Brant and Chen (2015) discuss the
444 dependence of deciduous trees on nutrient resorption efficiency as their investment in green
445 leaf nutrients is higher to keep fast physiological activity during growing season, or the entire
446 nutrient economy is compromised. With that, we can argue that leaf longevity may be an
447 important strategy for evergreen plants to conserve their lower leaf nutrient content, as the
448 nutrient residence time is higher in evergreens. These plants retain nutrients for as long as
449 possible, because once the nutrients are transferred to the soil through litterfall, they are
450 partially lost from the system.

451

452 **4.2 Effects of climate factors**

453 Our global dataset shows that NRE significantly increases from tropical to polar zones (Fig.
454 2a), while PRE is lowest in temperate zones and significantly increases toward the poles (Fig.
455 2b). This suggests that the resorption of both nutrients is governed to some extent by a
456 comparable dependency on climate, possibly related to slowed soil organic matter
457 decomposition at lower mean annual temperatures, which reduces the net rate of mineralization
458 and in turn, limits the availability of nutrients for plant uptake from the soil (Sharma and Kumar
459 2023). MAT emerges as one of the main drivers for PRE but not for NRE (Table 3). This result
460 may be the outcome of the overall distribution of deciduous and evergreen species across
461 climate zones, suggesting that global variations in N and P resorption along climatic gradients
462 may arise primarily from global patterns in deciduous vs. evergreen and needle-leaved vs.
463 broadleaved plants. This statement is important in the context of projecting nutrient cycling

464 under altered climate and indicates limited responses in resorption to temporal changes in
465 climate at decadal time scales – before the global distribution of leaf habit and type changes as
466 a result of shifts in species composition.

467 MAP emerged as an important driver for NRE (Table 3; Fig. 5). One explanation is that low
468 MAP leads to low soil moisture, constraining nutrient mobility and increasing the carbon cost
469 for plants to take up nutrients (Gill and Penuelas, 2016). Therefore, together with limited N
470 resorption mobility in leaf tissues discussed above (Estiarte and Penuelas, 2015), soil moisture
471 constrains N mobilization during the mineralization process (Thamdrup, 2012). Liu et al.
472 (2016) analyzed the relation between soil N mineralization and temperature sensitivity on a
473 global scale, and showed largest N mineralization rates at tropical latitudes and a general
474 poleward decrease. We can observe a similar pattern of NRE with latitude (Fig. C3). Deng et
475 al. (2018) observed a negative relationship between NRE and mineralisation rate, which
476 suggests a reciprocal causal relationship where systems emerge exhibiting either
477 simultaneously low mineralization and high resorption rates. The strong link found here
478 between NRE and leaf habit and leaf type - traits that are immutable within a given species -
479 indicates that the variations we observe in resorption might be a possible reflection of species
480 composition with direct consequence for N cycling. It suggests that a positive feedback
481 mechanism exists that leads ecosystems to be characterized by high resorption and a slower
482 soil cycling, or vice versa (Phillips et al. (2013). For example, species adapted to low soil N
483 are favored in N-limited environments, but they also produce low-N litter that decreases
484 mineralisation and further favors their competitiveness (Chapin et al., 2011).

485 In addition, we found a negative correlation between resorption and growing season length
486 (Figs. C1). Plant strategies in regions with short growing seasons (e.g. high latitudes or
487 seasonally dry subtropical regions) are focused on nutrient conservation to maximize growth
488 during the favorable period, despite nutrient availability. In very cold and seasonal
489 environments, as seen in grassy tundra vegetation, soil nutrients are often not available
490 concurrently with plant demand (Lacroix et al., 2022), implying that it may be more
491 advantageous for plants to retain their nutrients. While we did not include growing season
492 length in the multimodel inference analysis due to its high collinearity with MAT, this aspect
493 is partially reflected in leaf habit.

494 When we separate the global patterns for different climate zones in plant functional types
495 (PFTs), our results show that the major climatic pattern is consistent across the growth forms

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496 and leaf types and leaf habit (Fig. 4), in which NRE and PRE increases towards higher latitudes
497 and PRE shows a minimum at mid-latitudes. Our findings support that maximum NRE and
498 PRE may be firstly constrained by leaf properties, with secondary effects from climate and soil
499 texture (discussed below). Estiarte et al. (2023) suggest that a plant's leaf biochemistry
500 (biochemical and subcellular fractions of N and P) is the primary factor in limiting nutrient
501 resorption, followed by secondary regulation related to environmental conditions in space and
502 time. They present that resorption efficiency declines when soil nutrient availability rises, as
503 plant uptake becomes less costly in more fertile soil. However, the expenses linked to aging
504 leaves remain constant (Estiarte et al., 2023).

505

506 4.3 Effect of soil nutrient availability

507 N and P deposition and clay content emerged as important predictors for both PRE and NRE
508 (Table 3; Fig. 5). This likely reflects the influence of soil N and P availability for NRE and
509 PRE. Clay content is an important factor determining the nutrient retention capacity and cation
510 exchange capacity in soils (Chapin et al., 2011). Chronic N deposition has increased soil N
511 availability (Galloway et al., 2004) and leaf nutrient content (Chapin et al., 2011) over the 20th
512 century, and likely affected plant internal recycling and resorption as indicated by our spatial
513 results. In a fertilization experiment, higher P input had a negative effect on both NRE and PRE
514 (Yuan & Chen, 2015), suggesting that increased P deposition may reduce the plant internal
515 recycling and thus resorption. The cycling and accessibility of soil P are influenced by N
516 deposition (Marklein and Houlton, 2012) through various mechanisms, including changes in
517 plant P use strategies (Dalling et al., 2016; Wu et al., 2020a). Higher N deposition tends to
518 reduce total soil P content (Sardans et al., 2016) so plants would need to increase PRE to
519 compensate for the high soil N:P stoichiometry and P limitation. Jonard et al. (2014) suggested
520 that forest ecosystems are becoming less efficient at recycling P due to excessive N input and
521 climatic stress. This observation likely contributes to our finding that N and P deposition
522 emerge as a stronger driver in a negative correlation with PRE (Fig. 5; Table 3; Figs. C1). The
523 lack of effect by total soil P on NRE and PRE may result from the fact that this variable does
524 not represent the actual fraction of P available for plant uptake. Nevertheless, N deposition was
525 found here to have a strong positive effect on NRE (Fig. 5; Table 3) – contrary to expectations
526 (Aerts and Chapin, 1999; Yuan and Chen, 2015; Fisher et al., 2010). This indicates that the
527 influence of N deposition might be via effects on SLA, whereby increasing N deposition

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530 increases the fraction of non-structurally bound N and therefore increases the fraction of N that
531 can be resorbed. This effect, corrected for covariant factors such as leaf type and growth form,
532 overlaps the negative effect of soil clay content on NRE and PRE which suggests that
533 resorption decreases with nutrient availability in clay-rich soils. Our results raise an important
534 point on the correlation of leaf nutrient resorption and nutrient limitation, showing that the
535 relationships are complex and driven by multiple interacting and seemingly opposing factors.

536 Another soil factor found to be important for nutrient resorption is the clay content (Table 3).
537 Clay minerals are formed during soil weathering and have high surface area that influences the
538 soil's water retention capacity, and a negative charge that enables nutrients retention and
539 exchange with plant roots (Chapin et al., 2011). High-latitude soils that are younger and
540 experience slow rates of chemical weathering usually have low clay content and therefore, less
541 potential for mineral nutrient storage, which may affect their availability for plant uptake
542 (Chapin et al., 2011). As a result, plants in these environments need to invest more in
543 resorption. Thus, together with MAP and MAT, soil clay content is also closely related to soil
544 nutrient supply on a global scale, which is reflected in its role as driving resorption (Table 3;
545 Fig. 5), as well as in the negative correlation between clay content and nutrient resorption (Figs.
546 C1). In the context of an important effect on nutrient resorption found for leaf properties
547 together with climate, soil texture and soil fertility - previously suggested to be important (Aerts
548 and Chapin, 1999; Yuan and Chen, 2015; Xu et al., 2021) - may indicate that biological and
549 environmental factors are not fully independent, as it is also determined by multiple elements
550 such as litter quality, precipitation, parental materials and soil texture. For example, P
551 availability is geologically and pedologically limited in warm environments, which means
552 mainly determined by soil parent materials (Augusto et al., 2017), and therefore, soil texture
553 becomes an important factor for P limitation in tropical regions. Also, the role of P deposition
554 in relation to plant demand is high for tropical forests (Van Langenhove et al., 2020) but low
555 worldwide (Cleveland et al., 2013). PRE in the tropics did not differ statistically from other
556 climate zones although we observe an increase of PRE from mid to low latitudes (Figs. B1b
557 and C3), which could indicate data limitation for PRE. The combination of plant properties
558 with an underlying soil and climate control as driving factors for resorption variation is also
559 supported by Drenovsky et al. (2010; 2019), who suggested a combination of soil properties,
560 climatic factors, and plant morphology to explain changes in nutrient resorption.

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562 4.4 Data uncertainties and implications

563 Our study contributes to the existing research on nutrient resorption by using a comprehensive
564 approach to derive resorption values from the TRY database. However, we encountered
565 limitations in this derivation due to a lack or limited quality of data. The absence of co-located
566 nutrient measurements in leaf and litter led to a shortage of suitable data pairs, mainly for PRE,
567 in which the robustness of the model selection raised concerns about its reliability. In addition,
568 it is not possible to assess the entire temporal aspect of data collection, which increases
569 intraspecific variability. For NRE, 645 of a total of 954 observations are from the same growing
570 season, as we have collection information for green leaves and litter samples whether they were
571 picked from the plant, recently fallen or from litterfall traps cleared every week. Consequently,
572 for approximately 30% of the data, we cannot confirm that the leaf and litter measurements are
573 from the same growing season and legitimately from the same individual. This is indeed one
574 of the greatest limitations in assessing reliable nutrient resorption values. Nevertheless, it
575 remains the accepted - and only - method for evaluating resorption on a broad scale.

