

# Impact of remineralization profile shape on the air-sea carbon balance

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## Key Points:

- Six alternative flux profiles fit to a Martin curve yield large differences in atmospheric carbon.
- Structural uncertainty comprises one third of total uncertainty in the ocean's biological pump.

## Plain Language Summary

The ocean's "biological pump" regulates atmospheric carbon dioxide levels and climate by transferring organic carbon produced at the surface by phytoplankton to the ocean interior via "marine snow", where the organic carbon is consumed and respired by microbes. This surface to deep transport is usually described by a power-law relationship of sinking particle concentration with depth. Uncertainty in biological pump strength can be related to different variable values ("parametric" uncertainty) or the underlying equations ("structural" uncertainty) that describe organic matter export. We evaluate structural uncertainty using an ocean biogeochemistry model by substituting six alternative remineralization profiles fit to a reference power-law curve. Structural uncertainty makes a substantial contribution, about one third in atmospheric pCO<sub>2</sub> terms, to total uncertainty of the biological pump, highlighting the importance of improving biological pump characterization from observations and its mechanistic inclusion in climate models.

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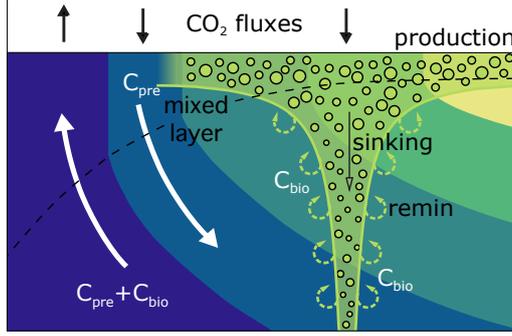
**Abstract**

The ocean’s “biological pump” significantly modulates atmospheric carbon dioxide levels. However, the complexity and variability of processes involved introduces uncertainty in interpretation of transient observations and future climate projections. Much work has focused on “parametric uncertainty”, particularly determining the exponent(s) of a power-law relationship of sinking particle flux with depth. Varying this relationship’s functional form introduces additional “structural uncertainty”. We use an ocean biogeochemistry model substituting six alternative remineralization profiles fit to a reference power-law curve, to characterize structural uncertainty, which, in atmospheric pCO<sub>2</sub> terms, is roughly 50% of the parametric uncertainty associated with varying the power-law exponent within its plausible global range, and similar to uncertainty associated with regional variation in power-law exponents. The substantial contribution of structural uncertainty to total uncertainty highlights the need to improve characterization of biological pump processes, and compare the performance of different profiles within Earth System Models to obtain better constrained climate projections.

**1 Introduction**

Carbon and nutrients are consumed by phytoplankton in the surface ocean during primary production, leading to a downward flux of organic matter (Fig. 1). This “marine snow” is transformed, respired, and degraded by heterotrophic organisms in deeper waters, ultimately releasing those constituents back into dissolved inorganic form. Oceanic overturning and turbulent mixing returns resource-rich deep waters back to the sunlit surface layer, sustaining global ocean productivity. The “biological pump” maintains this vertical gradient in nutrients through uptake, vertical transport, and remineralization of organic matter, storing carbon in the deep ocean that is isolated from the atmosphere on centennial and millennial timescales, lowering atmospheric CO<sub>2</sub> levels by hundreds of microatmospheres (Sarmiento & Toggweiler, 1984; Knox & McElroy, 1984; Volk & Hoffert, 1985; Ito et al., 2005). The biological pump resists simple mechanistic characterization due to the complex suite of biological, chemical, and physical processes involved (Boyd et al., 2019), so the fate of exported organic carbon is typically described using a depth-dependent profile to evaluate the degradation of sinking particulate matter.

Various remineralization profiles can be derived from assumptions about particle degradability and sinking speed(s) (Suess, 1980; Martin et al., 1987; Middelburg, 1989;



**Figure 1.** Schematic of the biological pump. Primary production by phytoplankton takes up carbon and nutrients in the sunlit surface ocean creating a pool of sinking particulate organic matter. Unused carbon and nutrients are subducted from the surface and conservatively transported into the ocean interior (the “preformed” carbon concentration,  $C_{pre}$ ). Exported and sinking particles are remineralized at depth returning the organic matter to its inorganic constituents that are accumulated by watermasses (as the “biological” carbon concentration,  $C_{bio}$ ). Upwelling from the deep ocean returns both preformed and remineralized carbon and nutrients to the surface mixed layer.

