

1 **Supplementary Information for**  
2 **Anthropogenically Induced Shift to Labile Phytoplankton-**  
3 **Derived Carbon Undermines Lake Carbon Burial Efficiency**

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25 **Text S1. Bayesian Isotope Mixing Model for Source Apportionment**

26 A Bayesian stable isotope mixing model was employed to quantitatively apportion  
27 the contributions of potential sources to sedimentary *n*-alkanes<sup>1,2</sup>. This approach  
28 integrates compound-specific dual-isotope ( $\delta^{13}\text{C}$  and  $\delta^2\text{H}$ ) signatures within a  
29 probabilistic framework to estimate source proportions. It provides a robust tool for  
30 resolving source mixtures in complex environmental systems. The model relies on the  
31 principle of isotopic mass balance, whereby the isotopic composition of a mixture is  
32 expressed as the weighted sum of contributions from distinct sources. Within a  
33 Bayesian framework, prior information (e.g., source isotopic ranges) can be  
34 incorporated, yielding posterior probability distributions for source contributions that  
35 explicitly quantify estimation uncertainty. Analyses were performed using the  
36 MixSIAR package in R, a widely adopted tool for such applications  
37 (<https://github.com/brianstock/MixSIAR>).

38 **S1.1 Rationale for a Dynamic End-Member Approach**

39 In geochemical studies, mid-chain *n*-alkanes ( $n\text{C}_{23}/n\text{C}_{25}$ ) have commonly been

40 used as biomarkers for aquatic macrophytes. However, recent research has questioned  
41 the specificity of this indicator. Terrestrial plants can contribute a notable proportion  
42 (~10%) of mid-chain homologues to their *n*-alkane profile, and their overall alkane  
43 abundance typically far exceeds that of aquatic vegetation<sup>3,4</sup>. Moreover, fossil fuel  
44 combustion emits mid-chain *n*-alkanes, further complicating source interpretation.  
45 Evidence from our study systems includes: (i) sustained accumulation of mid-chain *n*-  
46 alkanes in Lake Erhai despite documented macrophyte decline<sup>5</sup>; (ii) low odd-over-even  
47 predominance (OEP) values<sup>6,7</sup> (EH ~4.21, CH ~2.76, < 5 indicate mixed origins,  
48 potentially including fossil sources); and (iii) a shift in  $\epsilon^2\text{H}_{\text{C}_{29}/\text{C}_{23}}$  from positive (aquatic-  
49 like) to negative (terrestrial-like) values in EH, accompanied by a depletion trend in  
50 CH<sup>8</sup> (Fig. S7). Traditional isotope mixing models often apply static modern end-  
51 member values to historical samples, thereby ignoring temporal changes in  
52 environmental isotopic baselines<sup>9–11</sup> (e.g., precipitation  $\delta^2\text{H}$ , lake water  $\delta^2\text{H}$ , and DIC  
53  $\delta^{13}\text{C}$ ). This assumption can introduce substantial apportionment errors.

54 Our primary goal was to reconstruct the relative contributions of aquatic  
55 macrophytes, terrestrial plants, and fossil fuels to mid-chain *n*-alkanes ( $n\text{C}_{23}/n\text{C}_{25}$ ).  
56 Given clear evidence of mixed sources, we constructed layer-specific end-members  
57 using isotopic signals preserved in the sediment record itself, thereby capturing  
58 historical environmental conditions.

## 59 **S1.2 End-Member Derivation**

60 We defined three sources: fossil fuels, aquatic macrophytes, and terrestrial plants.

61       **Fossil fuel end-members.** The isotopic composition of n-alkanes emitted during  
62 fossil fuel combustion varies with fuel type (e.g., coal, petroleum) and combustion  
63 conditions, rendering direct inference of petrogenic signatures in sediments  
64 challenging<sup>12-15</sup>. Atmospheric intermediate-volatility n-alkanes primarily originate  
65 from fossil fuel emissions. After atmospheric mixing and transport, they enter  
66 watersheds via dry/wet deposition and are ultimately incorporated into lake sediments  
67 through hydrological processes, providing an integrated regional signal of fossil fuel  
68 combustion. Accordingly, we adopted the mean isotopic signature of atmospheric  
69 intermediate-volatility n-alkanes as the fossil source end-member<sup>16</sup>:  $\delta^{13}\text{C} = -28.0 \pm$   
70  $1.5 \text{ ‰}$ ,  $\delta^2\text{H} = -100 \pm 15 \text{ ‰}$ .

71       **Terrestrial plant end-member.** Sedimentary  $n\text{C}_{29}$  is predominantly derived from  
72 terrestrial plants and thus serves as a direct recorder of past terrestrial plant wax  $\delta^2\text{H}$ <sup>17,18</sup>.  
73 To estimate the  $\delta^2\text{H}$  value of terrestrial-derived  $n\text{C}_{23}$ , we applied a mean chain-length  
74 hydrogen isotope fractionation factor  $\epsilon^2\text{H}_{\text{C}_{29}/\text{C}_{23}} = -27.3 \pm 20.0 \text{ ‰}$ , synthesized from  
75 published measurements across diverse plant types (herbs, gymnosperms, and  
76 angiosperms)<sup>8</sup>. For  $\delta^{13}\text{C}$ , we accounted for the minor but consistent depletion with  
77 increasing chain length in terrestrial plants<sup>19</sup>, using  $\epsilon^{13}\text{C}_{\text{C}_{29}/\text{C}_{23}} = 1.5 \text{ ‰}$ .

78       **Aquatic macrophyte end-member.** The  $\delta^2\text{H}$  signature of aquatic macrophyte n-  
79 alkanes is primarily controlled by lake water  $\delta^2\text{H}$ <sup>20-22</sup>. We used sedimentary  $n\text{C}_{17}$   $\delta^2\text{H}$   
80 as a robust proxy for past lake water  $\delta^2\text{H}$ . Literature compilations indicate that hydrogen  
81 isotope fractionation between lake water and sedimentary  $n\text{C}_{17}$  is relatively constant.

82 Our surface-sediment analyses from Lakes Erhai and Chenghai showed fractionation  
83 from the annual mean lake water  $\delta^2\text{H}$  ( $-154.8\text{‰}$ ) consistent with values reported for  
84 lakes in the Americas ( $-166.6\text{‰}$ ) and Europe ( $-149.1\text{‰}$ )<sup>23,24</sup> (Fig. S8a). Critically, the  
85 fractionation between lake water and aquatic macrophyte  $n\text{C}_{23/25}$  is of similar  
86 magnitude. Therefore, we directly applied the measured sedimentary  $n\text{C}_{17}$   $\delta^2\text{H}$  as the  
87  $\delta^2\text{H}$  end-member for aquatic  $n\text{C}_{23/25}$ . For  $\delta^{13}\text{C}$ , values in large aquatic plants (primarily  
88 submerged macrophytes) are mainly governed by the  $\delta^{13}\text{C}$  of dissolved inorganic  
89 carbon (DIC)<sup>25</sup>. Sediment inorganic carbon (IC)  $\delta^{13}\text{C}$ , controlled by boundary-layer  
90 thickness and DIC  $\delta^{13}\text{C}$ <sup>26</sup>, remained stable in both lakes (EH:  $-3.0 \pm 0.6\text{‰}$ ; CH:  $-2.6 \pm$   
91  $0.6\text{‰}$ ; Fig. S8b), indicating minimal historical variation in the DIC pool utilized by  
92 aquatic plants for photosynthesis. Consequently, we used the mean  $\delta^{13}\text{C}$  value of  
93 modern regional aquatic plant  $n\text{C}_{23/25}$  ( $-22.7 \pm 2.0\text{‰}$ ) as the historical end-member.

94 End-member values for  $n\text{C}_{25}$  were subsequently derived from those for  $n\text{C}_{23}$ ,  
95 assuming consistent isotopic offsets between homologues<sup>17,19</sup>, with  $n\text{C}_{25}$  enriched by  
96  $\sim 5\text{‰}$  in  $\delta^{13}\text{C}$  and  $\sim 0.5\text{‰}$  in  $\delta^2\text{H}$  relative to  $n\text{C}_{23}$ .

### 97 **S1.3 Model Execution, Diagnostics and Validation**

98 Models were run using Markov Chain Monte Carlo (MCMC) sampling with  
99 300,000 iterations, a burn-in of 200,000, and a thinning interval of 100. The  $\delta^2\text{H}$  and  
100  $\delta^{13}\text{C}$  values of  $n\text{C}_{23/25}$  served as the mixture data (Fig. S9). Layer-specific end-member  
101 values and associated uncertainties ( $20.0\text{‰}$  for  $\delta^2\text{H}$ ,  $2.0\text{‰}$  for  $\delta^{13}\text{C}$ ) were used as source  
102 data. Convergence was confirmed by Gelman–Rubin diagnostics (all  $< 1.05$ ). An

103 uninformative Dirichlet prior with parameters (1,1,1) was specified for source  
104 proportions to minimize prior influence and allow the data to dominate the posterior  
105 estimates. To verify this setup, prior distributions were visualized using the ‘plot\_prior’  
106 function in MixSIAR. As illustrated for EH  $nC_{23}$  (Fig. S10), the user-specified prior  
107 (left panels, blue) matches the default uninformative prior (right panels, red), with  
108 marginal distributions showing the characteristic decline from low to high  
109 proportions—consistent with a uniform prior over the simplex. This confirms the  
110 neutrality and appropriateness of the model assumptions for the present study. The  
111 effectiveness of source separation is further validated by (i) the strengthened correlation  
112 between the model-derived terrestrial-sourced mid-chain *n*-alkane pool and the  
113 unambiguous long-chain *n*-alkane pool (Fig. S11), and (ii) the close agreement between  
114 the reconstructed decline in aquatic macrophyte OC and independent historical records  
115 of macrophyte coverage in Lake Erhai (Fig. S12).

## 116 **Text S2. First-Order kinetic Mineralization Model**

117 We developed a first-order kinetic mineralization model based on organic carbon  
118 (OC) source classification to quantitatively simulate the dynamic burial and  
119 mineralization processes of OC in lake sediments. The model is constructed within the  
120 theoretical framework of the “deposition–transformation–burial” carbon cycle and  
121 extends the core mechanism of the Dynamic Mineralization and Storage of Organic  
122 Carbon (DMSOC) model proposed by Jiang et al. <sup>27</sup>.