576 While our approach of accounting for the MLCF improved estimates of resorption (Appendix
577 A), we could not estimate the MLCF for all data pairs, and could not fill all gaps using average
578 functional type characteristics due to lacking trait attributes in the TRY database. These two
579 factors reduced the number of data points available for statistical analysis using multi-model
580 inference. Furthermore, although recognized the importance of leaf lifespan (LLS), it was not
581 possible to analyze the relationship between resorption and LLS due to the few measurements
582 of this functional trait. Nevertheless, applying the available statistical methods to analyze the
583 drivers behind NRE and PRE, we found consistent patterns for the key gradients of climate,
584 soil and plant functional type, that are informative for other studies despite remaining
585 unexplained variance. In addition, we found that even within species of the same family, the
586 distribution of NRE values is nearly as wide as the distribution for PFTs. This coordination in
587 the observed spread likely reflects a substantial contribution from environmental variability,
588 which would be interesting for further analysis if more data is available. In order to improve
589 the depth of resorption investigation, we encourage researchers in field work to perform
590 concurrent measurements of litter nutrient content as well as leaf and litter dry mass.

591 The statistical analysis of dredge multi-model inference is dependent on the specific factors
592 used in the analysis. We removed highly collinear variables and tested the impact of different
593 combinations of factors. Although such a change in factors affected the exact number of data

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595 points used in each multi-model inference, the overall identification of important and less
596 important factors for NRE and PRE was robust, especially for PFTs. However, ensuring that
597 our analysis is as global as possible, the statistical dredge model analysis can consequently be
598 influenced by temperate regions bias, which is an inherent limitation we cannot fully mitigate
599 but one that is present in any global meta-analysis of this kind.

600 By quantifying these trends that we have found, we can delve deeper into ecosystem models
601 by improving model parametrization and developing a dynamic nutrient resorption concept.
602 Studies that utilize data to infer nutrient cycling frequently simplify resorption making general
603 assumptions (Finzi et al., 2007; Cleveland et al., 2013), or simply representing this process as
604 a fixed value of 50% (Vergutz et al., 2013; Zaehle et al. 2014), which may cause inaccuracies
605 in their findings on nutrient cycling. The flow of recycling nutrients in land surface models is
606 a factor that determines how strong the soil nutrient availability controls plant production. N
607 resorption and N uptake in the FUN model (Fisher et al., 2010), for example, is defined by the
608 relative acquisition cost of the two sources. They discuss that the cost of resorption assumes a
609 constant based on global observations, but it may require a clearer connection to leaf
610 physiology. Here, we provide a start for a statistical model that can connect resorption and
611 plant properties and restrict how much plants could actually resorb nutrients, as well as the
612 dataset to test the predictions of a physiological model. In addition, environmental drivers that
613 have been shown to influence the overall patterns, such as soil texture and climate, could be
614 considered to influence the resorption efficiency after primary leaf physiology limitation. Such
615 information is essential when estimating how it can constrain carbon assimilation in face of
616 global changes (Galloway et al., 2008), and therefore, essential to predict future plant growth
617 and the capacity of the forest to act as a carbon sink (Thornton et al., 2007; Arora et al., 2022).

618

619 **5. Conclusions**

620 Our analysis of the global plant trait database indicates that variations of NRE and PRE are
621 driven by the combination of plant properties with an additional soil and climate control.
622 Systematic variations of NRE across leaf habit and type indicate that these traits are linked to
623 plant nutrient use and conservation strategies and that leaf structure plays an important role in
624 determining the proportion of nutrients that can be resorbed. Different metrics of soil fertility
625 and soil-related variables were tested and found to have an influence on NRE and PRE together
626 with climatic variables and leaf structure and habit. Clay content, N and P deposition had strong

627 influence with a negative relationship - possibly an expression of its role in nutrient retention -
628 as well as MAP. These trends provide a target to benchmark the simulation of nutrient recycling
629 in global nutrient-enabled models. A focus on considering the links between leaf structure and
630 nutrient resorption efficiency should enable a more realistic consideration of ecological and
631 environmental controls on nutrient cycling and limitation than the current state-of-the-art. The
632 importance of intrinsic plant properties raises important questions about the flexibility of leaf
633 resorption under future changes in climate, CO₂ concentrations and atmospheric deposition.

634

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640 **Author contributions**

641 GS, SC and SZ designed the study. GS performed the analysis. All authors contributed to
642 interpreting the results. GS drafted the manuscripts; all authors contributed to writing and
643 editing the manuscript.

644 **Data Availability Statement**

645 All data used in this study is publicly available through the TRY database [https://www.try-](https://www.try-db.org/)
646 [db.org/](https://www.try-db.org/).

647 **Conflict of Interests**

648 SZ is a member of the editorial board of Biogeosciences.

649 **References**

650 Aerts, R.: Nutrient Resorption from Senescing Leaves of Perennials: Are there General
651 Patterns?, *Journal of Ecology*, 84, 1996.

652

653 Aerts, R. and Chapin, F. S.: The Mineral Nutrition of Wild Plants Revisited: A Re-evaluation
654 of Processes and Patterns, in: *Advances in Ecological Research*, vol. 30, edited by: Fitter, A.
655 H. and Raffaelli, D. G., Academic Press, 1–67, 1999.

656

- 657 Arora, V. K., Seiler, C., Wang, L., and Kou-Giesbrecht, S.: Towards an ensemble-based
658 evaluation of land surface models in light of uncertain forcings and observations, *EGUsphere*,
659 <https://doi.org/10.5194/egusphere-2022-641>, 2022.
660
- 661 Augusto, L., Achat, D. L., Jonard, M., Vidal, D., and Ringeval, B.: Soil parent material-A major
662 driver of plant nutrient limitations in terrestrial ecosystems, *Glob. Chang. Biol.*, **23**, 3808–3824,
663 2017.
664
- 665 Barton, K.: *MuMIn : multi-model inference*, R package version 0.12.0, 2009.
666
- 667 Bazzaz, F. A.: The Response of Natural Ecosystems to the Rising Global CO₂ Levels, *Annu.*
668 *Rev. Ecol. Syst.*, **21**, 167–196, 1990.
669
- 670 Berg, B. and McLaugherty, C. A.: *Plant Litter. Decomposition, Humus Formation, Carbon*
671 *Sequestration*, Springer Verlag, 2014.
672
- 673
- 674 Brahney, J., Mahowald, N., Ward, D. S., Ballantyne, A. P., and Neff, J. C.: Is atmospheric
675 phosphorus pollution altering global alpine Lake stoichiometry?, *Global Biogeochem. Cycles*,
676 **29**, 1369–1383, 2015.
677
- 678 Brant, A. N. and Chen, H. Y. H.: Patterns and Mechanisms of Nutrient Resorption in Plants,
679 *CRC Crit. Rev. Plant Sci.*, **34**, 471–486, 2015.
680
- 681 Bryant, C., Wheeler, N. R., Rubel, F., French, R. H.: *kgc: Koeppen-Geiger Climatic Zones*, R
682 package version 1.0.0.2, 2017.
683
- 684 Burnham, K. P. and Anderson, D. R.: *Model Selection and Inference*, Springer New York, 20
685 pp., n.d.
686
- 687 Chapin, F. S.: The Mineral Nutrition of Wild Plants, *Annu. Rev. Ecol. Syst.*, **11**, 233–260,
688 1980.
689
- 690 ChapinIII, F. S., Matson, P. A., and Vitousek, P. M.: *Principles of Terrestrial Ecosystem*
691 *Ecology*, Springer, New York, NY, 2011.
692
- 693 Chen, H., Reed, S. C., Lü, X., Xiao, K., Wang, K., and Li, D.: Coexistence of multiple leaf
694 nutrient resorption strategies in a single ecosystem, *Sci. Total Environ.*, **772**, 144951, 2021.
695