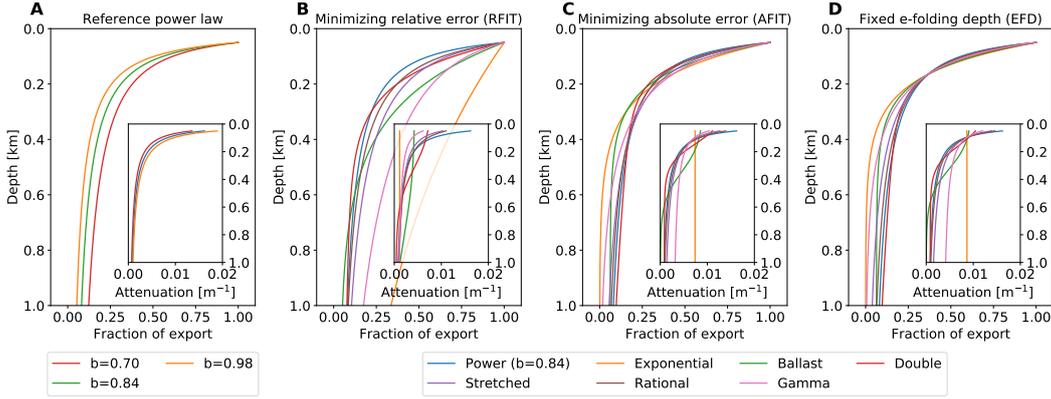
58 Banse, 1990; Armstrong et al., 2001; Lutz et al., 2002; Rothman & Forney, 2007; Kri-  
 59 est & Oschlies, 2008; Cael & Bisson, 2018). The ubiquitous “Martin Curve” (Martin et  
 60 al., 1987) is a power-law profile (Eq. 1) that assumes slower-sinking and/or more labile  
 61 organic matter is preferentially depleted near the surface causing increasing sinking speed  
 62 and/or remineralization timescale with depth (Fig. 2a).

$$63 \quad f_p(z) = C_p z^{-b}, \quad (1)$$

64 where  $f_p(z)$  (moles per square meter per second) representing a fraction of particulate  
 65 flux at depth  $z$  (meters),  $C_p$  (per meter) corresponds<sup>1</sup> to the initial flux from the pro-  
 66 ductive layer near the surface (Buesseler et al., 2020), and  $b$  is a nondimensional param-  
 67 eter controlling how  $f_p$  decreases with depth.

68 Considerable effort has been dedicated to determining value(s) for the exponent,  
 69  $b$  (e.g., Martin et al., 1987, 1993; Berelson, 2001; Primeau, 2006; Honjo et al., 2008; Hen-  
 70 son et al., 2012; Gloege et al., 2017; Wilson et al., 2019). Open ocean particulate flux  
 71 observations from the North Pacific (Martin et al., 1987) indicate a  $b$  value of 0.858. Fur-

<sup>1</sup> Eq. 1 is often normalized to a reference depth  $z_o$  but this parameter is readily absorbed into  $C_p$ .



**Figure 2.** Fraction of sinking particulate organic matter exported from the 50 m surface layer remaining at each depth for (a) the reference power-law (Eq. 1) with exponents  $0.84 \pm 0.14$ , and six alternative functions (Eq. S1–S6) fit to the reference power-law curve ( $b = 0.84$ ) by (b) statistically minimizing the relative error (“RFIT”), or (c) the absolute error (“AFIT”), and (d) matching the e-folding depth scale of 164 m (“EFD”). See Materials and Methods, Table S1 for fitting details, coefficients, and fit statistics. Inset plots show the attenuation rate of the export flux with depth  $\left[\frac{1}{f} \frac{\partial f}{\partial z}, m^{-1}\right]$ .

72 further analyses of expanded sediment trap datasets suggest a possible range of approxi-  
 73 mately  $0.84 \pm 0.14$  for the global  $b$  value (Martin et al., 1993; Berelson, 2001; Primeau,  
 74 2006; Honjo et al., 2008; Gloege et al., 2017), though a much wider range has been ob-  
 75 served when including regional variability in  $b$  and optically- and geochemically-derived  
 76 flux estimates (Henson et al., 2012; Guidi et al., 2015; Pavia et al., 2019). This may re-  
 77 sult from differences in temperature (Matsumoto, 2007), microbial community compo-  
 78 sition (Boyd & Newton, 1999), particle composition (Armstrong et al., 2001), oxygen con-  
 79 centration (Devol & Hartnett, 2001), or external factors such as mineral ballasting (Pabortsava  
 80 et al., 2017).

