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1 **Imbalance of global nutrient cycles exacerbated by retention of phosphorus in**
2 **lakes**

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25 **Abstract**

26 Imbalanced anthropogenic inputs of nitrogen (N) and phosphorus (P) have significantly increased
27 the ratio between N and P globally, degrading ecosystem productivity and environmental quality.
28 Lakes represent a large global nutrient sink, modifying the flow of N and P in the environment. It
29 remains unknown, however, the relative retention of these two nutrients in global lakes and their
30 role in the imbalance of the nutrient cycles. Here we compare the ratio between P and N in inflows
31 and outflows of more than 5000 lakes globally, using a combination of nutrient budget model and
32 generalized linear model, showing that over 80% of global lakes positively retain both N and P,
33 and almost 90% of the lakes show preferential retention of P. The greater retention of P over N
34 leads to a strong elevation in the ratios between N and P in the lake outflow, exacerbating the
35 imbalance of N and P cycles unexpectedly and potentially leading to biodiversity losses within
36 lakes and algal blooms in downstream N-limited coastal zones. The management of N or P in
37 controlling lake eutrophication has long been debated. Our results suggest that eutrophication
38 management that prioritizes the reduction of P in lakes---which causes a further decrease in P in
39 outflows---may unintentionally aggravate N:P imbalances in global ecosystems. Our results also
40 highlight the importance of nutrient retention stoichiometry in global lake management to benefit
41 watershed and regional biogeochemical cycles.

42

43 Global anthropogenic nitrogen (N) and phosphorus (P) inputs to the biosphere have increased
44 asymmetrically since the late 1980s due to human population expansion and industrialization¹. The
45 N:P ratio of global anthropogenic input increased from 19 to 32 (molar basis hereafter), which is
46 higher than the average N:P ratios of different biospheric compartments (15-16 for open ocean,
47 16-22 for soils, and 4-30 for organisms)¹⁻³. More specifically, the average N:P ratios imported into
48 lakes in the United States remains higher than the Redfield Ratio (16:1) since the 1980s⁴. This
49 imbalance between N and P inputs has altered biogeochemical cycles, negatively affecting
50 biodiversity, water and air quality, ecosystem productivity, and human health⁵⁻⁸. Mitigating these
51 negative effects requires understanding nutrient cycles in ecosystems, since they greatly modify
52 nutrient concentration and composition. Lakes are strong nutrient sinks, contributing about 20%
53 of global freshwater nutrient retention and reducing the export of anthropogenic nutrient pollution
54 to downstream ecosystems⁹. Meta-analyses have demonstrated temporal changes in global lake
55 N:P stoichiometry, while it remains unknown whether lake retention is a buffer or accelerator of
56 the imbalance of N:P supply ratios globally. There are notorious difficulties in interpreting
57 variations between studies and observations, as well as the complexity of underlying mechanisms
58 which include multiple processes (e.g., internal sediment release, sedimentation, and
59 denitrification) and various factors (e.g. water residence time, oxygen content, trophic state, and
60 the microbial community)¹⁰⁻¹². It is also unclear the extent to which internal cycling in lakes drives
61 preferential retention of N or P globally. The altered nutrient flows through lakes may exacerbate
62 adverse effects on primary producer diversity and food web functioning in lakes as well as
63 downstream ecosystems^{7,13}. In addition, the lake eutrophication management is primarily driven
64 by observed N:P stoichiometry and prioritization of N vs P mitigation is still under debate^{14,15}
65 among scientific and decision-making communities. A greater understanding of the controls over

66 nutrient retention is needed because lakes are increasingly impacted by global change, including
67 sustained eutrophication, warming and altered hydrology.