## 123 **S2.1 Theoretical Basis and Logical Framework**

124 The long-term preserved OC in sediments is not simply the initial deposited  
125 amount, but rather the net result of continuous mineralization and the differential  
126 stability of carbon from distinct sources. Traditional approaches that estimate carbon  
127 sequestration solely from measured total OC content overlook the dynamic changes in  
128 both the composition and total stock of the carbon pool during diagenetic mineralization.

129 To address this limitation, our model follows a clear logical sequence:

130 **a. Source Apportionment:** Source-specific biomarkers (*n*-alkanes) are first used  
131 to reconstruct historical input fluxes of OC from different sources. This serves as the  
132 foundation for dynamic simulation.

133 **b. Initial Carbon Pool Quantification:** Biomarker fluxes are converted into  
134 initial depositional masses of each OC type using source-specific conversion factors.  
135 This step bridges microscopic biomarkers to the macroscopic carbon pool.

136 **c. Kinetic Mineralization Simulation:** Because OC from different sources  
137 exhibits distinct chemical compositions and bioavailabilities, separate first-order  
138 kinetic equations with source-specific parameters are applied to simulate post-  
139 depositional decay.

140 **d. Residual Carbon Pool Integration:** The remaining OC from each source after  
141 a given burial period is summed to obtain the theoretical total OC content of a sediment  
142 layer at the time of sampling, allowing direct comparison and validation against  
143 measured values.

144 This framework transforms the static concept of a “carbon pool” into a dynamic  
145 “carbon flow” process, enabling quantitative assessment of long-term carbon burial  
146 efficiency and sink functionality.

## 147 **S2.2 Mathematical Expression and Mechanistic Rationale**

148 The core equation of the model predicts the total remaining OC content,  $OC_{predicted}$ ,  
149 in a sediment layer after a burial time  $t$ :

$$150 \quad OC_{predicted} = \sum [Source_i \times d_i \times (1 - m_i) + Source_i \times d_i \times m_i \times (1 - \exp(-k_i \times t))]$$

151 where the subscript  $i$  denotes the three OC sources: phytoplankton (Alg), aquatic  
152 macrophytes (Aqu), and terrestrial plants (Ter). The parameters and their mechanistic  
153 interpretations are as follows:

154  $Source_i$  – Source Source-Specific Input Flux ( $mg \cdot m^{-2} \cdot yr^{-1}$ ): The time-dependent  
155 driver of the model, reconstructed from down-core concentration profiles of diagnostic  
156 n-alkanes (Bio- $nC_{17}$  for algae, Aqu- $nAlk$  for aquatic plants, and Ter- $nAlk$  for terrestrial  
157 plants).

158  $d_i$  – Biomarker-to-OC Conversion Coefficient (g OC per  $\mu g$  biomarker): This  
159 source-specific coefficient converts biomarker flux into initial depositional OC flux. It  
160 reflects differences in lipid synthesis efficiency and the proportional contribution of  
161 lipids to total organic matter among sources (e.g., algae typically yield higher  $d_i$  values  
162 than terrestrial plants). The parameter is calibrated during model optimization.

163  $m_i$  – Maximum Mineralizable Fraction (dimensionless, 0–1): The proportion of  
164 OC from source  $i$  that is theoretically susceptible to microbial decomposition. The

165 remaining fraction ( $1-m_i$ ) is considered recalcitrant or inert on centennial timescales  
166 and may contribute to long-term geological carbon storage (e.g., kerogen precursors).  
167 For example, terrestrial OC, rich in refractory compounds like lignin, typically has a  
168 lower  $m_i$  value than labile algal OC.

169  $k_i$  – First-Order Decay Constant ( $\text{yr}^{-1}$ ): The kinetic parameter governing the  
170 decomposition rate of the mineralizable OC pool ( $m_i \times d_i \times \text{Source}_i$ ). The term  $\exp(-k_i \cdot t)$   
171 describes the exponential decay of this reactive carbon pool with burial time. higher  $k_i$   
172 values indicate faster mineralization. Differences in  $k_i$  among sources reflect variations  
173 in molecular complexity and degradability, typically following the order: algae >  
174 aquatic macrophytes > terrestrial plants.

175  $t$ – Burial Time (years): The age of each sediment layer, determined by  $^{210}\text{Pb}$  dating  
176 using the constant rate of supply (CRS) model (Fig. S2).

### 177 **S2.3 Key Model Assumptions**

178 **Validity of Source Classification:** The selected  $n$ -alkane biomarkers can  
179 effectively distinguish and quantify these three primary OC sources, and they are  
180 relatively stable during early diagenesis, preserving source information.

181 **Applicability of First-Order Kinetics:** On a centennial timescale, the  
182 mineralization rate of the reactive OC component from each source is proportional to  
183 its standing stock, conforming to first-order reaction kinetics—a common assumption  
184 in sedimentary organic matter degradation studies.

185 **Spatiotemporal Homogeneity of Parameters:** Within the studied time frame and

186 spatial scope (similar lake types), the degradation characteristics ( $m_i$ ,  $k_i$ ) and biomarker  
187 significance ( $d_i$ ) of OC from the same source remain essentially constant. This  
188 assumption allows us to simulate the historical process of the entire sediment core using  
189 a single set of parameters.

190 **Independence of Processes:** The mineralization processes of OC from different  
191 sources are independent; significant interactive effects, such as strong priming effects  
192 on mineralization rates, are not considered in this version.

193 Through this mathematical framework and mechanistic setup, the model integrates  
194 dating data, biomarker indices, and measured total OC to reconstruct the historical  
195 dynamics of OC deposition and mineralization, thereby enabling an assessment of long-  
196 term carbon burial efficiency.

## 197 **S2.4 Optimized Parameters and Model Performance**

198 The nine unknown parameters ( $d_{alg}$ ,  $m_{alg}$ ,  $k_{alg}$ ,  $d_{aqu}$ ,  $m_{aqu}$ ,  $k_{aqu}$ ,  $d_{ter}$ ,  $m_{ter}$ ,  $k_{ter}$ ) were  
199 simultaneously optimized by minimizing the sum of squared residuals between the  
200 measured OC profile and the modeled  $OC_{\text{predicted}}$  profile for the combined 110 data  
201 points from both lakes, using the ‘nls’ function in R. The optimization was constrained  
202 such that<sup>27</sup>,  $d_{alg} > d_{aqu} > d_{ter}$ ;  $m_{aqu} > m_{alg} > m_{ter}$ ;  $k_{alg} > k_{aqu} > k_{ter}$ .

203 The optimized parameters are:

204 **Phytoplankton:**  $m_{alg} = 0.94$ ,  $k_{alg} = 1.35 \text{ yr}^{-1}$ ,  $d_{alg} = 70.2 \text{ g OC per } \mu\text{g Bio-}n\text{C}_{17}$ .

205 **Aquatic macrophyte:**  $m_{aqu} = 0.96$ ,  $k_{aqu} = 0.40 \text{ yr}^{-1}$ ,  $d_{aqu} = 36.1 \text{ g OC per } \mu\text{g Aqu-}$   
206  $n\text{Alk}$ .

207 **Terrestrial plant:**  $m_{ter} = 0.79$ ,  $k_{ter} = 0.14 \text{ yr}^{-1}$ ,  $d_{ter} = 4.9 \text{ g OC per } \mu\text{g Ter-}n\text{Alk}$ .

208 The model explained 70.9% of the variance in observed OC (adjusted  $R^2 = 0.683$ ).

209 Key performance metrics include: Nash-Sutcliffe Efficiency (NSE) = 0.709, Root Mean

210 Square Error (RMSE) =  $3.42 \text{ mg g}^{-1}$ , Mean Absolute Error (MAE) =  $2.77 \text{ mg g}^{-1}$ , and

211 Bias =  $-0.08 \text{ mg g}^{-1}$ . Residuals were normally distributed (Shapiro-Wilk  $p = 0.87$ ).

212 To evaluate the robustness of burial efficiency (BE) trends to parameter

213 uncertainty, we conducted a sensitivity analysis by independently perturbing each of

214 the nine parameters by  $\pm 1\%$ . The maximum change in predicted OC for any sample

215 was less than 5%. This confirms that although absolute  $\text{OC}_{\text{predicted}}$  values are parameter-

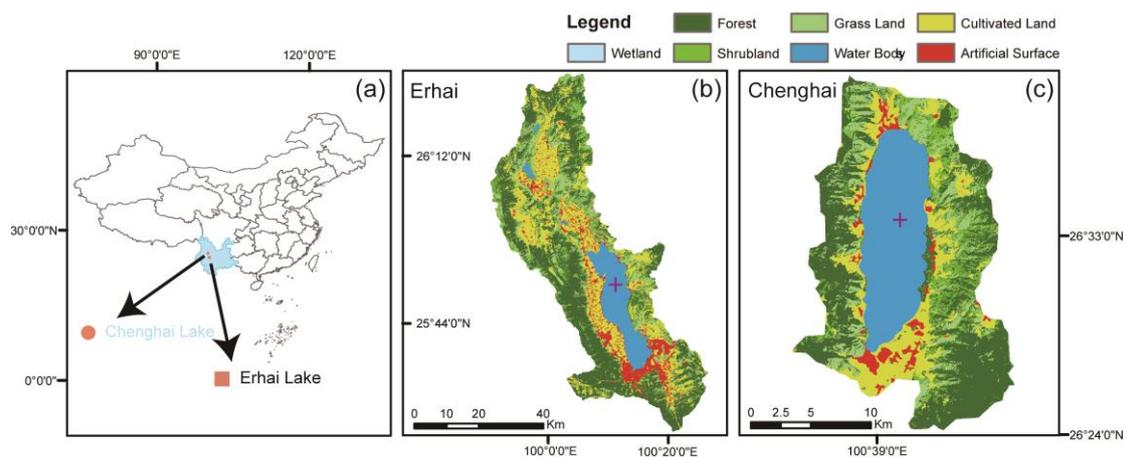
216 dependent, the relative temporal and spatial trends in BE—central to our mechanistic

217 interpretations—are highly robust. Detailed diagnostics are presented in [Fig. S14](#) and

218 summarized in [Table S1](#).