81 Uncertainty in the value of  $b$  translates to uncertainty in the biological pump’s im-  
 82 pact on the ocean carbon sink, atmosphere-ocean carbon partitioning, and climate model  
 83 projections. Thus, constraining  $b$  for the modern ocean and how it may differ in the past,  
 84 or the future, is of much interest from a climate perspective, with one estimate placing  
 85 an economic value of \$0.5 trillion USD on reducing these uncertainties (Jin et al., 2020).  
 86 Varying a global value of  $b$  between 0.50–1.4 altered atmospheric  $p\text{CO}_2$  by 86–185  $\mu\text{atm}$   
 87 in an influential modeling study (Kwon et al., 2009): Higher values of  $b$  result in enhanced

88 particle remineralization at shallower depths. Shallow watermasses are more frequently  
89 ventilated, allowing remineralized  $\text{CO}_2$  to be released back into the atmosphere on shorter  
90 timescales. Due to this depth-dependence, a small change of degradation depth can ap-  
91 preciously change atmospheric  $\text{pCO}_2$  (Yamanaka & Tajika, 1996; Kwon et al., 2009). Vary-  
92 ing  $b$  over the plausible range in global values between 0.70–0.98 produces a more mod-  
93 est change in atmospheric  $\text{pCO}_2$ , over the range of  $(-16,+12)\mu\text{atm}$  (Gloege et al., 2017),  
94 while the modeled uncertainty in atmospheric  $\text{pCO}_2$  associated with regional variation  
95 in  $b$  is estimated between 5–15  $\mu\text{atm}$  (Wilson et al., 2019).

96 Biogeochemical models are subject not only to parametric uncertainty (which value  
97 for  $b$  and how  $b$  varies in space and time), but also structural uncertainty, i.e. which equa-  
98 tion(s) to choose for the vertical flux of organic matter. The Martin Curve power-law  
99 is an empirical fit to sediment trap data, but several other functional forms have also been  
100 put forward (Suess, 1980; Middelburg, 1989; Banse, 1990; Armstrong et al., 2001; Lutz  
101 et al., 2002; Dutkiewicz et al., 2005; Rothman & Forney, 2007; Marsay et al., 2015) that  
102 fit sediment trap fluxes equivalently well and have equal if not better mechanistic jus-  
103 tification (Cael & Bisson, 2018). Atmospheric  $\text{pCO}_2$  and many other global biogeochem-  
104 ical properties will be affected by this structural uncertainty, so it is critical to evaluate  
105 the impact of choosing one remineralization profile “shape” over another.

106 We assess the effect of remineralization profile shape on biological pump strength  
107 and evaluate a comprehensive estimate of structural uncertainty in terms of atmosphere-  
108 ocean carbon partitioning in a global ocean biogeochemistry model. We substitute the  
109 reference power-law curve for six different remineralization profiles (exponential (Banse,  
110 1990; Dutkiewicz et al., 2005; Marsay et al., 2015; Gloege et al., 2017), ballast (Armstrong  
111 et al., 2001; Gloege et al., 2017), double exponential (Lutz et al., 2002), stretched ex-  
112 ponential (Middelburg, 1989; Cael & Bisson, 2018), rational (Suess, 1980), and gamma  
113 (Rothman & Forney, 2007) functions<sup>2</sup>), each corresponding to a basic mechanistic de-  
114 scription of particle flux (Cael & Bisson, 2018), that are constrained to the reference pro-  
115 file by statistically minimizing misfits or by matching degradation depth scales (Kwon  
116 et al., 2009). These simulations indicate that structural uncertainty is an appreciable com-  
117 ponent, around one third, of total uncertainty for understanding the biological pump:  
118 changing remineralization functional form alters atmospheric  $\text{pCO}_2$  by  $\sim 10\text{--}15\mu\text{atm}$  de-

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<sup>2</sup> See Supporting Information for derivations of these profiles

119 pending on how structural uncertainty is quantified, equivalent to  $\sim 0.08$  uncertainty in  
 120 a global value of the power-law exponent,  $b$ , and similar to the uncertainty resulting from  
 121 regional variation of  $b$ .