68

69 We use a multi-faceted approach to identify specific patterns of lake nutrient retention and
70 investigate the underlying factors that lead to observed preferential behavior across lakes of
71 different size, location, and trophic gradient. Four trophic states are defined by chlorophyll-a
72 concentration, oligotrophic ($<2 \mu\text{g/L}$), mesotrophic ($2-7 \mu\text{g/L}$), eutrophic ($7-30 \mu\text{g/L}$), and hyper-
73 eutrophic ($>30 \mu\text{g/L}$)¹⁶. Three datasets are employed in a progressive approach, with 596 lakes
74 from the U.S. NLA2012 database¹⁶ for the development of a mechanistic nutrient budget model
75 within a Bayesian hierarchical framework, 5,622 lakes from Chlorophyll and Water Chemistry
76 database¹⁷ for nutrient cycling imbalance verification, and 1.4 million lakes from HydroLAKES
77 database¹⁸ for global up-scaling (See Methods for details).

78

79 **General Patterns of Nutrient Retention**

80 We find that stoichiometric shifts in N:P is a common phenomenon, with higher outflow N:P than
81 inflow in 91.3% of the NLA2012 lakes (Fig. 1a). The average outflow N:P (33.19 ± 18.08) is much
82 higher than the Redfield Ratio of 16 and almost twice as high as the inflow (16.61 ± 12.42). A clear
83 upward trend of nutrient inflow and outflow fluxes emerges across the trophic gradient (Fig.
84 1e&g). Moreover, a steeper increase of N outflow than inflow along the trophic gradient suggests
85 that internal cycling processes of N may have a greater impact at higher trophic states (Fig. 1e).
86 However, the medians of P outflow are consistently lower than the inflow, indicating a stronger
87 retention capacity of P over N (Fig. 1g). Despite the apparent trends of nutrient fluxes, no
88 significant N:P trend is found in inflow nor outflow. However, the medians of outflow N:P are

89 consistently higher than inflow N:P across the trophic gradient (Fig. 1c), which is consistent with
90 the widely observed elevated N:P of anthropogenic nutrient inputs and a general higher retention
91 of P than N in lakes. Furthermore, the differences between the medians of N:P of outflow and
92 inflow increase with trophic states, corroborating a preferential influence of external nutrient
93 enrichment on process affecting nutrient removal and imbalance in lakes.

94

95 **Contribution of Internal Nutrient Cycling**

96 Our results further demonstrate that internal nutrient cycling in lakes exacerbate the imbalance of
97 N and P cycles in watersheds. The N:P of in-lake enrichment (defined here as the combined effects
98 of sediment release of P and reactive N and N fixation) is higher than that of in-lake depletion (i.e.
99 the combined effects of sedimentation and denitrification) in 76.5% of the studied lakes (Fig. 1b).
100 The imbalanced N:P ratios of these two processes mirror the imbalance of inflow and outflow N:P
101 ratios, together implying preferential retention of P. In addition, a clear upward trend of in-lake
102 enrichment N:P is found in Fig. 1d with increasing nutrient availability, implying more release of
103 N than P with increasing trophic state. This high release of N is not as well recognized as P release
104 in previous studies that emphasize the importance of internal loading of P in eutrophic lakes¹⁹⁻²².
105 More interestingly, the variation of in-lake enrichment N:P decreases along the trophic gradient;
106 while the variation of in-lake depletion N:P remains stable, indicating that the patterns of in-lake
107 nutrient enrichment is more sensitive to the changes of trophic state than in-lake depletion.
108 However, the patterns of preferential P retention persist, despite the increase of in-lake enrichment
109 N:P along trophic gradient as in-lake depletion N:P (9.17 ± 5.31) is always lower than in-lake
110 enrichment (15.85 ± 23.02). The fluxes of in-lake nutrient enrichment and depletion increase along
111 the trophic gradient, but do so unequally between N and P (Fig. 1f&h). Similar to Finlay et al.²³,

112 we find that in-lake N depletion is enhanced by external nutrient enrichment but the capacity to
113 retain N starts to decrease with increasingly high levels of eutrophication. The decline of retention
114 capacity is even faster for N compared to P, implying that preferential P retention drives
115 imbalances leading to increased N:P in lakes and lake outflows.