- 696 Chien, C.-T., Mackey, K. R. M., Dutkiewicz, S., Mahowald, N. M., Prospero, J. M., and
697 Paytan, A.: Effects of African dust deposition on phytoplankton in the western tropical Atlantic
698 Ocean off Barbados, *Global Biogeochem. Cycles*, 30, 716–734, 2016.
- 699
700 Cleveland, C. C., Houlton, B. Z., Smith, W. K., Marklein, A. R., Reed, S. C., Parton, W., Del
701 Grosso, S. J., and Running, S. W.: Patterns of new versus recycled primary production in the
702 terrestrial biosphere, *Proc. Natl. Acad. Sci. U. S. A.*, 110, 12733–12737, 2013.
- 703
704 Dalling, J. W., Heineman, K., Lopez, O. R., Wright, S. J., and Turner, B. L.: Nutrient
705 Availability in Tropical Rain Forests: The Paradigm of Phosphorus Limitation, in: *Tropical
706 Tree Physiology: Adaptations and Responses in a Changing Environment*, edited by:
707 Goldstein, G. and Santiago, L. S., Springer International Publishing, Cham, 261–273, 2016.
- 708
709 Deng, M., Liu, L., Jiang, L., Liu, W., Wang, X., Li, S., Yang, S., and Wang, B.: Ecosystem
710 scale trade-off in nitrogen acquisition pathways, *Nat Ecol Evol*, 2, 1724–1734, 2018.
- 711
712 Drenovsky, R. E., James, J. J., and Richards, J. H.: Variation in nutrient resorption by desert
713 shrubs, *J. Arid Environ.*, 74, 1564–1568, 2010.
- 714
715 Drenovsky, R. E., Pietrasiak, N., and Short, T. H.: Global temporal patterns in plant nutrient
716 resorption plasticity, *Glob. Ecol. Biogeogr.*, 28, 728–743, 2019.
- 717
718 Du, E., Terrer, C., Pellegrini, A. F. A., Ahlström, A., van Lissa, C. J., Zhao, X., Xia, N., Wu,
719 X., and Jackson, R. B.: Global patterns of terrestrial nitrogen and phosphorus limitation,
720 <https://doi.org/10.1038/s41561-019-0530-4>, 2020.
- 721
722 Elser, J. J., Bracken, M. E. S., Cleland, E. E., Gruner, D. S., Harpole, W. S., Hillebrand, H.,
723 Ngai, J. T., Seabloom, E. W., Shurin, J. B., and Smith, J. E.: Global analysis of nitrogen and
724 phosphorus limitation of primary producers in freshwater, marine and terrestrial ecosystems,
725 *Ecol. Lett.*, 10, 1135–1142, 2007.
- 726
727 Estiarte, M., Campioli, M., Mayol, M., and Penuelas, J.: Variability and limits of nitrogen and
728 phosphorus resorption during foliar senescence, *Plant Comm*, 4,
729 <https://doi.org/10.1016/j.xplc.2022.100503>, 2023.
- 730
731 Fay, P. A., Prober, S. M., Harpole, W. S., Knops, J. M. H., Bakker, J. D., Borer, E. T., Lind, E.
732 M., MacDougall, A. S., Seabloom, E. W., Wragg, P. D., Adler, P. B., Blumenthal, D. M.,
733 Buckley, Y. M., Chu, C., Cleland, E. E., Collins, S. L., Davies, K. F., Du, G., Feng, X., Firn,
734 J., Gruner, D. S., Hagenah, N., Hautier, Y., Heckman, R. W., Jin, V. L., Kirkman, K. P., Klein,
735 J., Ladwig, L. M., Li, Q., McCulley, R. L., Melbourne, B. A., Mitchell, C. E., Moore, J. L.,

- 736 Morgan, J. W., Risch, A. C., Schütz, M., Stevens, C. J., Wedin, D. A., and Yang, L. H.:
737 Grassland productivity limited by multiple nutrients, *Nat Plants*, 1, 15080, 2015.
738
- 739 Fick, S. E. and Hijmans, R. J.: WorldClim 2: new 1-km spatial resolution climate surfaces for
740 global land areas, *Int. J. Climatol.*, 37, 4302–4315, 2017.
741
- 742 Finzi, A. C., Norby, R. J., Calfapietra, C., Gallet-Budynek, A., Gielen, B., Holmes, W. E.,
743 Hoosbeek, M. R., Iversen, C. M., Jackson, R. B., Kubiske, M. E., Ledford, J., Liberloo, M.,
744 Oren, R., Polle, A., Pritchard, S., Zak, D. R., Schlesinger, W. H., and Ceulemans, R.: Increases
745 in nitrogen uptake rather than nitrogen-use efficiency support higher rates of temperate forest
746 productivity under elevated CO₂, *Proc. Natl. Acad. Sci. U. S. A.*, 104, 14014–14019, 2007.
747
- 748 Fisher, J. B., Sitch, S., Malhi, Y., Fisher, R. A., Huntingford, C., and Tan, S.-Y.: Carbon cost
749 of plant nitrogen acquisition: A mechanistic, globally applicable model of plant nitrogen
750 uptake, retranslocation, and fixation, *Global Biogeochem. Cycles*, 24,
751 <https://doi.org/10.1029/2009gb003621>, 2010.
752
- 753 Galloway, J. N., Dentener, F. J., Capone, D. G., Boyer, E. W., Howarth, R. W., Seitzinger, S.
754 P., Asner, G. P., Cleveland, C. C., Green, P. A., Holland, E. A., Karl, D. M., Michaels, A. F.,
755 Porter, J. H., Townsend, A. R., and Vöosmarty, C. J.: Nitrogen Cycles: Past, Present, and
756 Future, *Biogeochemistry*, 70, 153–226, 2004.
757
- 758 Galloway, J. N., Townsend, A. R., Erisman, J. W., Bekunda, M., Cai, Z., Freney, J. R.,
759 Martinelli, L. A., Seitzinger, S. P., and Sutton, M. A.: Transformation of the nitrogen cycle:
760 recent trends, questions, and potential solutions, *Science*, 320, 889–892, 2008.
761
- 762 Güsewell, S.: N : P ratios in terrestrial plants: variation and functional significance, *New*
763 *Phytol.*, 164, 243–266, 2004.
764
- 765 Han, W., Tang, L., Chen, Y., and Fang, J.: Relationship between the relative limitation and
766 resorption efficiency of nitrogen vs phosphorus in woody plants, *PLoS One*, 8, e83366, 2013.
767
- 768 Hedin, L. O., Brookshire, E. N. J., Menge, D. N. L., and Barron, A. R.: The Nitrogen Paradox
769 in Tropical Forest Ecosystems, *Annu. Rev. Ecol. Evol. Syst.*, 40, 613–635, 2009.
770
- 771 James, G., Witten, D., Hastie, T., and Tibshirani, R.: *An Introduction to Statistical Learning*,
772 Springer US, 15 pp., n.d.
773
- 774 Jonard, M., Fürst, A., Verstraeten, A., Thimonier, A., Timmermann, V., Potočić, N., Waldner,
775 P., Benham, S., Hansen, K., Merilä, P., Ponette, Q., de la Cruz, A. C., Roskams, P., Nicolas,

- 776 M., Croisé, L., Ingerslev, M., Matteucci, G., Decinti, B., Bascietto, M., and Rautio, P.: Tree
777 mineral nutrition is deteriorating in Europe, *Glob. Chang. Biol.*, 21, 418–430, 2015.
- 778
- 779 Joswig, J. S., Wirth, C., Schuman, M. C., Kattge, J., Reu, B., Wright, I. J., Sippel, S. D., Rüger,
780 N., Richter, R., Schaepman, M. E., van Bodegom, P. M., Cornelissen, J. H. C., Díaz, S.,
781 Hattigh, W. N., Kramer, K., Lens, F., Niinemets, Ü., Reich, P. B., Reichstein, M.,
782 Römermann, C., Schrodt, F., Anand, M., Bahn, M., Byun, C., Campetella, G., Cerabolini, B.
783 E. L., Craine, J. M., Gonzalez-Melo, A., Gutiérrez, A. G., He, T., Higuchi, P., Jactel, H., Kraft,
784 N. J. B., Minden, V., Onipchenko, V., Peñuelas, J., Pillar, V. D., Sosinski, È., Soudzilovskaia,
785 N. A., Weiher, E., and Mahecha, M. D.: Climatic and soil factors explain the two-dimensional
786 spectrum of global plant trait variation, *Nat Ecol Evol*, 6, 36–50, 2022.
- 787
- 788 Jung, M., Reichstein, M., Margolis, H. A., Cescatti, A., Richardson, A. D., Arain, M. A.,
789 Arneeth, A., Bernhofer, C., Bonal, D., Chen, J., Gianelle, D., Gobron, N., Kiely, G., Kutsch, W.,
790 Lasslop, G., Law, B. E., Lindroth, A., Merbold, L., Montagnani, L., Moors, E. J., Papale, D.,
791 Sottocornola, M., Vaccari, F., and Williams, C.: Global patterns of land-atmosphere fluxes of
792 carbon dioxide, latent heat, and sensible heat derived from eddy covariance, satellite, and
793 meteorological observations, *J. Geophys. Res.*, 116, <https://doi.org/10.1029/2010jg001566>,
794 2011.
- 795
- 796 Kattge, J., Díaz, S., Lavorel, S., Prentice, I. C., Leadley, P., Bönisch, G., Garnier, E., Westoby,
797 M., Reich, P. B., Wright, I. J., Cornelissen, J. H. C., Violle, C., Harrison, S. P., Van
798 BODEGOM, P. M., Reichstein, M., Enquist, B. J., Soudzilovskaia, N. A., Ackerly, D. D.,
799 Anand, M., Atkin, O., Bahn, M., Baker, T. R., Baldocchi, D., Bekker, R., Blanco, C. C.,
800 Blonder, B., Bond, W. J., Bradstock, R., Bunker, D. E., Casanoves, F., Cavender-Bares, J.,
801 Chambers, J. Q., Chapin, F. S., Iii, Chave, J., Coomes, D., Cornwell, W. K., Craine, J. M.,
802 Dobrin, B. H., Duarte, L., Durka, W., Elser, J., Esser, G., Estiarte, M., Fagan, W. F., Fang, J.,
803 Fernández-Méndez, F., Fidelis, A., Finegan, B., Flores, O., Ford, H., Frank, D., Freschet, G.
804 T., Fyllas, N. M., Gallagher, R. V., Green, W. A., Gutierrez, A. G., Hickler, T., Higgins, S. I.,
805 Hodgson, J. G., Jalili, A., Jansen, S., Joly, C. A., Kerkhoff, A. J., Kirkup, D., Kitajima, K.,
806 Kleyer, M., Klotz, S., Knops, J. M. H., Kramer, K., Kühn, I., Kurokawa, H., Laughlin, D., Lee,
807 T. D., Leishman, M., Lens, F., Lenz, T., Lewis, S. L., Lloyd, J., Llusià, J., Louault, F., Ma, S.,
808 Mahecha, M. D., Manning, P., Massad, T., Medlyn, B. E., Messier, J., Moles, A. T., Müller, S.
809 C., Nadrowski, K., Naeem, S., Niinemets, Ü., Nöllert, S., Nüske, A., Ogaya, R., Oleksyn, J.,
810 Onipchenko, V. G., Onoda, Y., Ordoñez, J., Overbeck, G., et al.: TRY - a global database of
811 plant traits, *Glob. Chang. Biol.*, 17, 2905–2935, 2011.
- 812
- 813 Kattge, J., Bönisch, G., Díaz, S., Lavorel, S., Prentice, I. C., Leadley, P., Tautenhahn, S.,
814 Werner, G. D. A., Aakala, T., Abedi, M., Acosta, A. T. R., Adamidis, G. C., Adamson, K.,
815 Aiba, M., Albert, C. H., Alcántara, J. M., Alcázar C. C., Aleixo, I., Ali, H., Amiaud, B., Ammer,
816 C., Amoroso, M. M., Anand, M., Anderson, C., Anten, N., Antos, J., Apgaua, D. M. G.,