122 Our results underscore the importance of characterizing basic mechanisms govern-  
 123 ing the biological pump. Furthermore, our results corroborate that depth-dependence  
 124 of these mechanisms is particularly important (Gehlen et al., 2006; Kriest & Oschlies,  
 125 2008): not only is biological pump-driven carbon storage an important control on atmo-  
 126 spheric  $p\text{CO}_2$ , but we find that particle degradation in the upper ocean must also de-  
 127 crease rapidly for a sufficient quantity of carbon to become isolated in the deep ocean.  
 128 While a given flux curve may be chosen for historical reasons or mathematical conve-  
 129 nience, its skill should be compared to those of other idealized flux profile parameter-  
 130 izations in Earth System Models used for projections of future climate.

## 131 2 Materials and Methods

### 132 2.1 Fitting the alternative remineralization curves.

133 We fit the alternative functions for export fluxes and remineralization (Fig. 2, Eq.  
 134 S1–S6, see Supporting Information) to the reference power-law curve (Eq. 1) with the  
 135 exponent  $b = 0.84$  using nonlinear regression on the native model grid interfaces to min-  
 136 imize the absolute curve mismatch (“ABS” simulations). Points were weighted equally,  
 137 except for the heavily weighted top level to ensure all the profiles pass through the same  
 138 value as the control profile (i.e. fraction of export from the surface layer is 1.0). We fur-  
 139 ther matched the e-folding depth of remineralization to the reference (“EFD” simula-  
 140 tions) by adding a second heavily weighted point to the reference power-law at 164 m  
 141 depth ( $z_0 e^{(1/b)}$ ), with an export fraction of  $e^{-1}$ . In a third set (“RFIT” simulations), the  
 142 nonlinear regression is performed in log-space to minimize the relative error the refer-  
 143 ence profile match. Goodness of fit is evaluated by the Standard Error of Regression,  $\mathcal{S}$ ,  
 144 which is the sum of squared residuals, divided by statistical degrees of freedom (num-  
 145 ber of points minus number of parameters). Coefficients and  $\mathcal{S}$  values for the eighteen  
 146 curves are given in Table S1.

## 147 **2.2 Numerical ocean biogeochemistry model.**

148 Alternative remineralization profiles are substituted into global ocean simulations  
 149 of a coarse resolution (3°, 15 vertical level) global configuration of the Massachusetts In-  
 150 stitute of Technology general circulation model, MITgcm (Marshall et al., 1997), cou-  
 151 pled to an idealized ocean biogeochemistry model (Najjar et al., 2007; Dutkiewicz et al.,  
 152 2006; Parekh et al., 2006) that captures the magnitude and variation of observed air-sea  
 153 fluxes of CO<sub>2</sub> (Lauderdale et al., 2016), and has been widely used in theoretical carbon  
 154 cycle studies (Parekh et al., 2006; Dutkiewicz et al., 2006; Goodwin et al., 2007; Naj-  
 155 jar et al., 2007; Lauderdale et al., 2013, 2017).

156 Two-thirds of surface production (which depends on light, nutrients, and iron) is  
 157 channelled into dissolved organic matter that is remineralized with a timescale of 6 months  
 158 (Yamanaka & Tajika, 1997), while one-third is exported via sinking particulate organic  
 159 matter subject to depth-dependent remineralization rates. Elemental biological trans-  
 160 formations are related using fixed stoichiometric ratios  $R_{C:N:P:Fe:O_2} = 117:16:1:4.68 \times 10^{-4}:-$   
 161 170 (Anderson & Sarmiento, 1994). The total ocean-atmosphere carbon inventory is con-  
 162 served as there is no riverine carbon input or sediment carbon burial. Our model includes  
 163 tracers to separate the *in situ* concentrations of carbon (Fig. 1) into: (i) a component  
 164 subducted from the surface layer and transported conservatively by ocean circulation (the  
 165 “preformed” carbon concentration,  $C_{pre}$ ), and (ii) a component that integrates export  
 166 and remineralization of organic matter as a watermass transits the ocean interior (the  
 167 “biological” carbon concentration,  $C_{bio}$ ), connecting more directly to the biological pump  
 168 (Ito & Follows, 2005). We integrate simulations for 10,000 years toward steady state in  
 169 atmosphere-ocean carbon partitioning.