116

117 **Global Implication of Nutrient Retention**

118 The preferential pattern of nutrient retention and nutrient cycling imbalance is verified using a
119 large dataset of 5,622 lakes (see Methods for details). 81% of the studied lakes positively retain N
120 and P (Quadrant C in Fig. 2) and 87.8% show a pattern of preferential P retention. In order to
121 quantify the effect of external loading on internal nutrient processes, we define *INCI* (internal
122 nutrient cycling intensity) as the ratio of the sum of absolute values of in-lake nutrient enrichment
123 and depletion to external nutrient loading (see Table 1 for equation of *INCI*). High *INCI* suggests
124 a greater contribution of internal nutrient processes to nutrient retention compared to external
125 loading. The numbers of lakes with $INCI > 1$ for both N and P increase along the trophic gradient,
126 while the numbers for N are always lower than those for P (Table 1). The proportion of lakes with
127 positive nutrient retention decrease along the trophic gradient, implying enhanced in-lake nutrient
128 enrichment in lakes of high trophic state (Table 1). The sharp decrease in the proportion of positive
129 N retention lakes supports previous studies where the contribution of in-lake N enrichment is
130 usually higher in eutrophic lakes than in lakes of lower trophic states^{22,24}. Although not all the
131 lakes positively retain N or P, the large majority that do may reduce nutrient levels at the landscape
132 scale. Positive nutrient retention in a single lake provides benefits from reducing the nutrient load
133 in the ecosystem, but may also contribute to the imbalance in global and regional N and P cycles.
134 The model results verify that the overall influence of lakes on global N and P cycles is therefore

135 double-edged. Positive outcomes are due to nutrient retention and act to reduce downstream
136 nutrient pollution. Negative consequences caused by increased N:P ratios may lead to reduced lake
137 food-web biodiversity, decreased drinking water quality, and algal blooms in downstream N-
138 limited coastal zones.

139

140 We propagate the distributions of internal nutrient fluxes to global scale with a joint distribution
141 of lake areas and trophic states using a Monte Carlo approach. The joint distribution is generated
142 from the Chlorophyll and Water Chemistry database¹⁷ and HydroLAKES¹⁸ of over 1.4 million
143 lakes (see Methods for details). Our global estimates of nutrient retention by lakes are 28.58
144 Tg/year (25.23, 31.92, 95% confidence interval, hereafter) for N and 8.16 Tg/year (6.71, 9.62) for
145 P (detailed results shown in supplement). The results are comparable with previous studies by
146 Harrison et al.²⁵ and Seitzinger et al.²⁶ with a range of 19.7 to 31 Tg/year for in-lake N depletion.
147 The average N:P of global lake nutrient retention is thus 7.76 (molar basis), much lower than the
148 Redfield Ratio of 16, corroborating the global pattern of preferential P retention. Only 53.2% of
149 global lakes positively retain N while 87.4% positively retain P (Fig. 3). The hotspots of N exports
150 are usually eutrophic lakes with high in-lake N enrichment fluxes but relatively low in-lake
151 depletion fluxes, mainly in East and Central Europe, India, Southeast China, the east coast of the
152 United States, Southeast and Southwest Canada, all with a high population density and intense
153 anthropogenic activities (detailed results shown in supplement).