- 817 Ashman, T.-L., Asmara, D. H., Asner, G. P., Aspinwall, M., Atkin, O., Aubin, I., Bastrup-
818 Spohr, L., Bahalkeh, K., Bahn, M., Baker, T., Baker, W. J., Bakker, J. P., Baldocchi, D.,
819 Baltzer, J., Banerjee, A., Baranger, A., Barlow, J., Barneche, D. R., Baruch, Z., Bastianelli, D.,
820 Battles, J., Bauerle, W., Bauters, M., Bazzato, E., Beckmann, M., Beeckman, H.,
821 Beierkuhnlein, C., Bekker, R., Belfry, G., Belluau, M., Beloiu, M., Benavides, R., Benomar,
822 L., Berdugo-Lattke, M. L., Berenguer, E., Bergamin, R., Bergmann, J., Bergmann Carlucci,
823 M., Berner, L., Bernhardt-Römermann, M., Bigler, C., Bjorkman, A. D., Blackman, C., Blanco,
824 C., Blonder, B., Blumenthal, D., Bocanegra-González, K. T., Boeckx, P., Bohlman, S.,
825 Böhning-Gaese, K., Boisvert-Marsh, L., Bond, W., Bond-Lamberty, B., Boom, A., Boonman,
826 C. C. F., Bordin, K., Boughton, E. H., Boukili, V., Bowman, D. M. J. S., Bravo, S., Brendel,
827 M. R., Broadley, M. R., Brown, K. A., Bruelheide, H., Brunnich, F., Bruun, H. H., Bruy, D.,
828 Buchanan, S. W., Bucher, S. F., Buchmann, N., Buitenwerf, R., Bunker, D. E., et al.: TRY
829 plant trait database - enhanced coverage and open access, *Glob. Chang. Biol.*, 26, 119–188,
830 2020.
- 831
- 832 Kikuzawa, K.: Leaf phenology as an optimal strategy for carbon gain in plants, *Can. J. Bot.*,
833 <https://doi.org/10.1139/b95-019>, 1995.
- 834
- 835 Kikuzawa, K. and Lechowicz, M. J.: Ecology of leaf longevity, 2011th ed., Springer, Tokyo,
836 Japan, 147 pp., 2011.
- 837
- 838 Killingbeck, K. T.: Nutrients in senesced leaves: Keys to the search for potential resorption and
839 resorption proficiency, *Ecology*, 77, 1716–1727, 1996.
- 840
- 841 Kobe, R. K., Lepczyk, C. A., and Iyer, M.: Resorption efficiency decreases with increasing
842 green leaf nutrients in a global data set, *Ecology*, 86, 2780–2792, 2005.
- 843
- 844 Lacroix, F., Zaehle, S., Caldararu, S., Schaller, J., Stimmler, P., Holl, D., Kutzbach, L., and
845 Goeckede, M.: Decoupling of permafrost thaw and vegetation growth could mean both ongoing
846 nutrient limitation and an emergent source of N₂O in high latitudes, *Earth and Space Science*
847 Open Archive, <https://doi.org/10.1002/essoar.10510605.1>, 2022.
- 848
- 849 Lam, O. H. Y., Tautenhahn, S., Walther, G., Boenisch, G., Baddam, P., and Kattge, J.: The
850 “rtry” R package for preprocessing plant trait data, <https://doi.org/10.5194/egusphere-egu22-13251>, 2022.
- 851
- 852
- 853 Lang, F., Bauhus, J., Frossard, E., George, E., Kaiser, K., Kaupenjohann, M., Krüger, J.,
854 Matzner, E., Polle, A., Prietzel, J., Rennenberg, H., and Wellbrock, N.: Phosphorus in forest
855 ecosystems: New insights from an ecosystem nutrition perspective, *J. Plant Nutr. Soil Sci.*, 179,
856 129–135, 2016.
- 857

- 858 [Lawrence, D. M., Fisher, R. A., Koven, C. D., Oleson, K. W., Swenson, S. C., Bonan, G.,](#)
859 [Collier, N., Ghimire, B., van Kampenhou, L., Kennedy, D., Kluzek, E., Lawrence, P. J., Li,](#)
860 [F., Li, H., Lombardozzi, D., Riley, W. J., Sacks, W. J., Shi, M., Vertenstein, M., Wieder, W.](#)
861 [R., Xu, C., Ali, A. A., Badger, A. M., Bisht, G., van den Broeke, M., Brunke, M. A., Burns, S.](#)
862 [P., Buzan, J., Clark, M., Craig, A., Dahlin, K., Drewniak, B., Fisher, J. B., Flanner, M., Fox,](#)
863 [A. M., Gentine, P., Hoffman, F., Keppel-Aleks, G., Knox, R., Kumar, S., Lenaerts, J., Leung,](#)
864 [L. R., Lipscomb, W. H., Lu, Y., Pandey, A., Pelletier, J. D., Perket, J., Randerson, J. T.,](#)
865 [Ricciuto, D. M., Sanderson, B. M., Slater, A., Subin, Z. M., Tang, J., Thomas, R. Q., Val](#)
866 [Martin, M., and Zeng, X.: The community land model version 5: Description of new features,](#)
867 [benchmarking, and impact of forcing uncertainty, *J. Adv. Model. Earth Syst.*, 11, 4245–4287,](#)
868 [2019.](#)
- 869
- 870 LeBauer, D. S. and Treseder, K. K.: Nitrogen limitation of net primary productivity in
871 terrestrial ecosystems is globally distributed, *Ecology*, 89, 371–379, 2008.
- 872
- 873 Liu, Y., Wang, C., He, N., Wen, X., Gao, Y., Li, S., Niu, S., Butterbach-Bahl, K., Luo, Y., and
874 Yu, G.: A global synthesis of the rate and temperature sensitivity of soil nitrogen
875 mineralization: latitudinal patterns and mechanisms, *Glob. Chang. Biol.*, 23, 455–464, 2017.
- 876
- 877 Luo, Y., Su, B., Currie, W. S., Dukes, J. S., Finzi, A., Hartwig, U., Hungate, B., McMurtrie, R.
878 E., Oren, R., Parton, W. J., Pataki, D. E., Shaw, R. M., Zak, D. R., and Field, C. B.: Progressive
879 Nitrogen Limitation of Ecosystem Responses to Rising Atmospheric Carbon Dioxide,
880 *Bioscience*, 54, 731–739, 2004.
- 881
- 882 Marklein, A. R. and Houlton, B. Z.: Nitrogen inputs accelerate phosphorus cycling rates across
883 a wide variety of terrestrial ecosystems, *New Phytol.*, 193, 696–704, 2012.
- 884
- 885 Onoda, Y., Wright, I. J., Evans, J. R., Hikosaka, K., Kitajima, K., Niinemets, Ü., Poorter, H.,
886 Tosens, T., and Westoby, M.: Physiological and structural tradeoffs underlying the leaf
887 economics spectrum, *New Phytol.*, 214, 1447–1463, 2017.
- 888
- 889 Patil, I.: Visualizations with statistical details: The “ggstatsplot” approach, *J. Open Source*
890 *Softw.*, 6, 3167, 2021.
- 891
- 892 Phillips, R. P., Brzostek, E., and Midgley, M. G.: The mycorrhizal-associated nutrient
893 economy: a new framework for predicting carbon-nutrient couplings in temperate forests, *New*
894 *Phytol.*, 199, 41–51, 2013.
- 895
- 896 Reed, S. C., Townsend, A. R., Davidson, E. A., and Cleveland, C. C.: Stoichiometric patterns
897 in foliar nutrient resorption across multiple scales, *New Phytol.*, 196, 173–180, 2012.
- 898