## 170 **3 Results**

### 171 **3.1 Varying the exponent of the reference power-law curve.**

172 Global power-law exponent,  $b$ , estimates range from 0.70 (Primeau, 2006) based  
 173 on sediment traps to 0.97 based on inverse models fit to tracer distributions (Kwon &  
 174 Primeau, 2008; Kwon et al., 2009). These values match the global  $b$  interquartile range  
 175 of 0.70–0.98 in (Gloege et al., 2017). We integrate three simulations with  $b = 0.84 \pm$   
 176 0.14 (Fig. 2a) using the standard power-law parameterization (Eq. 1) to produce a base-

177 line estimate of biological pump parametric uncertainty. The reference simulation has  
 178 the exponent  $b = 0.84$ .

179 Higher  $b$  values cause the fraction of sinking particulate matter to decrease faster  
 180 with depth, that is, attenuation ( $1/f_p \cdot \partial f_p / \partial z$ ) is higher in the upper ocean, whereas  
 181 lower exponents have less attenuation and a larger proportion of export reaching the deep  
 182 ocean (Figs. 2a and S1a–f). A negative feedback occurs near the surface in our simula-  
 183 tions. For example, when  $b$  is increased, higher rates of upper ocean attenuation cause  
 184 an increase in surface nutrient availability, and therefore more overall biological produc-  
 185 tion (see  $\Delta B_C$ , Table S2). Local biological activity enhancement increases local rates of  
 186 particle export, evaluated by integrated fluxes through the deepest mixed layer depth  
 187 ( $\Delta E_{mld}$ , Table S2). However, higher shallow export is compensated by greater upper ocean  
 188 remineralization, due to larger exponent value, resulting instead in reduced export flux  
 189 anomalies through 1 km depth ( $\Delta E_{1km}$ , Table S2), and vice versa when  $b$  is decreased.  
 190 The global ocean reservoir of biological carbon changes proportionally with  $\Delta E_{1km}$  (Figs. 3,  
 191 blue symbols, S1g–i, and  $\Delta C_{bio}$ , Table S2) and inversely-proportional to  $\Delta E_{mld}$  (Fig. S4a).

### 192 **3.2 Impact of alternative remineralization curve shape.**

193 Six alternative remineralization profiles, obtained from simplifying assumptions about  
 194 the balance between particles' vertical transport and degradation (Eq. S1–S6), are char-  
 195 acterized by objectively evaluating parameters to match the reference power-law curve  
 196 ( $b = 0.84$ ) as closely as possible (Fig. 2b–d, Table S1): In two groups of simulations,  
 197 parameters are found by statistically minimizing the relative error (“RFIT”) or the ab-  
 198 solute error (“AFIT”) of the nonlinear fit of each curve to the reference profile. In a third  
 199 group of simulations, parameters are found that match the reference curve’s 164 m e-folding  
 200 depth of remineralization (“EFD”, the depth at which the flux has been attenuated to  
 201 a factor of  $1/e$ ).

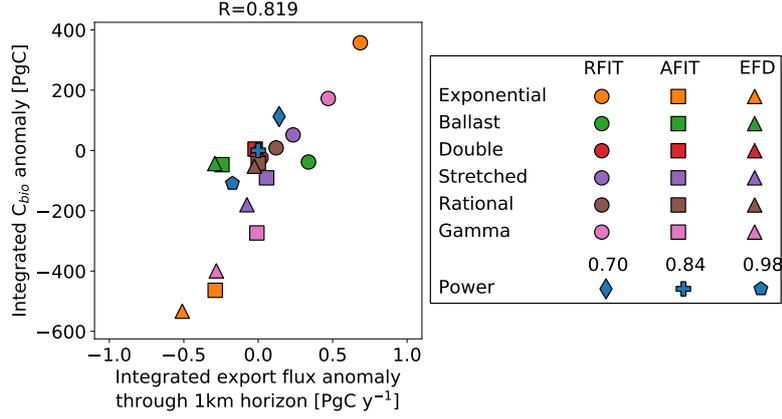
202 The simple exponential and gamma function fits are poorer than the other func-  
 203 tions (Fig. 2b–d) because these profiles cannot capture a strong depth-change in rem-  
 204 ineralization. Simulations with lower-attenuation profiles result in increased export fluxes  
 205 through the 1 km depth horizon ( $\Delta E_{1km}$ ), and vice versa, as with the simulations vary-  
 206 ing  $b$  (Fig. 3). These particulate flux anomalies translate into changes in the distribu-  
 207 tion of biological carbon ( $C_{bio}$ ), with positive export flux anomalies corresponding to in-