154

155 **Nutrient Retention-based Perspective for Eutrophication Management**

156 Our results demonstrate that lake nutrient retention weakens with external nutrient enrichment
157 (Fig. 1). Lakes increasingly but asymmetrically release N and P along the trophic gradient,

158 amplifying the impacts of nutrient pollution and imbalance on downstream ecosystems like coastal
159 regions²³ that are more vulnerable to external N enrichment. Global lake eutrophication
160 management strategies, primarily determined by trophic state and observed N:P ratios, have long
161 been under the debate^{14,15,27}. We propose that lake management could be guided by insights gained
162 in our study. Relative patterns of N vs. P fluxes, described by the coordinate system in Fig. 2, could
163 be explicitly incorporated with trophic gradient and physical characters (e.g. water residence time
164 and lake depth). Lakes characterized by export of N and P (due to high in-lake enrichment of N
165 and P, Quadrant A, Fig. 2) are at risk of elevated trophic state, and thus require attention or control
166 of both N and P. Lakes with imbalanced N and P retention (Quadrant B and D, Fig. 2) require
167 special attention to nutrient export from the lake. Oligotrophic and mesotrophic lakes in Quadrant
168 C (Fig. 2) that positively retain both N and P represent low risk of eutrophication and may not
169 require nutrient management; while eutrophic and hyper-eutrophic lakes in Quadrant C are likely
170 to require nutrient management based on the analysis of temporal dynamics of internal nutrient
171 cycling derived from nutrient budget models. Overall, past eutrophication restoration prioritizing
172 P reduction benefits many lakes but may further aggravate the N:P imbalance unintentionally;
173 thus, in consideration of global nutrient cycling, we argue that nutrient retention and stoichiometry
174 balance should be prioritized in lake eutrophication management, particularly in hotspot regions
175 as identified in Fig. 3. Our work further emphasizes the importance of retention stoichiometry as
176 an explicit factor in global lake management.

177

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187

188 **Author contributions:** ZW and YL conceived the study. ZW and GLB developed the Bayesian
189 mechanistic nutrient budget model. JL, QJ and WG calculated NANI and NAPI for the nutrient
190 budget model. YS carried out the GLM analysis and JH performed the global up-scaling analysis.
191 ZW and YL wrote the paper with direct contributions from JP, JS, JCF, GLB, MJF, BQ, JN, SH.

192

193 **Competing interests:** Authors declare that they have no competing interests.

194

195 **Table 1. Classification of N and P cycling stoichiometry** ^a. The ratio of in-lake nutrient enrichment to depletion less
 196 than 1 indicates positive net nutrient retention. The numbers represent the proportions of lakes in each trophic state.

Trophic States	N		P	
	$EN_N/DE_N < 1$	$INCI > 1$ ^b	$EN_P/DE_P < 1$	$INCI > 1$
Oligotrophic	94.88%	45.59%	99.67%	46.90%
Mesotrophic	83.50%	48.38%	90.88%	56.92%
Eutrophic	73.83%	60.38%	85.63%	66.87%
Hyper-eutrophic	56.46%	69.82%	79.82%	75.04%

197 ^a EN_N denotes in-lake N enrichment, DE_N denotes in-lake N depletion, EN_P denotes in-lake P enrichment, DE_P denotes in-lake P depletion.

198 ^b Internal nutrient cycling intensity ($INCI = \frac{|in-lake\ enrichment| + |in-lake\ depletion|}{external\ loading}$).

199

200 **Figure 1. Fluxes and stoichiometry of nutrient cycling across the trophic gradient.** Panel (a) and (b) show the
201 N:P ratios of nutrient inflow and outflow, and in-lake enrichment and depletion. Panel (c) shows the N:P distributions
202 of inflow and outflow across the trophic gradient. The dashed line in panel (c) represents the difference between the
203 medians of inflow N:P and outflow N:P. Panel (d) shows the N:P distributions of in-lake enrichment and depletion.
204 The dashed line in panel (d) represents the difference between the medians of in-lake enrichment N:P and in-lake
205 depletion N:P. Panels (e), (f), (g) and (h) show the distributions of fluxes of nutrient inflow, outflow, in-lake
206 enrichment, and in-lake depletion across the trophic gradient (N in panel (e) and (f), P in panel (g) and (h)). The dashed
207 lines in panel(e), (f), (g) and (h) represent the medians of contributions of inflow, in-lake enrichment, outflow, and in-
208 lake depletion to total nutrient input (or output). The white dot in each violin plot represents the median, the thick
209 black line represents the 25th and 75th percentiles, and the thin black line represents the 10th and 90th percentiles.