- 899 Reich, P. B. and Flores-Moreno, H.: Peeking beneath the hood of the leaf economics spectrum,
900 *New Phytol.*, 214, 1395–1397, 2017.
- 901 Reich, P. B., Walters, M. B., and Ellsworth, D. S.: Leaf Life-Span in Relation to Leaf, Plant,
902 and Stand Characteristics among Diverse Ecosystems, *Ecol. Monogr.*, 62, 365–392, 1992.
- 903 Reich, P. B., Walters, M. B., and Ellsworth, D. S.: From tropics to tundra: global convergence
904 in plant functioning, *Proc. Natl. Acad. Sci. U. S. A.*, 94, 13730–13734, 1997.
- 905 Reich, P. B., Rich, R. L., Lu, X., Wang, Y.-P., and Oleksyn, J.: Biogeographic variation in
906 evergreen conifer needle longevity and impacts on boreal forest carbon cycle projections, *Proc.*
907 *Natl. Acad. Sci. U. S. A.*, 111, 13703–13708, 2014.
- 908 Sardans, J., Alonso, R., Janssens, I. A., Carnicer, J., Vereseoglou, S., Rillig, M. C., Fernández-
909 Martínez, M., Sanders, T. G. M., and Peñuelas, J.: Foliar and soil concentrations and
910 stoichiometry of nitrogen and phosphorous across European *Pinus sylvestris* forests:
911 relationships with climate, N deposition and tree growth, *Funct. Ecol.*, 30, 676–689, 2016.
- 912 Sharma, P. K. and Kumar, S.: Soil Temperature and Plant Growth, in: *Soil Physical*
913 *Environment and Plant Growth: Evaluation and Management*, edited by: Sharma, P. K. and
914 Kumar, S., Springer International Publishing, Cham, 175–204, 2023.
- 915 Sun, X., Li, D., Lü, X., Fang, Y., Ma, Z., Wang, Z., Chu, C., Li, M., and Chen, H.: Widespread
916 controls of leaf nutrient resorption by nutrient limitation and stoichiometry, *Funct. Ecol.*, 37,
917 1653–1662, 2023.
- 918 Tang, L., Han, W., Chen, Y., and Fang, J.: Resorption proficiency and efficiency of leaf
919 nutrients in woody plants in eastern China, *J Plant Ecol*, 6, 408–417, 2013.
- 920 Terrer, C., Vicca, S., Hungate, B. A., Phillips, R. P., and Prentice, I. C.: Mycorrhizal association
921 as a primary control of the CO₂ fertilization effect, *Science*, 353, 72–74, 2016.
- 922 Thornton, P. E., Lamarque, J.-F., Rosenbloom, N. A., and Mahowald, N. M.: Influence of
923 carbon-nitrogen cycle coupling on land model response to CO₂ fertilization and climate
924 variability, *Global Biogeochem. Cycles*, 21, <https://doi.org/10.1029/2006gb002868>, 2007.
- 925 Van Heerwaarden, L. M., Toet, S., and Aerts, R.: Current measures of nutrient resorption
926 efficiency lead to a substantial underestimation of real resorption efficiency: facts and
927 solutions, *Oikos*, 101, 664–669, 2003.
- 928 Van Langenhove, L., Verryck, L. T., Bréchet, L., Courtois, E. A., Stahl, C., Hofhansl, F.,

- 940 Bauters, M., Sardans, J., Boeckx, P., Fransen, E., Peñuelas, J., and Janssens, I. A.: Atmospheric
941 deposition of elements and its relevance for nutrient budgets of tropical forests,
942 *Biogeochemistry*, 149, 175–193, 2020.
- 943
- 944 Veneklaas, E. J.: Phosphorus resorption and tissue longevity of roots and leaves – importance
945 for phosphorus use efficiency and ecosystem phosphorus cycles, *Plant Soil*, 476, 627–637,
946 2022.
- 947
- 948 Vergutz, L., Manzoni, S., Porporato, A., Novais, R. F., and Jackson, R. B.: Global resorption
949 efficiencies and concentrations of carbon and nutrients in leaves of terrestrial plants, *Ecol.*
950 *Monogr.*, 82, 205–220, 2012.
- 951
- 952 Wang, H., Prentice, I. C., Wright, I. J., Warton, D. I., Qiao, S., Xu, X., Zhou, J., Kikuzawa, K.,
953 and Stenseth, N. C.: Leaf economics fundamentals explained by optimality principles, *Sci Adv*,
954 9, eadd5667, 2023.
- 955
- 956 Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L., François, R., Golemund, G.,
957 Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T., Miller, E., Bache, S., Müller, K.,
958 Ooms, J., Robinson, D., Seidel, D., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo,
959 K., and Yutani, H.: Welcome to the tidyverse, *J. Open Source Softw.*, 4, 1686, 2019.
- 960
- 961 Wieder, W.: RegridDED Harmonized World Soil Database v1.2,
962 <https://doi.org/10.3334/ORNLDAAC/1247>, 2014.
- 963
- 964 Wright, I. J., Reich, P. B., Westoby, M., Ackerly, D. D., Baruch, Z., Bongers, F., Cavender-
965 Bares, J., Chapin, T., Cornelissen, J. H. C., Diemer, M., Flexas, J., Garnier, E., Groom, P. K.,
966 Gulias, J., Hikosaka, K., Lamont, B. B., Lee, T., Lee, W., Lusk, C., Midgley, J. J., Navas, M.-
967 L., Niinemets, U., Oleksyn, J., Osada, N., Poorter, H., Poot, P., Prior, L., Pyankov, V. I.,
968 Roumet, C., Thomas, S. C., Tjoelker, M. G., Veneklaas, E. J., and Villar, R.: The worldwide
969 leaf economics spectrum, *Nature*, 428, 821–827, 2004.
- 970
- 971 Wu, H., Xiang, W., Ouyang, S., Xiao, W., Li, S., Chen, L., Lei, P., Deng, X., Zeng, Y., Zeng,
972 L., and Peng, C.: Tree growth rate and soil nutrient status determine the shift in nutrient-use
973 strategy of Chinese fir plantations along a chronosequence, *For. Ecol. Manage.*, 460, 117896,
974 2020.
- 975
- 976 Xu, M., Zhu, Y., Zhang, S., Feng, Y., Zhang, W., and Han, X.: Global scaling the leaf nitrogen
977 and phosphorus resorption of woody species: Revisiting some commonly held views, *Sci. Total*
978 *Environ.*, 788, 147807, 2021.
- 979
- 980 Yan, T., Zhu, J., and Yang, K.: Leaf nitrogen and phosphorus resorption of woody species in

981 response to climatic conditions and soil nutrients: a meta-analysis,
982 <https://doi.org/10.1007/s11676-017-0519-z>, 2018.
983

984 Yang, X., Post, W. M., Thornton, P. E., and Jain, A.: The distribution of soil phosphorus for
985 global biogeochemical modeling, *Biogeosciences*, 10, 2525–2537, 2013.
986

987 Yuan, Z. Y. and Chen, H. Y. H.: Global-scale patterns of nutrient resorption associated with
988 latitude, temperature and precipitation, *Glob. Ecol. Biogeogr.*, 18, 11–18, 2009.
989

990 Yuan, Z. Y. and Chen, H. Y. H.: Negative effects of fertilization on plant nutrient resorption,
991 *Ecology*, 96, 373–380, 2015.
992

993 Yuan, Z.-Y., Li, L.-H., Han, X.-G., Huang, J.-H., Jiang, G.-M., Wan, S.-Q., Zhang, W.-H., and
994 Chen, Q.-S.: Nitrogen resorption from senescing leaves in 28 plant species in a semi-arid region
995 of northern China, *J. Arid Environ.*, 63, 191–202, 2005.
996

997 Zaehle, S.: Terrestrial nitrogen-carbon cycle interactions at the global scale, *Philos. Trans. R.
998 Soc. Lond. B Biol. Sci.*, 368, 20130125, 2013.
999

1000 Zaehle, S., Medlyn, B. E., De Kauwe, M. G., Walker, A. P., Dietze, M. C., Hickler, T., Luo,
1001 Y., Wang, Y.-P., El-Masri, B., Thornton, P., Jain, A., Wang, S., Warlind, D., Weng, E., Parton,
1002 W., Iversen, C. M., Gallet-Budynek, A., McCarthy, H., Finzi, A., Hanson, P. J., Prentice, I. C.,
1003 Oren, R., and Norby, R. J.: Evaluation of 11 terrestrial carbon-nitrogen cycle models against
1004 observations from two temperate Free-Air CO₂ Enrichment studies, *New Phytol.*, 202, 803–
1005 822, 2014.
1006

1007 Zhang, M., Luo, Y., Meng, Q., and Han, W.: Correction of leaf nutrient resorption efficiency
1008 on the mass basis, *J Plant Ecol*, 15, 1125–1132, 2022.
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1030 **Appendix A - Sensitivity study of the importance of MLCF**

1031 We assembled the global dataset from the gap-filled version of TRY Plant Trait database
1032 (<https://www.try-db.org>, Kattge et al., 2020, version 5.0) containing field measurements of
1033 paired leaf and litter mass-based tissue N and P concentrations ($N_{\text{mass, leaf}}$, $P_{\text{mass, leaf}}$, $N_{\text{mass, litter}}$,
1034 $P_{\text{mass, litter}}$) to derive the fractional nutrient resorption (described in Methods Sect. 2.1).