208 crease in the biological carbon pool (Fig. 3), while negative export flux anomalies result  
 209 in lower biological carbon concentrations (Fig. S3). For instance, in RFIT simulations,  
 210 the exponential and gamma profiles show an increase in 1 km export fluxes and biolog-  
 211 ical carbon storage, while the reverse occurs for exponential and gamma profiles in AFIT  
 212 and EFD simulations. The ballast profile has a more complex distribution of biological  
 213 carbon anomalies in surface, intermediate, and deep waters (Fig. S3) such that the re-  
 214 lationship between export flux and  $\Delta C_{bio}$  is better captured by considering deeper hori-  
 215 zons (e.g. 2 km, Fig. S4b).

### 216 **3.3 Evaluating structural uncertainty of the biological pump.**

217 Altering the strength of the biological pump leads to changes in air-sea carbon bal-  
 218 ance. The reference simulation has a steady-state atmospheric  $p\text{CO}_2$  of  $269.3 \mu\text{atm}$ . In-  
 219 creasing  $b$  from 0.70 to 0.98 increases  $p\text{CO}_2$  by  $46.36 \mu\text{atm}$  in this model (range:  $-21.6$ –  
 220  $24.8 \mu\text{atm}$ , wide grey bars in Fig. 4, Table S2). This is higher than the “nutrient restor-  
 221 ing” case in (Kwon et al., 2009), but lower than their “constant export” case, consistent  
 222 with our model’s dynamic biological productivity response.

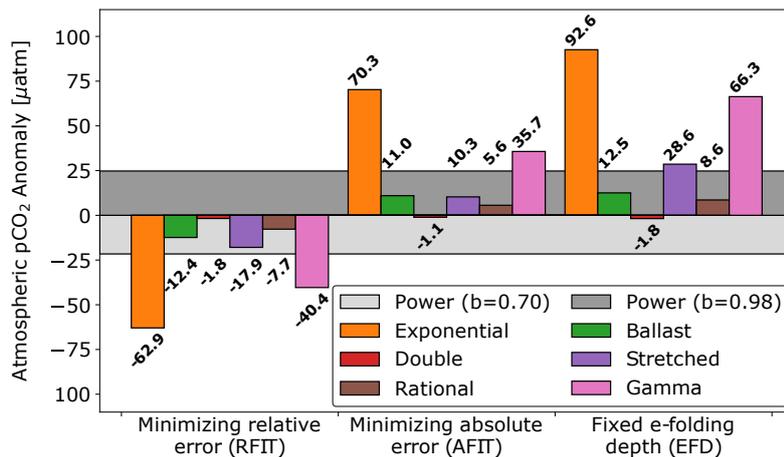
223 Alternative profiles with reduced export flux through 1 km and reduced biological  
 224 carbon storage result in increased atmospheric  $p\text{CO}_2$ , and vice versa (Fig. 4, Table S3).  
 225 The double exponential function has the most free parameters (four) and therefore fits  
 226 the power-law extremely well, producing small differences in atmospheric  $p\text{CO}_2$  (less than  
 227  $2 \mu\text{atm}$ ). The rational function also agrees well, but could produce larger anomalies if  
 228 the reference profile’s  $b$ -value was further from 1.0, i.e. 0.70. Stretched exponential and  
 229 ballast curves produce moderate changes in atmospheric  $p\text{CO}_2$  but are generally smaller  
 230 than, or similar to, the 0.14 changes in  $b$  for the power-law curves (Fig. 4). However, the  
 231 simple exponential and gamma anomalies clearly deviate from the other simulations, with  
 232 greater biological carbon concentrations and drawdown of atmospheric  $\text{CO}_2$  for the RFIT  
 233 simulations, and the inverse for AFIT and EFD simulations. Export fluxes and reminer-  
 234 alization are significantly different in the upper ocean for these parameterizations, which  
 235 can be explained by their small dynamic range in attenuation (Fig. 2 insets): simple ex-  
 236 ponential and gamma parameterizations cannot have both short remineralization length-  
 237 scales in the upper ocean and long remineralization lengthscales in the deep ocean.