210

211

212 **Figure 2. Global pattern of preferential nutrient retention.** Lakes located in Quadrant A (8%) all have a negative
213 net N and P retention. Lakes located in Quadrant B (< 1% of total) retain N but release P, while lakes located in
214 Quadrant D (10%) retain P but release N. Lakes located in Quadrant C (81%) retain both N and P. Lakes located
215 below the black dashed line (87.8%) tend to retain more P than N. EN_N denotes in-lake N enrichment, DE_N denotes
216 in-lake N depletion, EN_P denotes in-lake P enrichment, DE_P denotes in-lake P depletion.

217

218

219 **Figure 3. Imbalance of nutrient retention in global lakes.** Panels (a) and (b) show the global distribution of in-lake
220 enrichment/depletion ratio in lakes (N in panel (a) and P in panel (b)). Yellow dots represent lakes that positively
221 retain N or P; and the blue dots represent lakes that export N or P to downstream ecosystems.

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281

282 **Materials and Methods**

283 ***Data***

284 Three datasets were employed in a progressive approach in this study. The first one is NLA2012
285 (U.S. National Lakes Assessment 2012) dataset for the nutrient budget model development and
286 the estimation of internal nutrient cycling fluxes¹. Data used in this model include total nitrogen
287 (TN), total phosphorus (TP), chlorophyll-a (Chla), and landscape characteristics from NLA2012,
288 along with lake volumes and discharge rates from HydroLAKES dataset². A total of 596 lakes are
289 identified based on the intersection of the NLA2012 and HydroLAKES databases (Extended Data
290 Fig.1). We use NANI (net anthropogenic nitrogen input) and NAPI (net anthropogenic phosphorus
291 input)^{3,4} approach to estimate nutrient inputs of each lake. Briefly, NANI is defined as the sum of
292 five components: atmospheric deposition, fertilizer nitrogen input, agricultural nitrogen fixation,
293 net food and feed import, and non-food crop export. NAPI is the sum of three components:
294 fertilizer phosphorus input, net food and feed import, and non-food crop export^{3,4}. We use the data
295 of agricultural census year 2012 to calculate the agricultural nitrogen fixation, net food and feed
296 import, and non-food crop export. Atmospheric deposition is calculated from the data of 2012 in
297 the National Atmospheric Deposition Program⁵.

298
299 Next, a dataset of 5,622 lakes from Chlorophyll and Water Chemistry database (Extended Data
300 Fig.2) is used for nutrient cycling imbalance verification⁶. The dataset is a combination of the
301 Chlorophyll and Water Chemistry database⁶ and HydroLAKES², which shares similar
302 distributions on lake characteristics of NLA2012 dataset (Extended Data Fig.3). A generalized
303 linear model (GLM) is trained for the 596 lakes in NLA2012, to examine the relationship between
304 the modeled internal nutrient cycling fluxes and a series of physical characteristics of lakes. Data

305 used in the GLM training include trophic state and surface water temperature from NLA2012 and
306 water residence time, lake area, and lake depth from HydroLAKES. Then the fitted GLM is applied
307 to predict the patterns of internal nutrient cycling fluxes for the 5,622 lakes.

308

309 A dataset of 1.4 million lakes from HydroLAKES database (including the above dataset of 5,622
310 lakes) is used for global upscaling of retention flux and preferential retention estimation. The two
311 most significant variables, lake surface area and trophic state, are used in the estimation. A two-
312 layer Monte Carlo approach is adopted to predict the global fluxes from the distribution of internal
313 fluxes in the results of nutrient budget model. The joint distribution of global lake areas and trophic
314 states are generated from the Chlorophyll and Water Chemistry database⁶ and HydroLAKES².