1035 In order to understand the importance of considering MLCF in the formula to derive reliable
1036 nutrient resorption values, we compared four sub datasets from the final global dataset:

- 1037 (a) we derived nutrient resorption from nutrient resorption database, in which MLCF was
1038 calculated directly from leaf dry mass or leaf mass loss measurements;
- 1039 (b) the second dataset we derived nutrient resorption from nutrient resorption database as well,
1040 but we filled the missing values of MLCF using the mean for each plant functional type: 0.712
1041 for deciduous, 0.766 for evergreen, 0.69 for conifers, and 0.75 for woody lianas, respectively.
- 1042 (c) the third dataset we derived nutrient resorption using leaf nutrient and litter data from TRY
1043 traits, in which we did not include MLCF in the formula, calculated as:

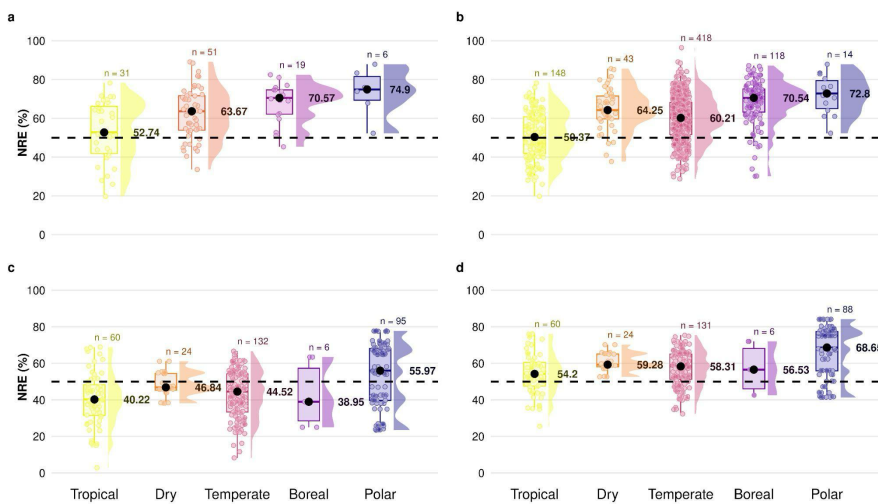
$$1044 \quad \text{NuRE} = \left(1 - \frac{\text{Nu}_{\text{senesced}}}{\text{Nu}}\right) \times 100 \quad (2)$$

1045 (d) the fourth dataset we derived nutrient resorption using leaf nutrient and litter data from
1046 TRY, but here we filled MLCF with the mean per PFT calculated before, in which we
1047 associated these means with leaf phenology, leaf type and growth form information. For that,
1048 trees with needle evergreen leaves received conifers MLCF, deciduous trees/shrubs received
1049 deciduous woody MLCF, and evergreen trees/shrubs received evergreen woody MLCF,
1050 respectively.

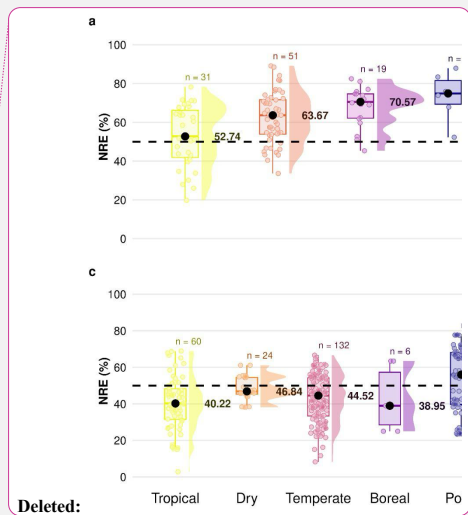
1051 Figure A1 shows nitrogen resorption efficiency (NRE) between different climate zones, where
1052 we can see underestimated values of resorption only when we do not consider MLCF in the
1053 formula (Fig. A1c), with values around or lower 50% of N resorption. We can see more reliable

1054 resorption values around 60% when considering MLCF in the formula (Fig. A1a A1b A1d).
 1055 When applying the mean of MLCF for the table deriving NRE from TRY traits (Fig. A1d), we
 1056 could reproduce a similar pattern compared to the resorption database imported from TRY
 1057 (Fig. A1a). Figure A2 shows the distribution of NRE for each subset described before, where
 1058 we can see a clear difference in data distribution only when we do not consider MLCF in the
 1059 formula (Fig. A2c). For our final dataset, we then considered together the dataset (b) and (d),
 1060 in which are the most reliable data for nutrient resorption as it is providing more data points
 1061 for resorption, **and considers** MLCF in the formula.

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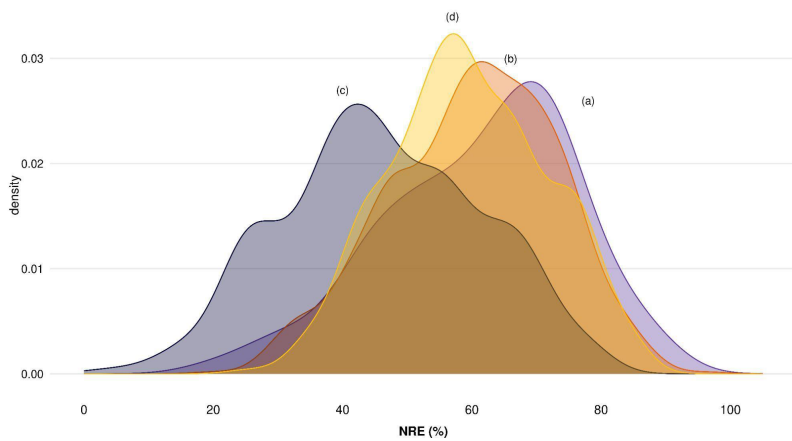


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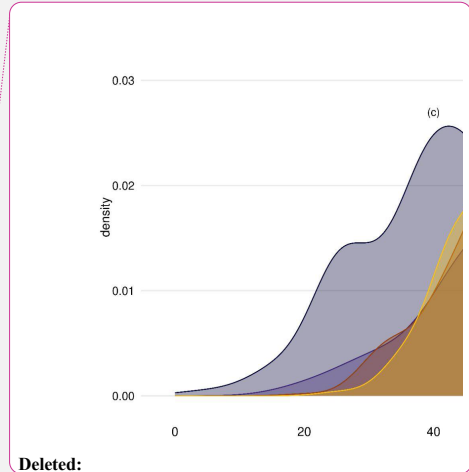


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 1064 **Figure A1:** Nitrogen resorption efficiency (NRE %) between climate zones by Köppen climate classification. (a)
 1065 nutrient resorption values derived directly from nutrient resorption dataset, with MLCF calculated from leaf dry
 1066 mass or leaf mass loss measurements; (b) nutrient resorption values derived directly from nutrient resorption
 1067 dataset, but with missing MLCF filled by the mean for each plant functional type; (c) nutrient resorption values
 1068 derived from TRY traits with no MLCF in the formula; (d) nutrient resorption values derived from TRY traits,
 1069 but with missing MLCF filled by the mean for each plant functional type.
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Figure A2: Distribution of Nitrogen resorption efficiency (NRE %) for all subsets: (a) nutrient resorption values derived directly from nutrient resorption dataset, with MLCF calculated from leaf dry mass or leaf mass loss measurements; (b) nutrient resorption values derived directly from nutrient resorption dataset, but with missing MLCF filled by the mean for each plant functional type; (c) nutrient resorption values derived from TRY traits with no MLCF in the formula; (d) nutrient resorption values derived from TRY traits, but with missing MLCF filled by the mean for each plant functional type.

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1082 Appendix B - Global patterns of nutrient resorption efficiency for N and P 1083 by PFTs and climate zones

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Table B1 | Summary of Nitrogen resorption efficiency (NRE; %) and Phosphorus resorption efficiency (PRE; %) in different climate zones. For each relationship, the number of observations (N), minimum (Min), maximum (Max), median, and standard deviation (SD) were reported. Letters in Significance show the statistical comparison between each climate zone.

Resorption (%)	Climate zone	N	Min	Max	Median	SD	Significance
NRE	Tropical	178	19.77	78.23	52.46	12.15	a
	Dry	65	37.17	85.48	61.66	9.72	bc
	Temperate	507	28.77	89.11	59.18	11.06	c
	Boreal	102	29.64	86.72	69.03	11.0	b
	Polar	102	41.42	87.89	69.62	12.84	b
PRE	Tropical	100	27.65	87.23	61.7	12.84	ns
	Dry	5	42.55	72.31	66.09	11.47	ns
	Temperate	273	29.14	95.11	57.80	13.65	a
	Boreal	57	35.92	88.88	67.36	13.65	b
	Polar	12	52.16	83.58	68.02	8.84	ns

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Table B2 | Summary of Nitrogen resorption efficiency (NRE; %) and Phosphorus resorption efficiency (PRE; %) in different plant functional types (PFTs). For each relationship, the number of observations (N), minimum (Min),

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1092 maximum (Max), median, p value and standard deviation (SD) were reported. 'p-value' < 0.05 indicates statistical
 1093 significance.

Resorption (%)	PFT	N	Min	Max	Median	p value	SD
NRE	Deciduous	400	29.64	89.11	65.27		12.48
	Evergreens	551	19.77	87.89	57.96	<0.001	11.45
	Broad-leaves	841	19.77	89.11	59.8		12.53
	Needle-leaves	103	40.19	87.89	61.84	0.05	9.97
	Shrubs	230	30.13	85.48	63.17		12.48
	Trees	724	19.77	89.11	59.27	<0.001	12.17
PRE	Deciduous	220	29.22	95.78	60.04		12.86
	Evergreens	231	27.65	91.78	61.7	0.46	14.41
	Broad-leaves	404	27.65	95.11	59.64		13.50
	Needle-leaves	45	51.35	88.88	72.2	<0.001	9.23
	Shrubs	59	32.97	87.23	64.4		13.50
	Trees	395	27.65	95.11	61.1	0.89	13.67