**Figure 3.** Change in the integrated export flux rate [ $\text{PgC y}^{-1}$ ] passing through the 1 km depth level against integrated biological carbon reservoir anomaly [ $\text{PgC}$ ], both with respect to the power-law curve where  $b=0.84$  (Martin et al., 1987). Three power-law simulations ( $b=0.84\pm 0.14$ ) are indicated by the blue symbols (diamond, cross, and pentagon), circle, square, and triangle symbols indicate that profile coefficients (Eq. S1–S6) were derived by minimizing the relative fit error (“RFIT”), minimizing the absolute fit error (“AFIT”), and fixing the e-folding depth of remineralization (“EFD”) to the reference power-law curve. Values are given in Tables S2 and S3.

238 There are multiple ways to compare parametric and structural uncertainty quan-  
 239 titatively. Parametric uncertainty is found by varying the power-law exponent within  
 240 its plausible global range ( $b = 0.84\pm 0.14$ ), producing atmospheric  $\text{pCO}_2$  anomalies of  
 241  $21.6\text{--}24.8 \mu\text{atm}$  (Fig. 4, Table S3). For structural uncertainty, the median change in ab-  
 242 solute atmospheric  $\text{pCO}_2$  is  $12.47\pm 10.67 \mu\text{atm}$  ( $b$ -anomaly equivalent of  $0.07\pm 0.06$ ) across  
 243 all simulations with alternate functional forms<sup>3</sup>. For RFIT, AFIT, and EFD simulations  
 244 separately, the medians are  $15.15\pm 10.40$ ,  $10.65\pm 7.30$ , and  $20.57\pm 15.37 \mu\text{atm}$ , respectively,  
 245 giving a  $15.15\pm 4.51 \mu\text{atm}$  grand median ( $b$ -anomaly equivalent of  $0.09\pm 0.03$ ). Exclud-  
 246 ing profiles with small dynamic ranges in attenuation, the overall medians for RFIT, AFIT,  
 247 and EFD are  $10.07\pm 2.32$ ,  $7.96\pm 2.69$ , and  $10.57\pm 1.98 \mu\text{atm}$ , respectively, with a  $10.07\pm 0.50 \mu\text{atm}$   
 248 grand median ( $b$ -anomaly equivalent of  $0.06\pm 0.00$ ). In summary, our results are largely  
 249 robust, indicating a structural uncertainty of  $10\text{--}15 \mu\text{atm}$ , roughly half of parametric un-

<sup>3</sup> We choose the median $\pm$ median absolute deviation so that our result is robust to large anomalies associated with simple exponential and gamma functional forms.



**Figure 4.** Atmospheric pCO<sub>2</sub> anomalies ( $\mu\text{atm}$ ) of different remineralization profiles with respect to the reference power-law ( $b = 0.84$ ) for power-law exponent values  $b = 0.70$  and  $0.98$ , and statistical fits of alternative profiles minimizing relative error (“RFIT”, left), minimizing absolute error (“AFIT”, middle), and matching the 164 m e-folding depth (“EFD”, right) of the reference curve.

250 certainty for the biological pump ( $22\text{--}25 \mu\text{atm}$ ,  $b = 0.84 \pm 0.14$ ), analogous to a  $\sim 0.08$   
 251 change in  $b$ .

### 252 3.4 Role of nonlinearity in the biological pump.

253 Our simulations also allow us to tease apart two fundamental aspects of the bio-  
 254 logical pump: In terms of atmospheric CO<sub>2</sub> influence, (i) how much is due to ocean bi-  
 255 ological carbon storage, and (ii) how much is due to the shape of remineralization pro-  
 256 file?

257 A simulation “NOPOM” represents a hypothetical ocean with no particulate or-  
 258 ganic matter export and without a biological carbon pool. Instead, biological produc-  
 259 tion is channelled into semi-labile dissolved organic matter that is remineralized near the  
 260 surface. Atmospheric pCO<sub>2</sub> in NOPOM increases  $165.4 \mu\text{atm}$  (Table S2) with respect  
 261 to the reference power-law.

262 Compared to NOPOM, the simple exponential simulations in AFIT and EFD have  
 263 significant 1 km export fluxes and large stores of biological carbon (Table S3). That is,  
 264 they have a substantial biological pump, but atmospheric pCO<sub>2</sub> is only  $95.1$  and  $72.8 \mu\text{atm}$

265 lower than NOPOM, respectively. Thus, only about half of the biological pump's influ-  
266 ence on atmosphere-ocean carbon partitioning ( $\sim 80 \mu\text{atm}$ ) can be attributed to export  
267 of particulate organic matter and biological carbon storage (Fig. S5).