219

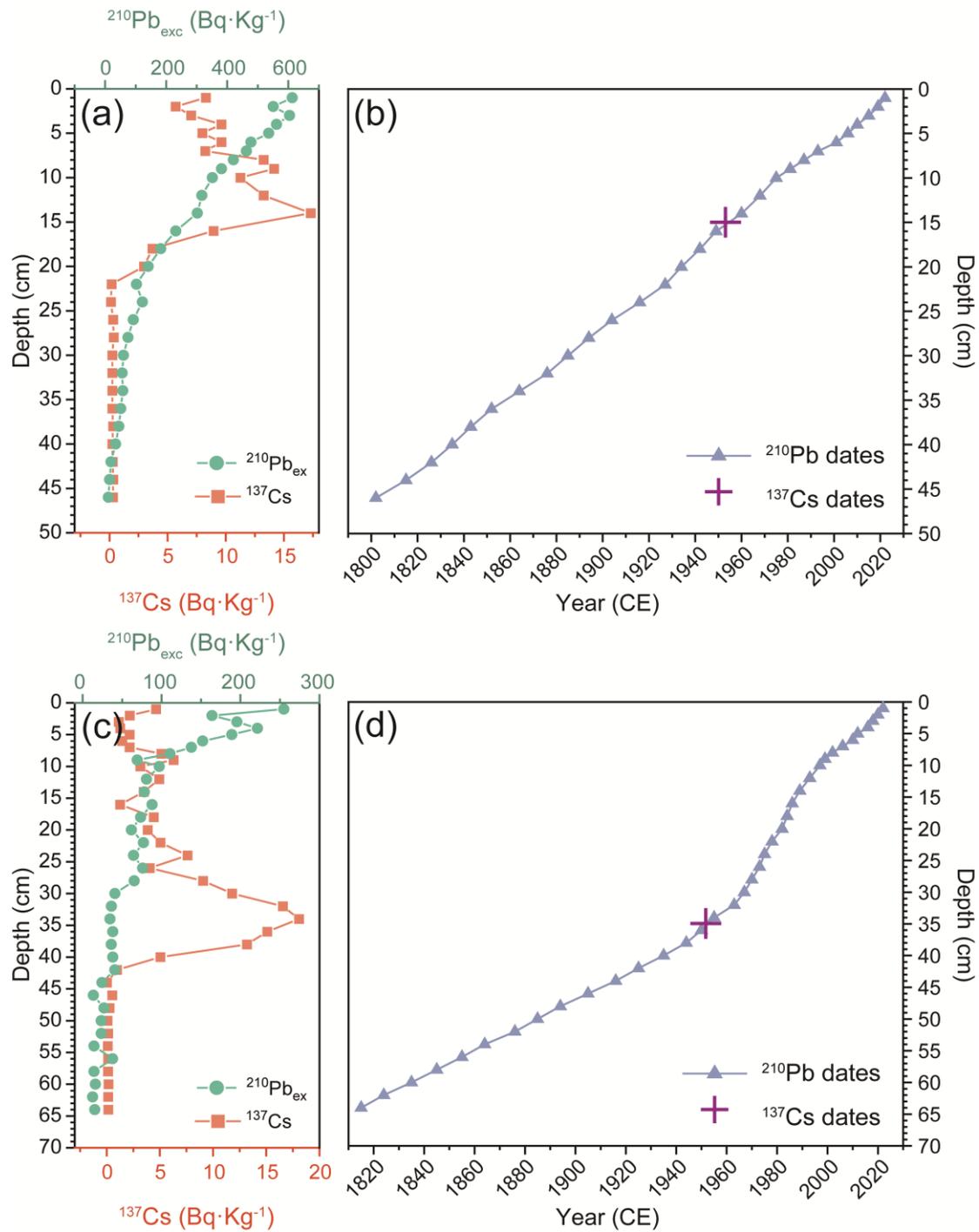
220 **Supplementary Figures (Figure S1 – S13)**



221

222 **Figure S1. Study area and sampling sites.** (a) Location of Lake Erhai and Lake Chenghai on the  
223 Yunnan-Guizhou Plateau, Southwest China. (b, c) Schematic land-use context of the Erhai and  
224 Chenghai drainage basins, respectively. The cross indicates the sediment coring location at the  
225 deepest point of each lake.

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227

228 **Figure S2. Radionuclide profiles and age-depth models for Lake Erhai and Lake Chenghai**

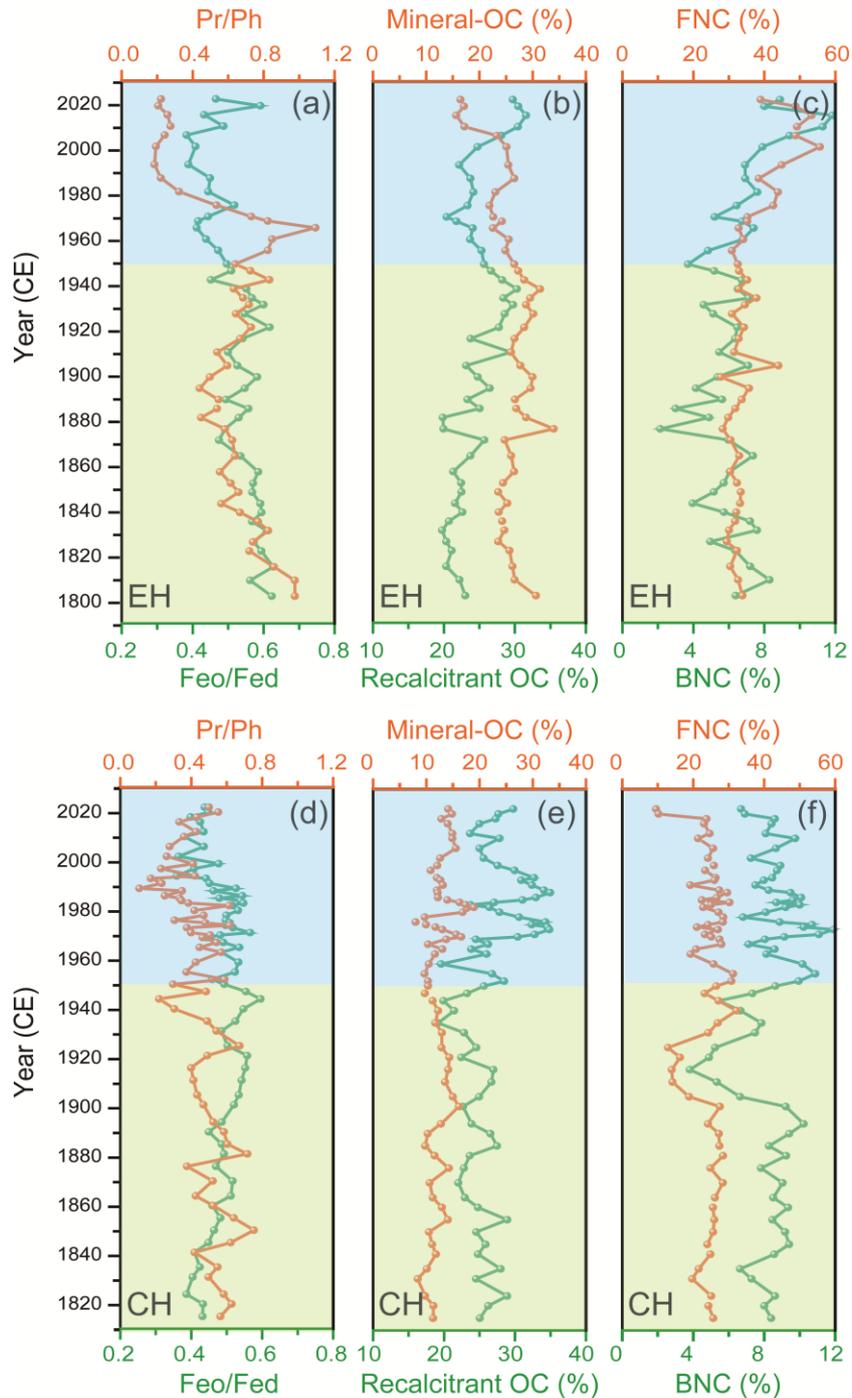
229 **sediment cores.** (a, c) Down-core distributions of unsupported  $^{210}\text{Pb}$  ( $^{210}\text{Pb}_{\text{exc}}$ , green circles) and

230  $^{137}\text{Cs}$  (yellow triangles) activities in the Erhai (EH) and Chenghai (CH) cores. (b, d) Corresponding

231 age-depth models established using the Constant Rate of Supply (CRS) model. The  $^{137}\text{Cs}$  peak (1963)

232 is marked with a cross for validation.

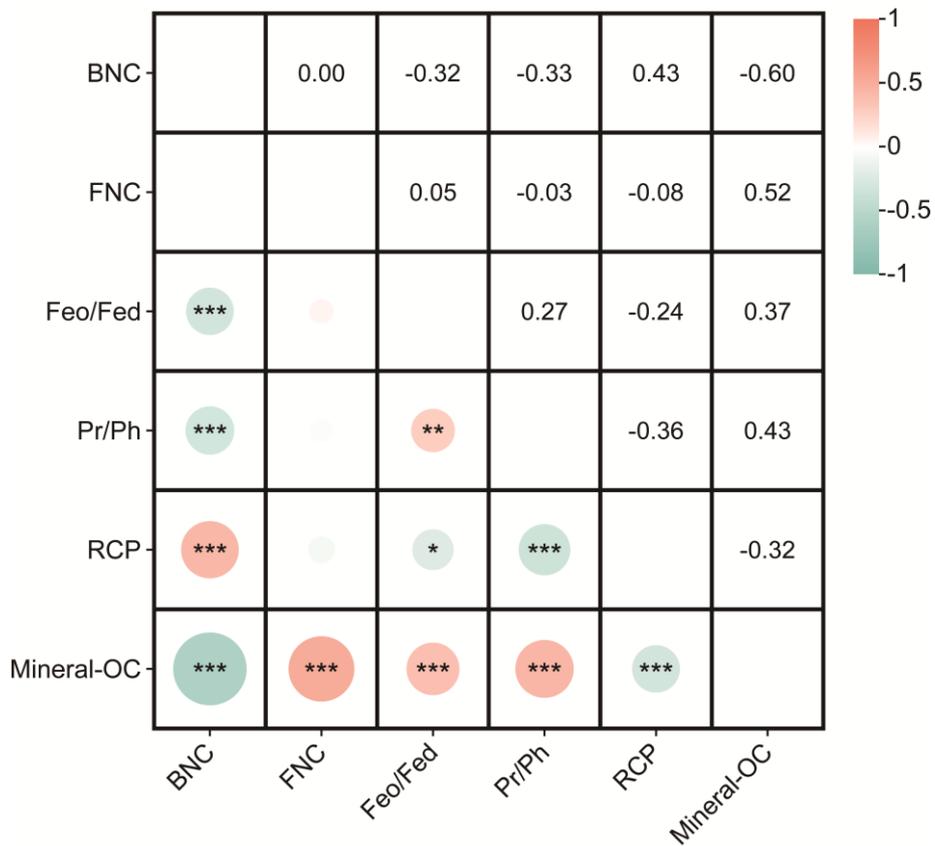
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235 **Figure S3. Temporal variations of sedimentary preservation-condition indicators.** (a-c) Down-  
 236 core profiles for Erhai: (a) redox indicators (Feo/Fed; Pr/Ph), (b) protection indicators (RCP;  
 237 Mineral-OC), (c) proportion of microbial necromass carbon to OC (BNC; FNC). (d-f)  
 238 Corresponding profiles for Chenghai. Abbreviations: BNC, bacterial necromass carbon fraction;  
 239 FNC, fungal necromass carbon fraction; Feo/Fed, reactive free iron to total free iron ratio; Pr/Ph,  
 240 Pristane/Phytane ratio; RCP, proportion of recalcitrant carbon pool; Mineral-OC, mineral-associated