315

316 ***Nutrient Budget Model***

317 *Model Development*

318 A nutrient budget model is developed to describe the fluxes and internal nutrient cycling processes.
319 The internal nutrient cycling is defined with two processes, including (a) nutrient in-lake
320 enrichment, which represents the internal input of nutrients such as sediment release; and (b)
321 nutrient in-lake depletion, which represents the internal removal of nutrients such as sedimentation
322 and denitrification. Previous studies have shown that the intensity of in-lake enrichment is directly
323 related to the abundance of algae in lakes, as most often indicated by Chla^{7,8}. Lakes with high algal
324 biomass tend to have high nutrient enrichment flux. In-lake nutrient enrichment is described as a
325 modified Michaelis-Menten function of Chla, similar to Carpenter (2005)⁹. In-lake nutrient
326 depletion is described as a first order process of TN (or TP). We followed the equations in Sinha

327 et al.^{10,11} to estimate the nutrient loading of each lake from NANI and NAPI (Eq.3 and 4), using
 328 the same hierarchical structure as below.

$$329 \quad \frac{dT_N}{dt} = \frac{L_N}{V} + \frac{a_N}{V} \cdot \frac{Chla^{b_N}}{Chla^{b_N} + m_N^{b_N}} - S_N \cdot TN - \frac{F_{out}}{V} \cdot TN \quad (1)$$

$$330 \quad \frac{dTP}{dt} = \frac{L_P}{V} + \frac{a_P}{V} \cdot \frac{Chla^{b_P}}{Chla^{b_P} + m_P^{b_P}} - S_P \cdot TP - \frac{F_{out}}{V} \cdot TP \quad (2)$$

$$331 \quad \ln(L_N) = \theta_1^N * \text{asinh}(NANI/2) + \theta_2^N * LU_{forest} + \theta_3^N * LU_{wetland} + \theta_4^N \quad (3)$$

$$332 \quad \ln(L_P) = \theta_1^P * \text{asinh}(NAPI/2) + \theta_2^P * LU_{forest} + \theta_3^P * LU_{wetland} + \theta_4^P \quad (4)$$

333 where L_N is the external loading input of TN ($g N \cdot day^{-1}$); L_P is the external loading input of
 334 TP ($g P \cdot day^{-1}$); a_N is the coefficient of in-lake N enrichment ($g N \cdot day^{-1}$); m_N is the half
 335 saturation constant of Chla for in-lake N enrichment ($mg Chl \cdot m^{-3}$); b_N is the shape parameter
 336 of Chla for in-lake N enrichment; a_P is the coefficient of in-lake P enrichment ($g P \cdot day^{-1}$); m_P
 337 is the half saturation constant of Chla for in-lake P enrichment ($mg Chl \cdot m^{-3}$); b_P is the shape
 338 parameter of Chla for in-lake P enrichment; S_N is the rate of in-lake N depletion (day^{-1}); S_P is
 339 the rate of in-lake P depletion (day^{-1}); F_{out} is the discharge rate ($m^3 \cdot day^{-1}$); V is the lake
 340 volume (m^3); and asinh is the inverse hyperbolic sine function. The θ_1^N , θ_2^N , θ_3^N , and θ_4^N are the
 341 parameters to estimate the external loading of TN. The θ_1^P , θ_2^P , θ_3^P , and θ_4^P are the parameters to
 342 estimate the external loading of TP. The LU_{forest} is the percentage of the basin area classified as
 343 forest (%); and $LU_{wetland}$ is the percentage of the basin area classified as wetland (%).