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1096 **Table B3** | Summary of Nitrogen resorption efficiency (NRE; %) and Phosphorus resorption efficiency (PRE; %) in different plant functional types (PFT) separated in different climate zones. For each relationship, the number of observations (N), minimum (Min), maximum (Max), median, and standard deviation (SD) were reported. Letters in Significance show the statistical comparison between each climate zone.
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NRE							
PFT	Climate zones	N	Min	Max	Median	SD	Significance
Deciduous	Tropical	31	31.97	71.80	52.53	11.64	a
	Dry	31	37.17	85.48	65.95	11.68	b
	Temperate	216	31.95	89.11	62.39	11.84	cb
	Boreal	61	29.64	86.72	68.28	11.17	db
	Polar	61	47.15	84.16	75.60	9.99	e
Evergreens	Tropical	147	19.77	78.23	52.43	12.28	a
	Dry	34	40.97	79.57	60.42	7.06	bc
	Temperate	288	28.77	81.56	58.40	9.93	cd
	Boreal	41	30.13	82.44	70.57	10.87	b
	Polar	41	41.42	87.89	56.03	13.44	d
Broad-leaves	Tropical	174	19.77	78.23	52.46	12.15	a
	Dry	63	37.17	85.48	61.66	9.42	bc
	Temperate	453	28.77	89.11	59.18	11.36	c
	Boreal	69	29.64	86.72	68.28	12.13	b
	Polar	82	41.42	84.16	75.10	12.34	b
Needle-leaves	Tropical	1	65.25	65.25	65.25	-	ns

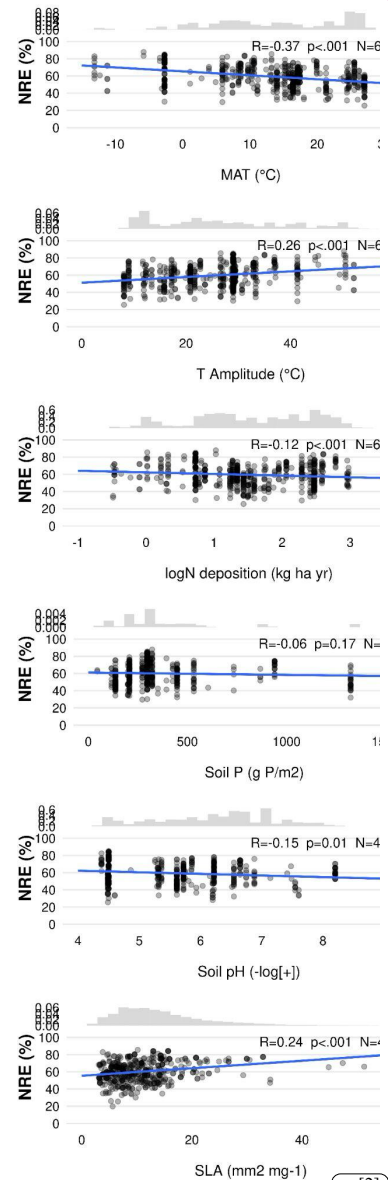
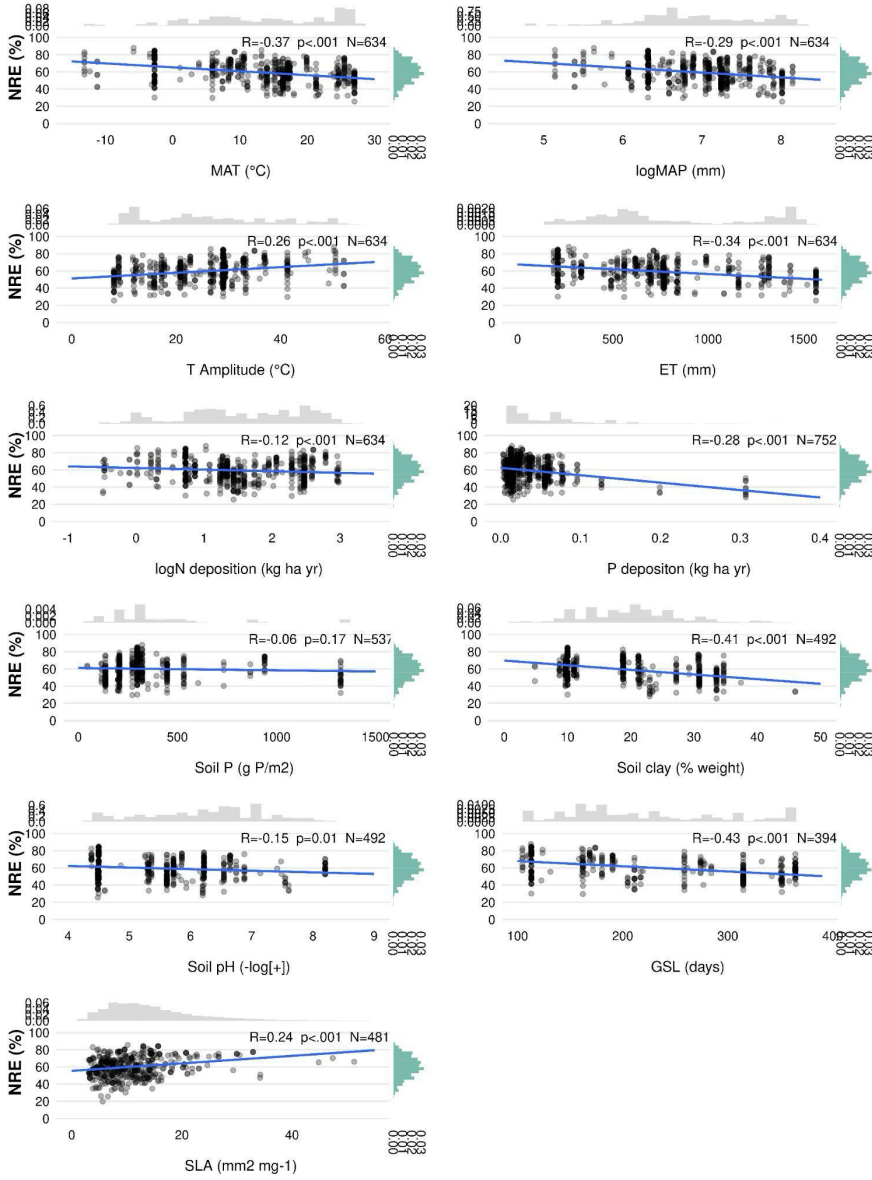
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	Dry	2	46.60	79.65	63.13	23.37	ns
	Temperate	47	40.19	81.56	58.80	7.45	a
	Boreal	33	51.02	82.44	71.52	7.33	b
	Polar	20	46.76	87.89	56.03	11.58	a
Shrubs	Tropical	21	33.81	74.33	59.60	11.45	a
	Dry	33	37.17	85.48	63.72	12.08	ns
	Temperate	77	31.29	80.96	59.16	10.63	a
	Boreal	27	30.13	85.15	65.77	13.66	ns
	Polar	72	41.42	84.16	71.16	11.92	b
Trees	Tropical	157	19.77	78.23	52.35	12.18	a
	Dry	32	47.10	76.26	60.08	6.59	bc
	Temperate	430	28.77	89.11	59.18	11.13	c
	Boreal	75	29.64	86.11	70.05	9.49	b
	Polar	30	46.76	87.89	68.44	14.89	bc
PRE							
PFT	Climate zones	N	Min	Max	Median	SD	Significance
Deciduous	Tropical	25	35.92	76.26	64.40	13.14	ns
	Dry	4	64.40	72.31	66.29	3.44	ns
	Temperate	145	29.22	95.11	59.95	13.32	ns
	Boreal	33	35.92	84.33	59.31	12.18	ns
	Polar	6	59.31	71.52	64.51	4.90	ns
Evergreens	Tropical	75	27.65	87.23	61.70	12.81	a
	Dry	1	42.55	42.55	42.55	-	ns
	Temperate	125	29.14	91.78	57.44	13.85	a
	Boreal	24	61.38	88.88	79.26	7.58	b
	Polar	6	52.16	83.58	73.73	11.03	ns
Broad-leaves	Tropical	97	27.65	87.23	61.70	12.98	ns
	Dry	5	42.55	72.31	66.10	11.47	ns
	Temperate	249	29.14	95.11	57.28	13.93	ns
	Boreal	36	35.92	84.33	60.14	11.92	ns
	Polar	10	52.16	83.58	68.03	9.63	ns
Needle-leaves	Temperate	22	51.35	82.62	65.25	7.06	a
	Boreal	21	61.38	88.88	80.14	7.22	b
	Polar	2	67.02	73.00	70.01	4.22	ns
Shrubs	Tropical	14	47.85	79.97	61.95	10.39	ns
	Dry	3	42.55	66.09	64.40	13.13	ns
	Temperate	20	32.97	87.23	52.72	17.36	ns
	Boreal	13	46.60	82.20	67.17	10.70	ns
	Polar	9	52.16	83.58	71.52	10.0	ns
Trees	Tropical	86	27.65	87.23	61.70	13.24	ns
	Dry	2	66.49	72.31	69.40	4.11	ns
	Temperate	253	29.14	95.11	58.78	13.35	a
	Boreal	44	35.92	88.88	67.78	14.48	b

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	Polar	3	61.11	68.68	67.03	3.97	ns
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1113	Appendix C - Linear regressions of nutrient resorption with environmental						
1114	and biological factors						