241 organic carbon. Shaded bands represent the three anthropogenic phases defined in the main text.  
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244 **Figure S4. Linear correlation matrix of sedimentary parameters in cores from Lakes Erhai**

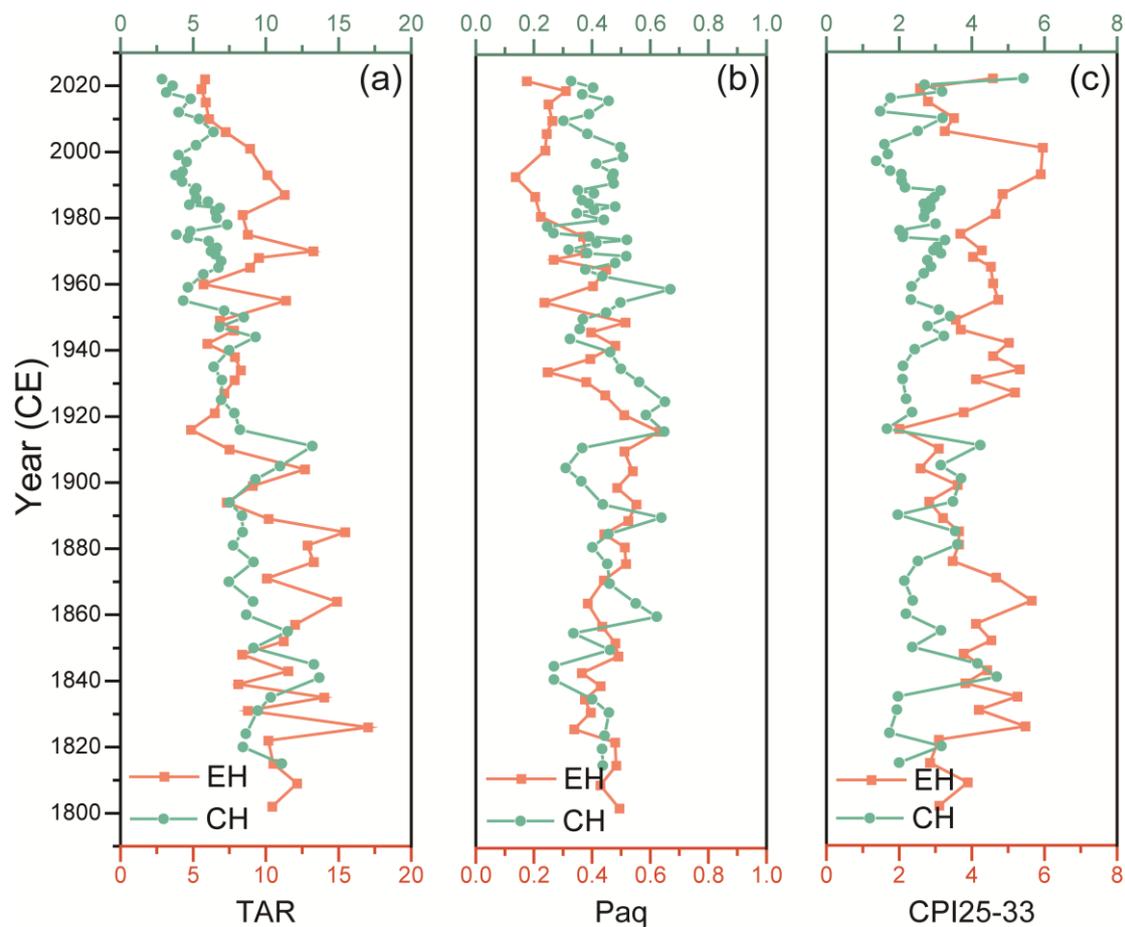
245 **and Chenghai.** Abbreviations: BNC, bacterial necromass carbon fraction; FNC, fungal necromass

246 carbon fraction; Feo/Fed, reactive free iron to total free iron ratio; Pr/Ph, Pristane/Phytane ratio;

247 RCP, proportion of recalcitrant carbon pool; Mineral-OC, mineral-associated organic carbon.

248 Asterisks denote statistical significance (\* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$ ).

249



250

251 **Figure S5. Down-core distributions of n-alkane source proxies in sediments from Lakes Erhai**

252 **(EH) and Chenghai (CH).** (a) Decreasing terrestrial-to-aquatic ratio (TAR) toward the present,

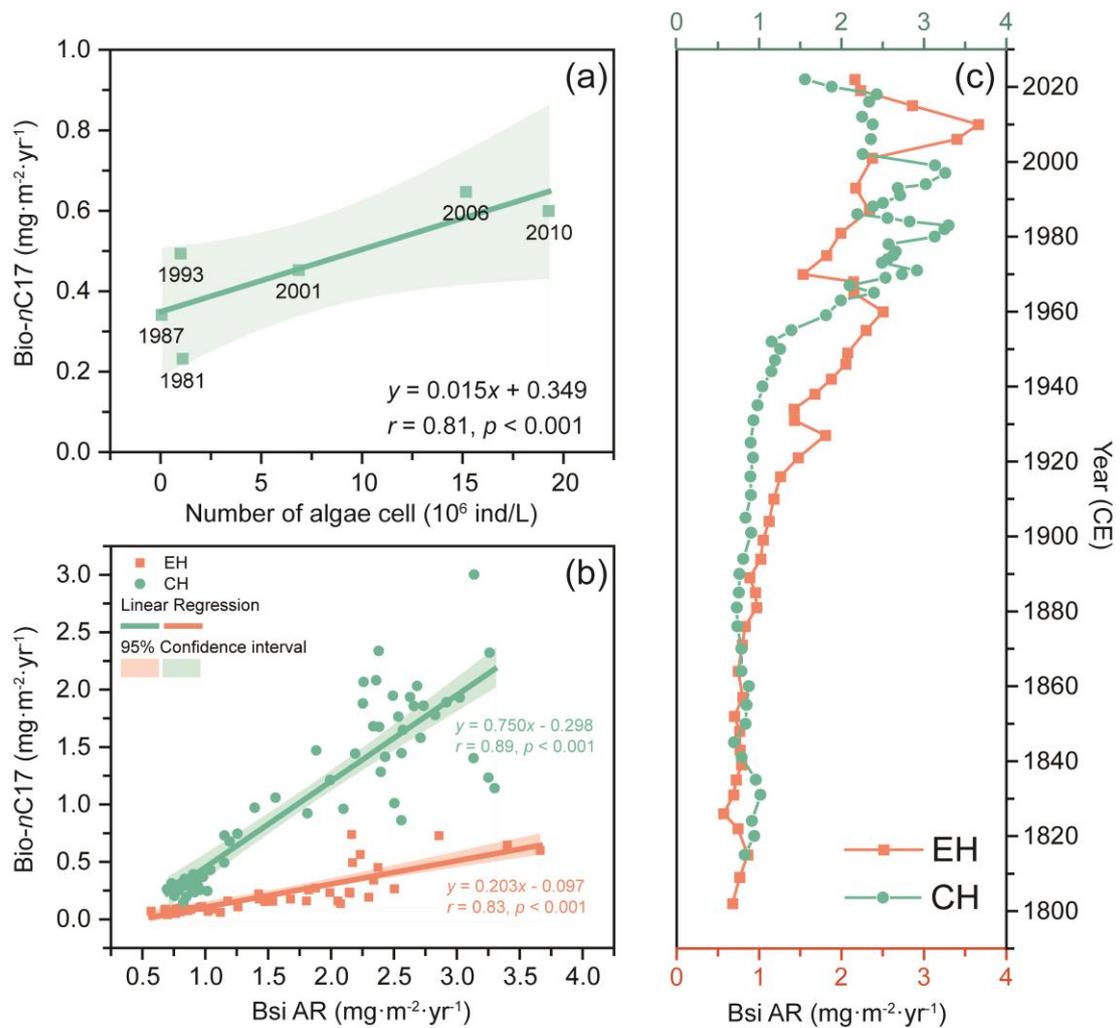
253 consistent with increasing phytoplankton contributions over time. (b) Decline in the Paq index in

254 recent EH sediments, indicating a reduction in aquatic macrophyte inputs. (c) Low carbon

255 preference index (CPI<sub>25-33</sub>) values, suggesting the influence of fossil-fuel contamination and/or

256 early diagenetic alteration.