344

345 The in-lake N enrichment (EN_N) and in-lake P enrichment (EN_P) of a lake are calculated as Eq.5
 346 and Eq.6, i.e., in-lake N depletion (DE_N) and in-lake P depletion (DE_P) of a lake are calculated as
 347 Eq.7 and Eq.8.

$$EN_N = \frac{a_N}{V} \cdot \frac{Chla^{b_N}}{Chla^{b_N} + m_N^{b_N}} \quad (5)$$

$$EN_P = \frac{a_P}{V} \cdot \frac{Chla^{b_P}}{Chla^{b_P} + m_P^{b_P}} \quad (6)$$

$$DE_N = S_N \cdot TN \quad (7)$$

$$DE_P = S_P \cdot TP \quad (8)$$

352 *Bayesian Inference*

353 We adopt a Bayesian hierarchical framework to implement and analyze the nutrient budget model
 354 of the NLA2012 dataset. Due to the heterogeneity in the attributes of both water body and basin
 355 of lakes, a hierarchical structure is applied to the equations of mass balance and loading estimation
 356 which allowed for variability in model parameters at the level of ecological region. The lakes were
 357 categorized into 8 regions based on the Level I definition of ecological regions of North America¹².
 358 The lakes within the same ecological region share similar features of landscape, soil
 359 characteristics, and climate, which lead to similar patterns of nutrient flux producing and nutrient
 360 cycling behaviors. Thus, the lakes located in the same ecological region use the same set of
 361 parameters. More specifically, parameters $\theta_1^N, \theta_2^N, \theta_3^N, \theta_4^N, \theta_1^P, \theta_2^P, \theta_3^P, \theta_4^P, a_N, a_P, b_N, b_P, S_N,$
 362 and S_P , denoted by p , each follow a normal distribution:

$$363 \quad p_i \sim normal(\mu_p, \sigma_p) \quad (9)$$

364 where p_i is the parameter p that used in ecoregion i . It is drawn from a normal distribution with
 365 μ_p as mean and σ_p as standard deviation (Eq.9). Parameter inference is carried out in the software
 366 Stan (version 2.28) with Hamiltonian Monte Carlo (HMC) algorithm, which has been shown to
 367 have superior speed and performance for fitting complex dynamic models compared to other
 368 Markov Chain Monte Carlo (MCMC) methods¹³. We use No-U-Turn Sampler (NUTS) in Stan to
 369 avoid manual selection of application-specific tuning parameters. Four HMC chains were run for

370 2000 iterations (including 1000 iterations for warm-up). The \hat{R} convergence diagnostic is
371 monitored for model fits to ensure $\hat{R} < 1.05$. The prior distributions of parameters are shown in
372 Extended Data Table 1. The posterior distributions of the parameters are shown in Extended Data
373 Fig.4. The hierarchical parameters are shown in Fig.S1-S2 and model performance is shown in
374 Fig.S3 and Fig.S4.

375

376 **Generalized Linear Model**

377 The relationship between nutrient retention ability (f) and physical characteristics was estimated
378 for the lakes in NLA2012 dataset using a generalized linear model (GLM), i.e.

$$379 \quad \ln(f) = \beta_0 + \beta_1 \ln(WRT) + \beta_2 \ln(SWT) + \beta_3 \ln(\text{Depth}) + \beta_4 \ln(\text{Area}) + \beta_5 TI_2 + \beta_6 TI_3 + \beta_7 TI_4 \quad (10)$$

380 where f is the estimated dependent variable representing either E_N/L_N , E_P/L_P , D_N/L_N , or D_P/L_P ;
381 $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$, and β_7 are parameters of the GLM; WRT is water residence time (days);
382 SWT is the water temperature 0.5 meter below surface ($^{\circ}C$); Depth is the lake average depth
383 (meters); TI_2, TI_3 , and TI_4 are ordinal dummy variables representing trophic states, parameterized
384 relative to trophic state level 1 (the oligotrophic state). Four trophic states are grouped by Chla
385 concentration, oligotrophic ($< 2 \mu\text{g/L}$), mesotrophic ($2-7 \mu\text{g/L}$), eutrophic ($7-30 \mu\text{g/L}$), and hyper-
386 eutrophic ($> 30 \mu\text{g/L}$). All the continuous variables used in the GLM are log-transformed because
387 the distributions of these variables approximately follow a log-normal distribution. Instead of
388 predicting in-lake nutrient enrichment and depletion directly, the ratios of in-lake nutrient
389 enrichment (or depletion) to external nutrient loading are predicted to normalize the external
390 impact across different nutrient inputs to the lakes. We use the *glm* function in R (version 4.1.2)
391 to fit the model. The model performance is shown in Fig.S5 and S6 and the results are shown in
392 Extended Data Table 2-5. The derived GLM results of NLA2012 were then used to verify the