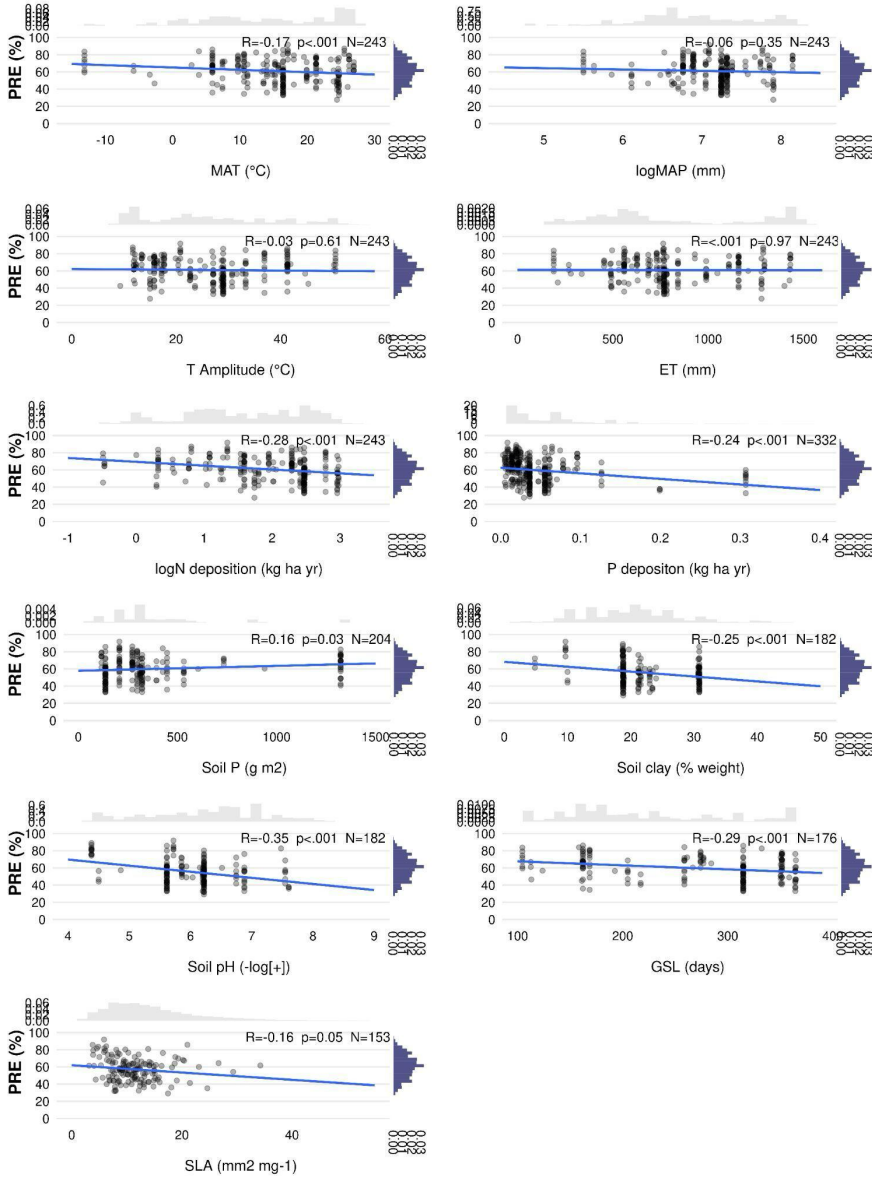
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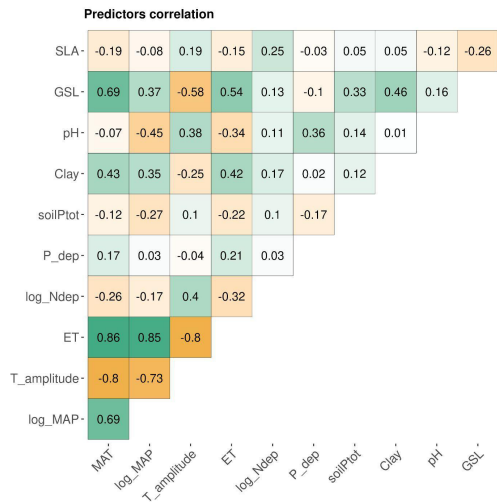
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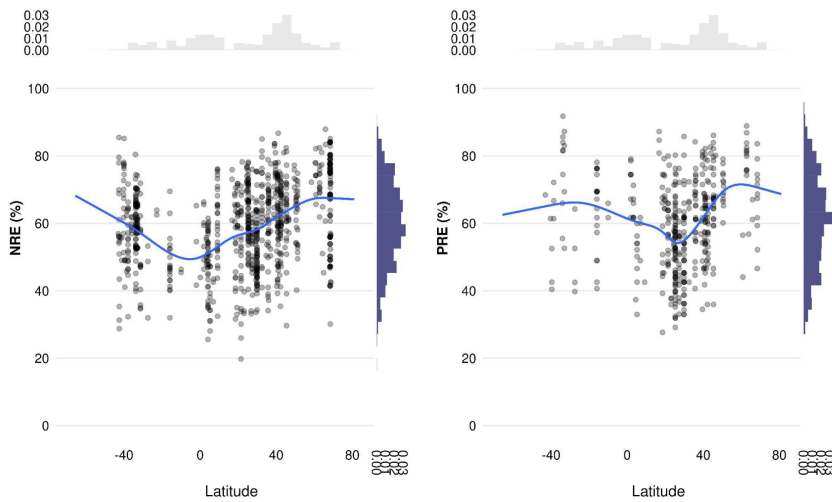
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1118 **Figure C1.** Linear regression of Nitrogen resorption efficiency (NRE; %) and Phosphorus resorption efficiency
 1119 (PRE; %) with all possible predictor variables. Environmental predictors: Mean Annual Temperature (MAT),
 1120 Mean Annual Precipitation (MAP), Evapotranspiration (ET), Temperature amplitude (T amplitude), Nitrogen
 1121 deposition (N deposition), Phosphorus deposition (P deposition), total soil P (soil P) soil clay fraction (Soil Clay),

1122 soil pH. Biological predictors: Growing Season Length (GSL), Specific Leaf Area (SLA). R: Pearson correlation;
 1123 $p < 0.05$ indicates statistical significance; N: number of observations.
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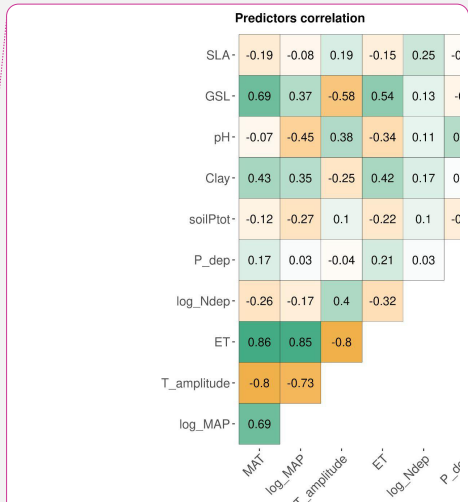


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 1127 **Figure C2:** Multiple Pearson correlation between all predictors. Mean Annual Temperature (MAT); Mean Annual
 1128 Precipitation (MAP); Evapotranspiration (ET); Temperature amplitude (T amplitude); Nitrogen deposition (N
 1129 deposition); Phosphorus deposition (P deposition); total soil P (soilPtot); soil clay fraction (Clay); soil pH;
 1130 Growing Season Length (GSL); Specific Leaf Area (SLA).
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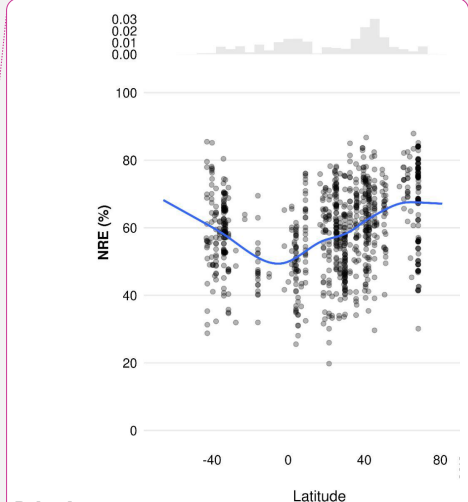


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 1133 **Figure C3:** Linear regression of nitrogen and phosphorus resorption efficiency (NRE %; PRE %;) with latitude.

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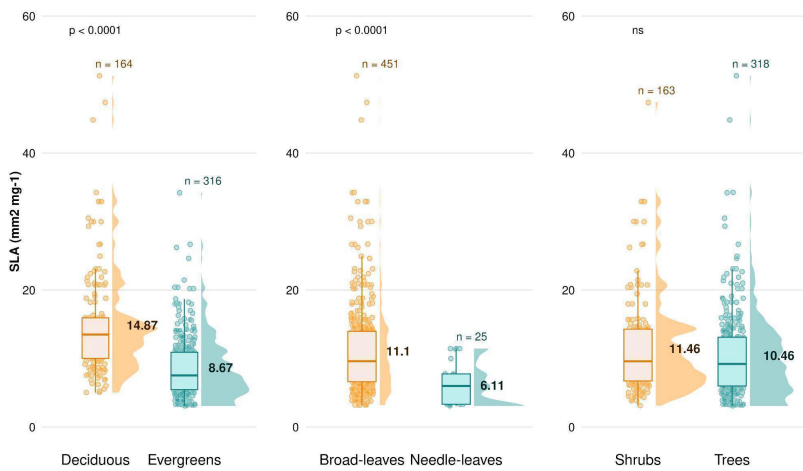


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1136 Plant functional type (PFT) does not appear in the correlation matrix shown in Fig. C1 and C2,
 1137 as it is a categorical variable. However, we explore the implication of SLA on nutrient
 1138 resorption based on the strong and known relationship between SLA and PFTs in our dataset
 1139 (Fig. C4), which derives from the leaf economics spectrum (LES) theory.



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 1141 **Figure C4:** Difference in the specific leaf area (SLA; mm² mg⁻¹) between plant functional types (PFTs) on a
 1142 global scale, comparing deciduous versus evergreens, broadleaved species versus needle leaves, and shrubs versus
 1143 trees. 'n' represents the number of observations, and 'p' indicates the significant difference of nutrient resorption
 1144 between each PFT. ▲

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