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258

259 **Figure S6. Multi-proxy validation of the phytoplankton biomarker Bio-*n*C<sub>17</sub>.** (a) Biogenic silica

260 accumulation rate (BSi AR) in Lakes Erhai (EH) and Chenghai (CH). Values remain low and stable

261 over time (coefficient of variation  $\sim 0.5$ ), with only minor fluctuations after 1950 (EH) and 1920

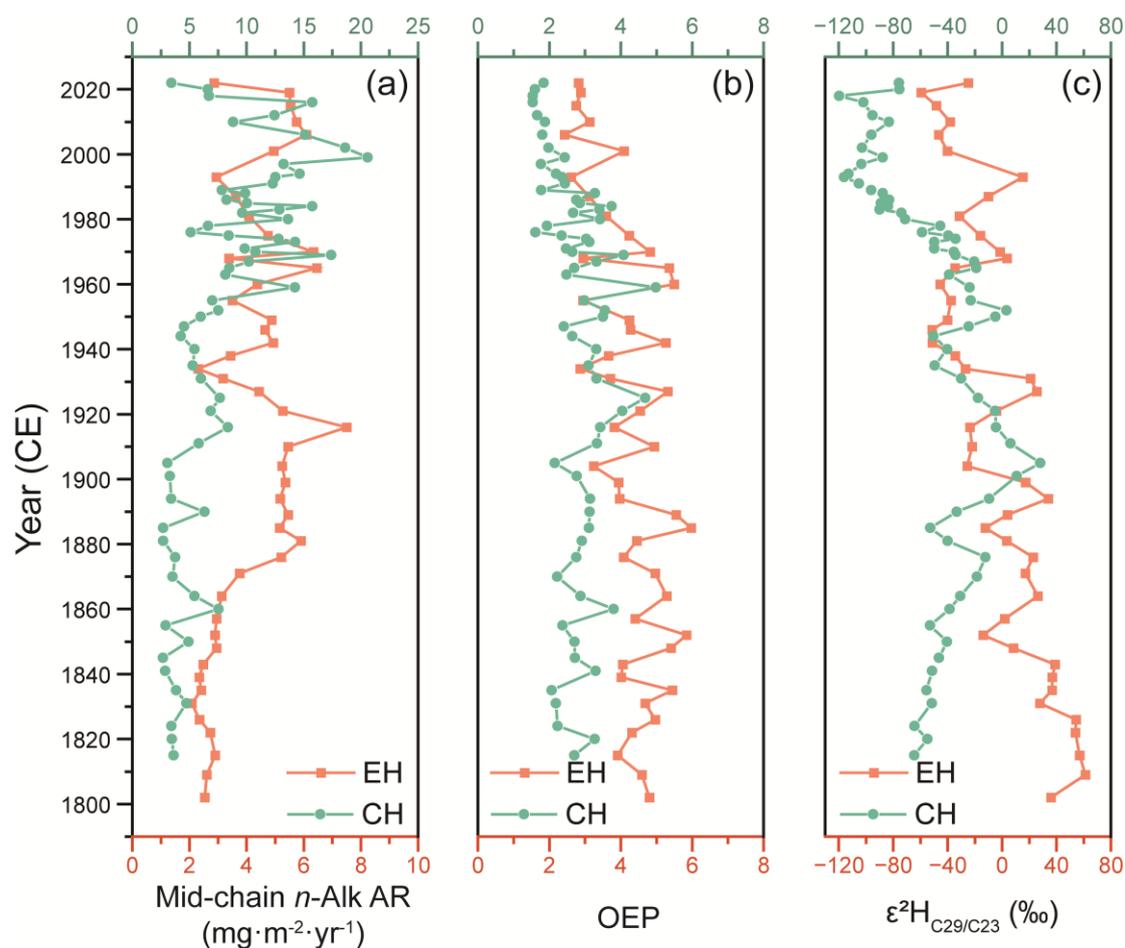
262 (CH). (b) Strong positive correlation between Bio-*n*C<sub>17</sub> AR and BSi AR in both lakes (EH:  $r = 0.83$ ;

263 CH:  $r = 0.89$ ;  $p < 0.001$ ). (c) Significant correlation between modern phytoplankton biomass

264 (instrumental record) and sedimentary Bio-*n*C<sub>17</sub> AR in Lake Erhai ( $r = 0.81, p < 0.001$ ), with points

265 labeled by sediment burial year.

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268 **Figure S7. Multi-proxy evidence for mixed sources of mid-chain *n*-alkanes.** (a) Persistence of

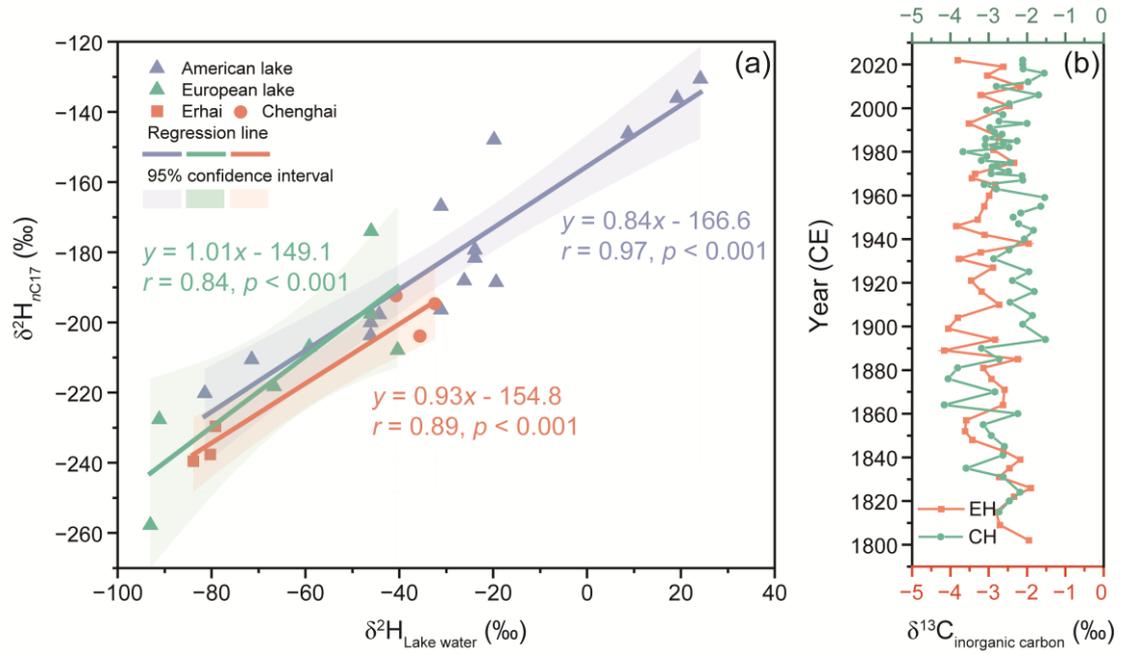
269 *n*C<sub>23</sub>+*n*C<sub>25</sub> accumulation in Lake Erhai despite documented aquatic macrophyte decline. (b) Low

270 odd-over-even predominance (OEP) values, consistent with inputs from non-biogenic sources

271 and/or diagenetic alteration. (c) Temporal change in the hydrogen isotope offset between *n*C<sub>29</sub> and

272 *n*C<sub>23</sub> (ε<sup>2</sup>H<sub>C29/C23</sub>), reflecting a shift in predominant source contributions over time.

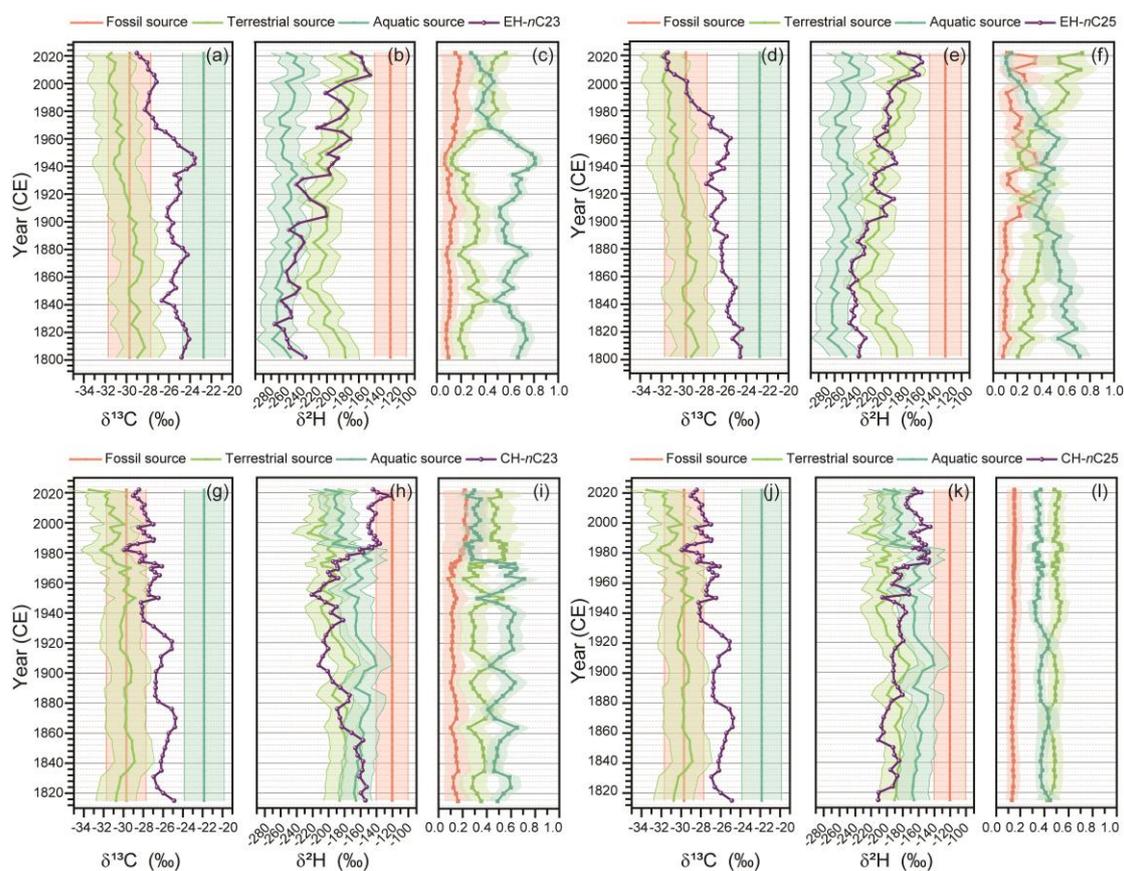
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275 **Figure S8. Isotopic constraints for defining the aquatic end-member.** (a) Hydrogen isotope  
 276 fractionation between water and  $n\text{C}_{17}$  in surface sediments from this study aligns with reported  
 277 values from global lakes. (b) Stable sedimentary inorganic carbon  $\delta^{13}\text{C}$  in both lakes, suggesting  
 278 minimal historical variation in the  $\delta^{13}\text{C}$  of dissolved inorganic carbon utilized by aquatic plants.