393 imbalance of nutrient cycling for a larger dataset of 5,622 lakes with similar distributions of the
394 dependent variables (Extended Data Fig.2 and Extended Data Fig.3).

395

396 ***Up-scaling Global Estimation***

397 Global lakes can be divided into different categories according to lake size (area), trophic state
398 (Chla), and other characteristics. In order to upscale the internal nutrient cycling fluxes, it is
399 necessary to know the global joint distribution of these characteristics. Lake surface area and
400 trophic state, two significant variables with available data globally, are used in the estimation. A
401 global joint distribution of lake surface area and trophic state is generated from the Chlorophyll
402 and Water Chemistry database⁶ and HydroLAKES² (Table S1). More specifically, global lakes are
403 grouped into 9 categories of surface area ranging from 0.001 km² to 1 × 10⁶ km². In each category
404 of lake surface area, lakes are then grouped into 4 categories based on trophic states. Since the data
405 are skewed, we perform a logarithmic transformation before Bayesian inference. We then apply a
406 Monte Carlo approach to predict the areal internal nutrient cycling fluxes (EN_N , EN_P , DE_N , DE_P)
407 for each unique combination of lake size and trophic state from the distribution of the nutrient
408 budget model results. Next, we multiplied the predicted areal fluxes for each joint category by the
409 total surface area of the category, then summed across the categories of trophic state to find the
410 total fluxes of each size category. The global internal nutrient cycling fluxes are generated by
411 summing across the categories of lake size. The results of different trophic states are shown in
412 Table S2. We further grouped the global 1.4 million lakes in the HydroLAKES dataset into the
413 above categories and roughly estimate the internal cycling fluxes for each lake plotted in Extended
414 Data Figure 5.

415

416 **Data availability**

417 The data of National Lake Assessment 2012 were obtained from USEPA
418 (<https://www.epa.gov/national-aquatic-resource-surveys/nla>). The Chlorophyll and Water
419 Chemistry database were retrieved from Scientific Data ([https://doi.org/10.1038/s41597-020-](https://doi.org/10.1038/s41597-020-00648-2)
420 [00648-2](https://doi.org/10.1038/s41597-020-00648-2)). The HydroLAKES dataset was retrieved from Global HydroLAB
421 (<https://wp.geog.mcgill.ca/hydrolab/hydrolakes/>). The processed data to reproduce the results in
422 this study are available at GitHub
423 (https://github.com/zhenwu0728/Preferential_Nutrient_Rentention_in_Global_Lakes, DOI:
424 [10.5281/zenodo.5944260](https://doi.org/10.5281/zenodo.5944260)).

425

426 **Code availability**

427 The CmdStan (version 2.28) software used for the nutrient budget model is available at [https://mc-](https://mc-stan.org/users/interfaces/cmdstan)
428 [stan.org/users/interfaces/cmdstan](https://mc-stan.org/users/interfaces/cmdstan). Julia (version 1.6.5) used as the interface to run CmdStan is
429 available at <https://julialang.org>. R (version 4.1.2) used for GLM analysis is available from the R
430 Core Team (<https://www.r-project.org/>). Python (version 3.10) used for global up-scaling analysis
431 is available at <https://www.python.org/>. The codes to reproduce the results in this study is available
432 at https://github.com/zhenwu0728/Preferential_Nutrient_Rentention_in_Global_Lakes.

433

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