279



280

281 **Figure S9. End-member characterization and Bayesian source apportionment of *n*-alkanes in**

282 **Lakes Erhai and Chenghai.** (a, b)  $\delta^{13}\text{C}$  versus  $\delta^2\text{H}$  of  $n\text{C}_{23}$  in Lake Erhai (EH) plotted with

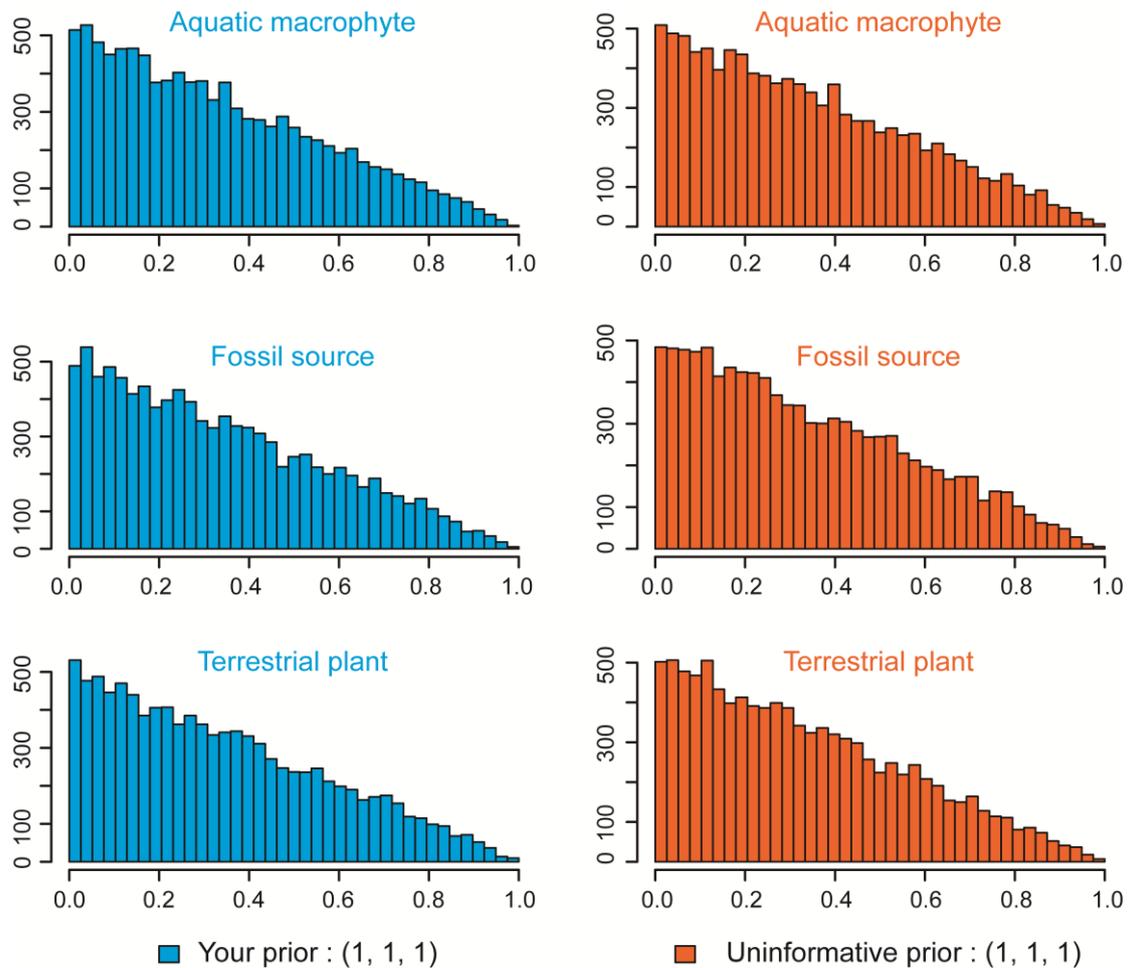
283 end-member isotopic ranges. (c) Bayesian-derived source contributions to  $n\text{C}_{23}$  in EH. (d, e) Same

284 as (a, b) for  $n\text{C}_{25}$  in EH. (f) Source contributions to  $n\text{C}_{25}$  in EH. (g, h)  $\delta^{13}\text{C}$  versus  $\delta^2\text{H}$  of  $n\text{C}_{23}$  in

285 Lake Chenghai (CH) with end-members. (i) Source contributions to  $n\text{C}_{23}$  in CH. (j, k) Same as (g,

286 h) for  $n\text{C}_{25}$  in CH. (l) Source contributions to  $n\text{C}_{25}$  in CH.

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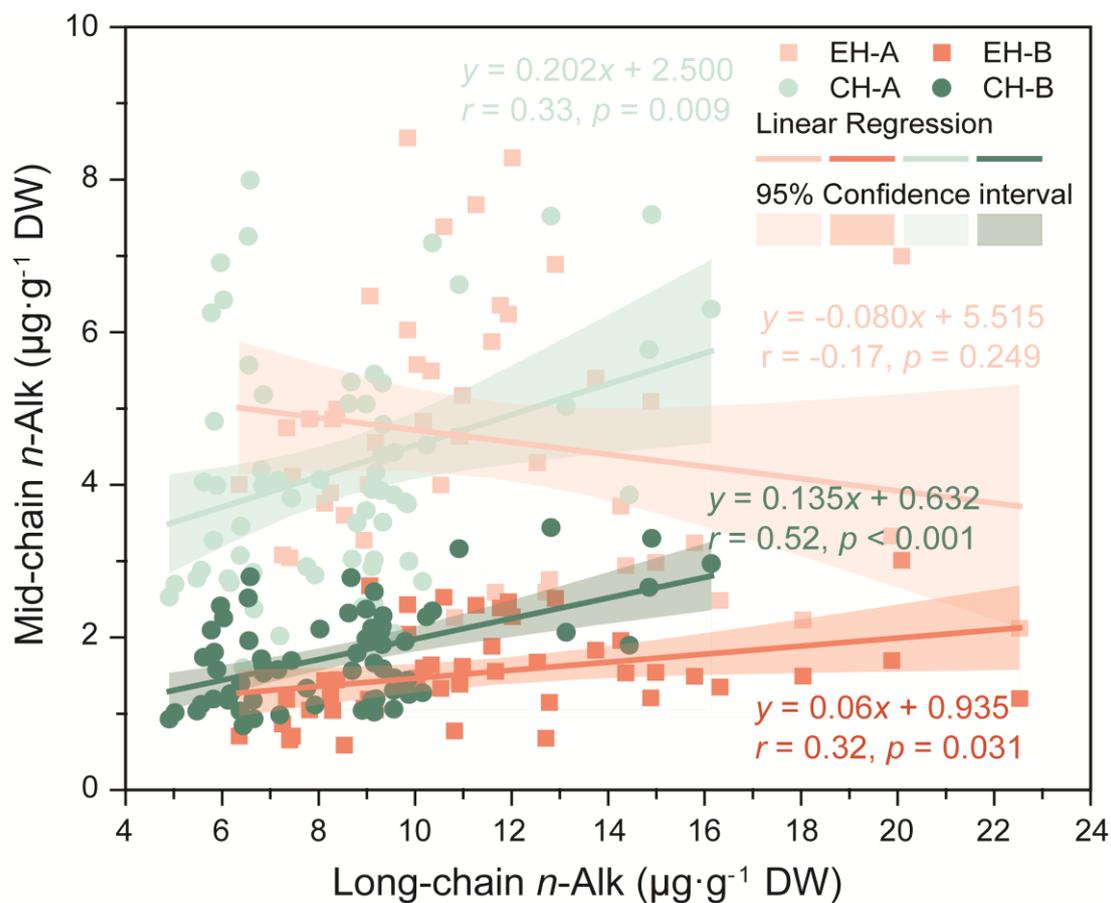
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**Figure S10. Prior distributions for source proportions in the MixSIAR model.** Histograms depict samples drawn from the Dirichlet prior distributions for the three sources: Aquatic macrophyte (top row), Fossil source (middle row), and Terrestrial plant (bottom row). The left panels (blue) show the user-specified prior with parameters (1,1,1), while the right panels (red) display the default uninformative prior with the same parameters. Both sets exhibit identical marginal distributions, declining from high frequency at low proportions to low frequency at high proportions, indicating a neutral, data-driven modeling approach.



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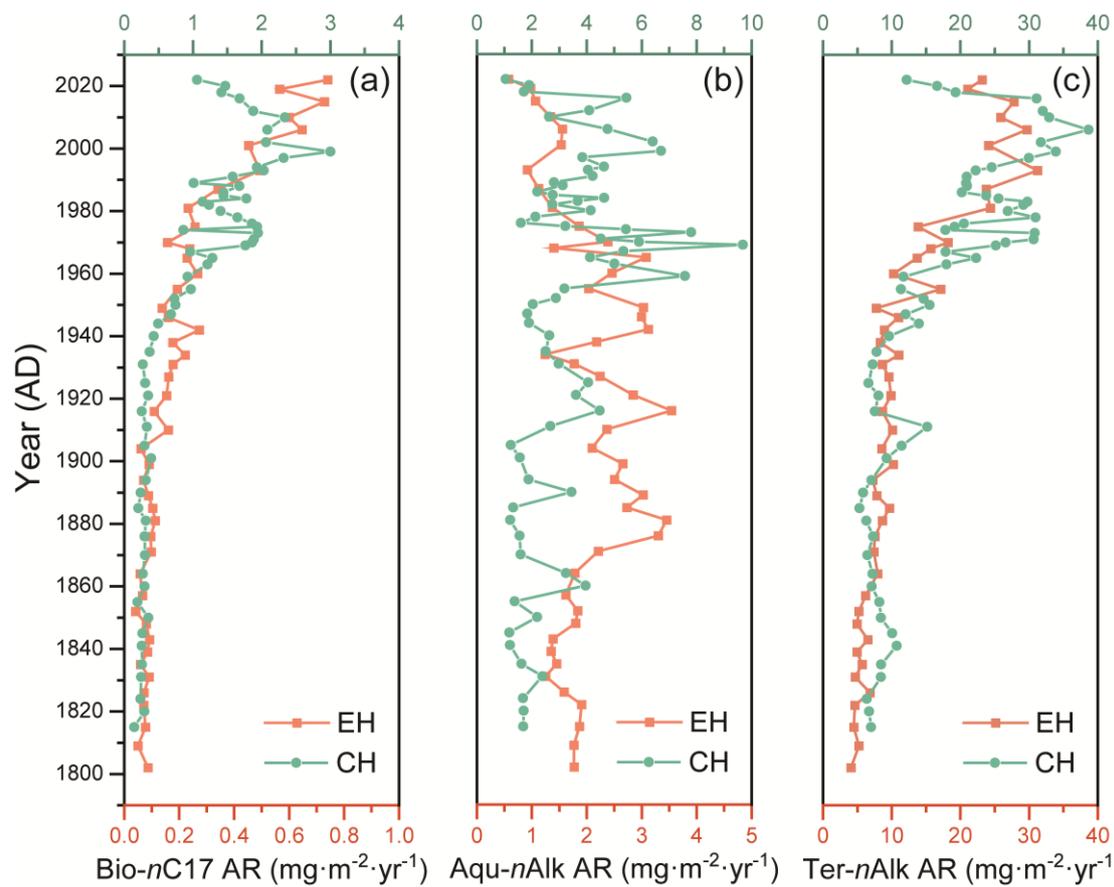
299 **Figure S11. Internal validation of the source-separation achieved by the Bayesian model.**

300 Correlation between the terrestrial-plant-derived mid-chain alkane pool (derived post-model) and

301 the long-chain *n*-alkane pool (Ter-*n*Alk) is significantly stronger ( $r = 0.32, 0.52$ ) than the correlation302 between the total mid-chain alkane pool and Ter-*n*Alk ( $r = -0.17, 0.32$ ). This confirms the model

303 successfully isolated a coherent terrestrial signal from the mixed mid-chain pool.

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306 **Figure S12. Historical accumulation rates of source-apportioned *n*-alkanes in Lakes Erhai**

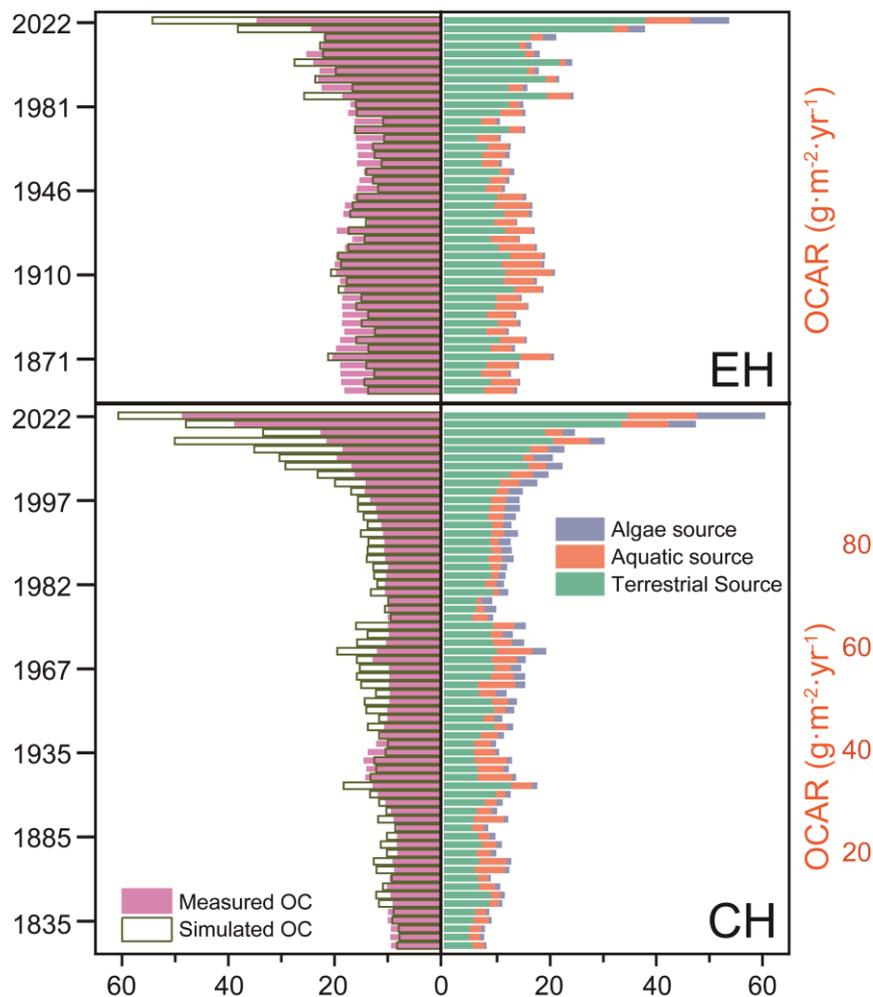
307 **(EH) and Chenghai (CH).** (a) Phytoplankton-derived Bio-*n*C<sub>17</sub> shows an upward trend toward the

308 present in both lakes. (b) Aquatic macrophyte-derived Aqu-*n*Alk exhibits a marked decline in EH

309 in recent decades. (c) Terrestrial-derived Ter-*n*Alk increases in recent sediments, with superimposed

310 episodic pulses.

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314 **Figure S13. Modelled mineralization and source-specific organic carbon burial in Lakes Erhai**315 **and Chenghai.** (a) Down-core variations in measured (solid bars) and first-order kinetic

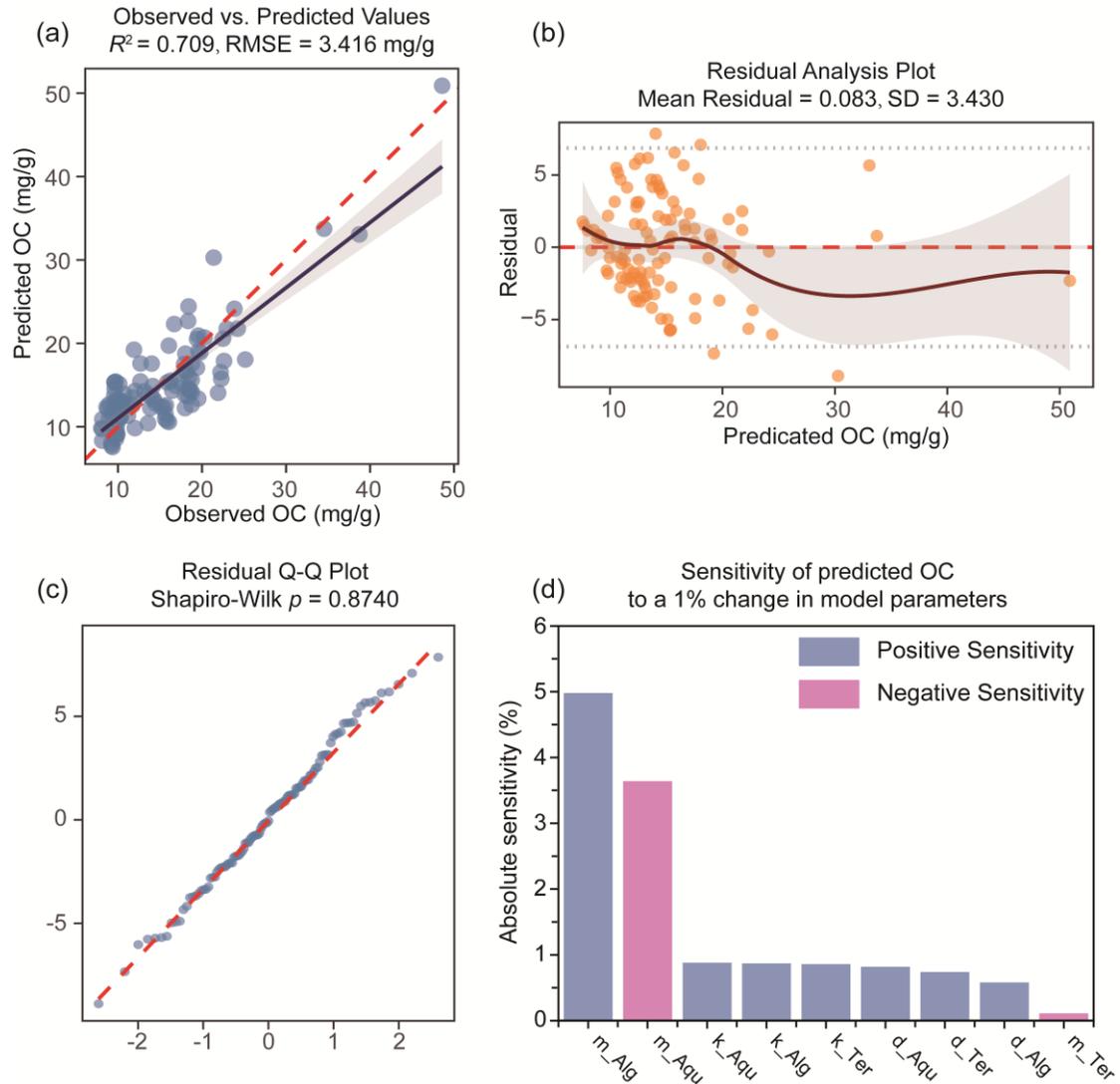
316 mineralization model simulated (open bars) organic carbon (OC) content in Erhai (EH, top) and

317 Chenghai (CH, bottom). Adjacent stacked bars show the modelled proportional contributions to OC

318 from three sources: phytoplankton (light blue), aquatic macrophytes (green), and terrestrial plants

319 (brown).

320



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322 **Figure S14. Diagnostic and sensitivity analysis for the first-order mineralization model.** (a)

323 Observed versus predicted organic carbon (OC) content. The dashed line indicates 1:1

324 correspondence (model  $R^2 = 0.709$ ). (b) Residuals plotted against predicted OC content. The

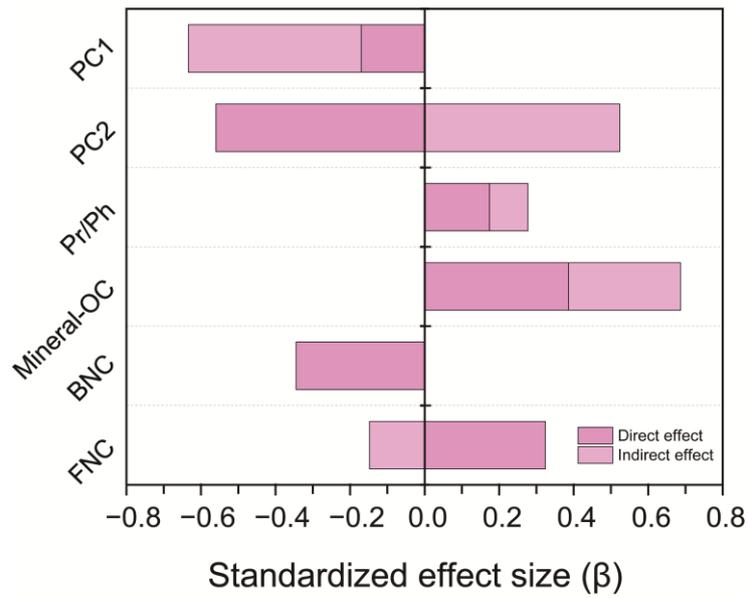
325 horizontal zero-line shows no systematic bias. (c) Quantile–quantile (Q–Q) plot of residuals. The

326 dashed line represents the expected normal distribution (Shapiro–Wilk  $p = 0.87$ ). (d) Sensitivity of

327 predicted OC to a  $\pm 1\%$  change in each model parameter. Blue/red bars denote positive/negative

328 responses; all perturbations yielded output changes of  $< 5\%$ , supporting model stability.

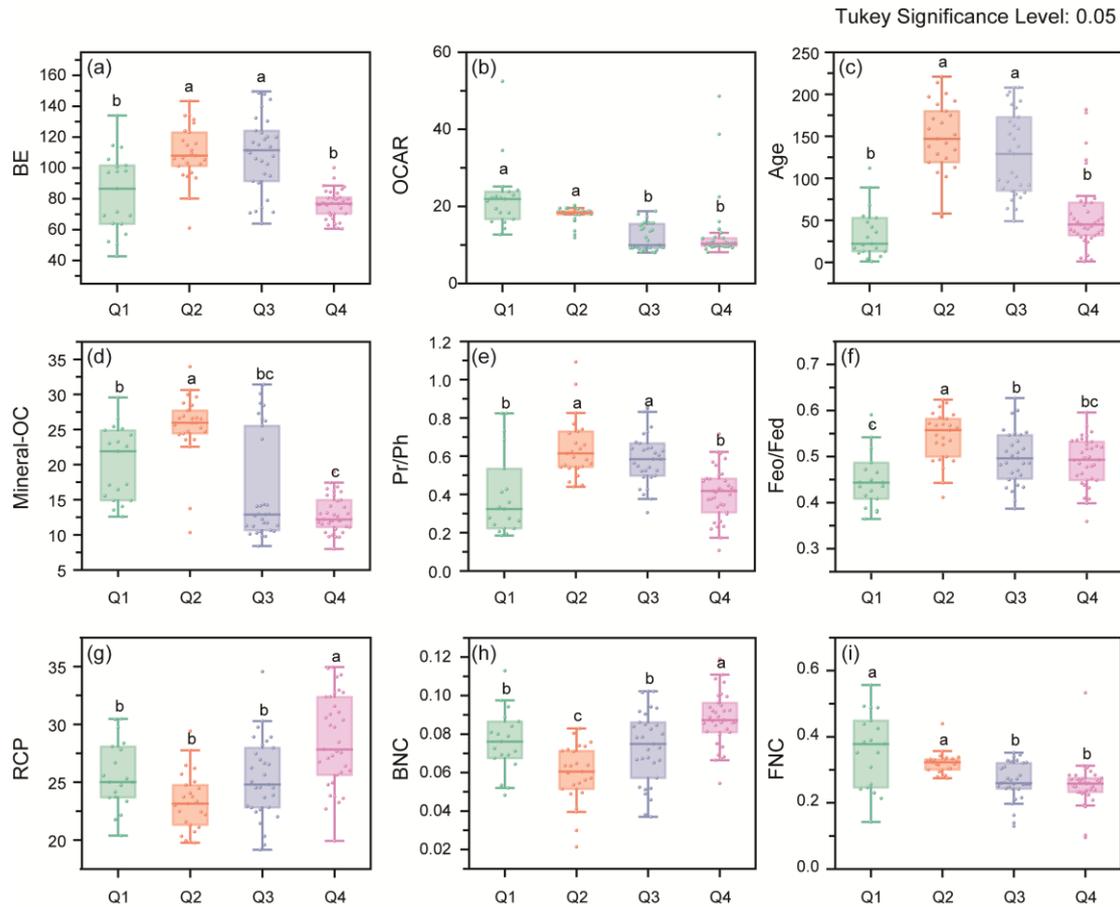
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331 **Figure S15. Direct, indirect, and total standardized effects of each predictor on burial**  
 332 **efficiency, derived from the SEM.** Abbreviations: Pr/Ph, Pristane/Phytane ratio; Mineral-OC,  
 333 mineral-associated organic carbon; BNC, bacterial necromass carbon fraction; FNC, fungal  
 334 necromass carbon fraction

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**Figure S16. Variations in key sedimentary indicators across PCA-defined source regimes**

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**(Quadrants Q1-Q4, Fig. 1e).** Boxplots compare the distributions of (a) burial efficiency (BE), (b)

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organic carbon accumulation rate (OCAR), (c) sediment age (Age), (d) mineral-associated organic

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carbon (Mineral-OC), (e) Pristane/Phytane ratio (Pr/Ph), (f) reactive free iron to total free iron ratio

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(Feo/Fed), (g) proportion of recalcitrant carbon pool (RCP), (h) bacterial necromass carbon fraction

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(BNC), and (i) fungal necromass carbon fraction (FNC) among four quadrants. Letters denote

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statistically significant differences (Tukey's HSD,  $p < 0.05$ ). Quadrants Q1/Q4 represent

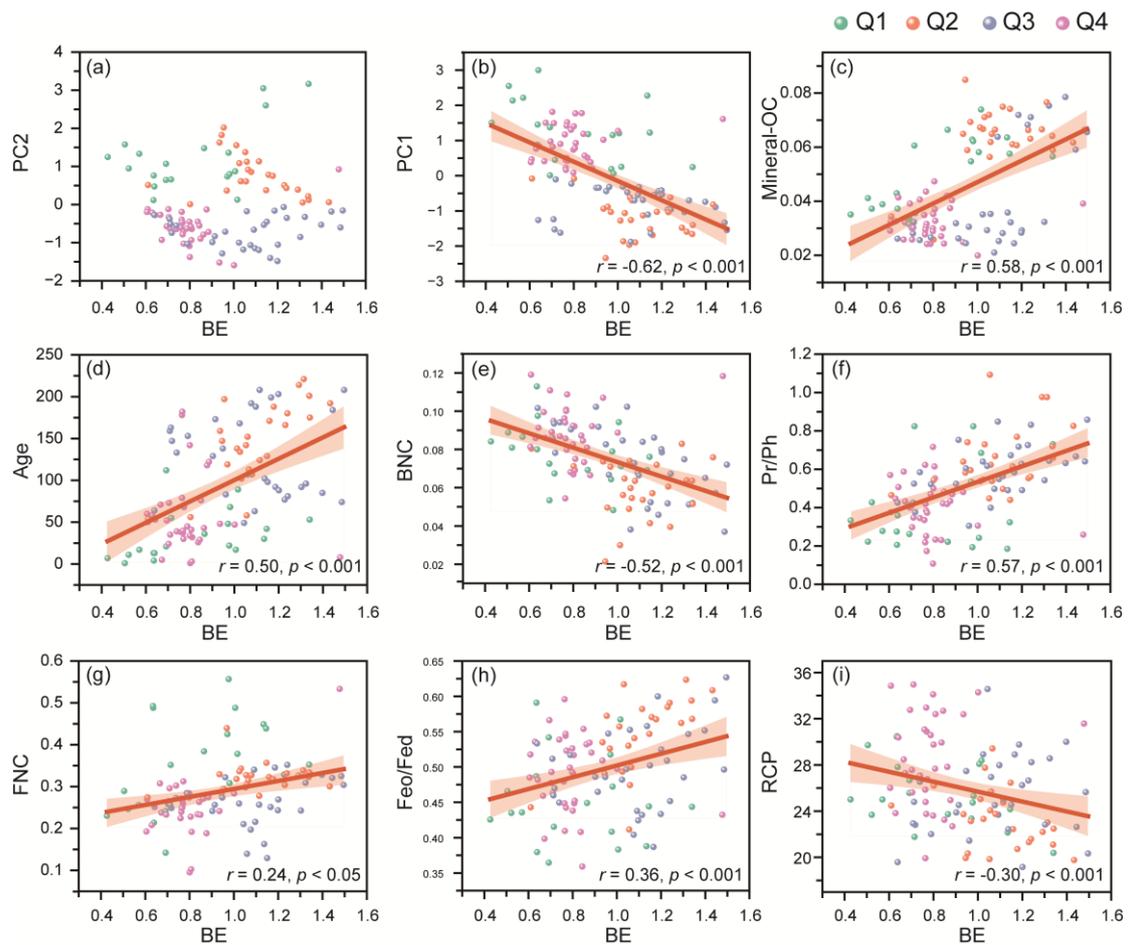
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phytoplankton-rich regimes (recent eutrophication), and Q2/Q3 reflect macrophyte-dominated

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states (early natural states).

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348 **Figure S17. Associations between burial efficiency (BE) and key sedimentary parameters**

349 **across source regimes.** Scatter plots show BE versus (a) PC2 (b) PC1, (c) mineral-associated

350 organic carbon (Mineral-OC), (d) sediment age (Age), (e) bacterial necromass carbon fraction

351 (BNC), (f) Pristane/Phytane ratio (Pr/Ph), (g) fungal necromass carbon fraction (FNC), (h) reactive

352 free iron to total free iron ratio (Feo/Fed) and (i) proportion of recalcitrant carbon pool (RCP). Points

353 are coloured according to the PCA-defined source quadrant (Fig. 1e). Regression lines with 95%

354 confidence intervals are shown per quadrant, illustrating distinct relationships under different source

355 conditions.

356

357 **Supplementary Tables (Table S1 – S2)**

358 **Table S1. Mineralization model diagnostic statistics.**

Metric	Value	Interpretation
$R^2$	0.709	Explains 70.9% variance
Adjusted $R^2$	0.683	Good fit accounting for predictors
NSE	0.709	Good predictive skill
RMSE	3.416 mg·g <sup>-1</sup>	Low error relative to mean OC
MAE	2.774 mg·g <sup>-1</sup>	Average absolute error
MAPE	19.9%	Acceptable relative error
Bias	-0.083 mg·g <sup>-1</sup>	Minimal systematic error
Residual Mean	0.083	Close to zero
Residual SD	3.430	Moderate spread
Shapiro-Wilk $p$	0.874	Normally distributed residuals

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**Table S2. Hierarchical regression blocks and variance explanation.**

Block	Variables entered	$\Delta R^2$	Adjusted $R^2$	F-change	$p$ -value
1	PC1	0.387	0.382	68.254	<0.001
2	+ Pr/Ph, Age	0.054	0.425	5.108	0.008
3	+ Feo/Fed, RCP, Mineral-OC	0.108	0.522	8.142	<0.001
4	+ BNC, FNC	0.031	0.547	2.866	0.062

362 Note: The attenuation of PC1's standardized coefficient from  $-0.622$  (Block 1) to  $-0.207$  (Block 4)

363 indicates mediation by mineral protection and microbial variables.

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