268 Now, comparing AFIT/EFD exponential profiles to the reference power-law (or in-  
269 deed any high dynamic-range curves), there are only modest differences in 1 km export  
270 fluxes and biological carbon storage. Nevertheless, AFIT/EFD exponential profile 2 km  
271 export fluxes remain closer to NOPOM than the other curves (Table S3). Thus, we can  
272 attribute the remaining  $\sim 80 \mu\text{atm}$  atmospheric  $\text{pCO}_2$  anomaly to the effect of decreas-  
273 ing remineralization with depth (Fig. 2c–d insets), since attenuation is constant for the  
274 simple exponential profiles, but varies with the other curves.

275 In other words, increasing remineralization lengthscale with depth appears to be  
276 as important for air-sea carbon partitioning as export and storage of biological carbon  
277 (Fig. S5).

## 278 4 Discussion and Conclusions

279 Atmospheric  $\text{CO}_2$  levels are intimately tied to the strength of the ocean's biolog-  
280 ical pump, comprising linked processes of primary production, export of organic mat-  
281 ter from the upper ocean, and the degradation of particles back to inorganic constituents  
282 with depth. The challenge of measuring particulate fluxes via sediment traps, optical prox-  
283 ies, or geochemical methods (Martin et al., 1987; Berelson, 2001; Honjo et al., 2008; Hen-  
284 sen et al., 2012; Guidi et al., 2015; Pavia et al., 2019), the spatiotemporal variability of  
285 fluxes, and the complexity of the mechanisms governing them all introduce uncertainty  
286 into representation of the biological pump in ocean biogeochemistry, ecosystem, and cli-  
287 mate models. We explored the impact of structural uncertainty—remineralization pro-  
288 file shape—on atmosphere-ocean carbon partitioning, using seven mechanistically-distinct  
289 functional forms of particulate organic matter flux that capture observational spread equiv-  
290 alently well (Cael & Bisson, 2018). Steady-state atmospheric  $\text{pCO}_2$  is inversely related  
291 to the biological carbon pool, thus profiles with more efficient export through 1 km, and  
292 greater biological carbon storage, lead to atmospheric  $\text{CO}_2$  drawdown.

293 In our model, a 0.14 change in the power-law exponent,  $b$ , results in a 22–25  $\mu\text{atm}$   
294 change in atmospheric  $\text{pCO}_2$ , indicating that structural uncertainty revealed by our sim-  
295 ulations of 10–15  $\mu\text{atm}$  is equivalent to  $\sim 0.08$  change in the global  $b$  value. Thus struc-

296 tural uncertainty is roughly half that of parameteric uncertainty, a substantial portion,  
297 one third, of total uncertainty in understanding the biological pump. In addition our re-  
298 sult is in the upper range of the 5-15  $\mu\text{atm}$  uncertainty associated with regional varia-  
299 tion in  $b$  (Wilson et al., 2019).

300 Historically, the focus been on remineralization lengthscale (Kwon et al., 2009), but  
301 our results imply that multiple lengthscales of attenuation are critical to the biological  
302 pump’s global impact, indicating that vertical gradient in attenuation is a first-order con-  
303 trol on climate. The simple exponential functional form, with constant depth attenua-  
304 tion, results in much larger atmospheric  $\text{pCO}_2$  anomalies of  $\sim 80\mu\text{atm}$  for AFIT and EFD  
305 simulations, despite being statistically fit to be as similar to the reference power law as  
306 possible (and similarly for gamma function profiles). This is roughly half the  $\sim 165\mu\text{atm}$   
307 increase that results from removing the biological pump altogether (NOPOM), highlight-  
308 ing the importance for the air-sea carbon balance, not only of the existence of a biolog-  
309 ical pump that maintains interior ocean biological carbon stores, but also its non-linearity  
310 (Fig. S5). More specifically, significant decrease of attenuation with depth is a key fac-  
311 tor in the biological pump’s modulation of atmospheric  $\text{CO}_2$  levels. Even when the ex-  
312 ponential profiles’ parameters are determined by matching the e-folding remineraliza-  
313 tion depth of the reference power-law curve (Kwon et al., 2009), the result is still large  
314 atmospheric  $\text{pCO}_2$  anomalies caused by small dynamic range in attenuation.

315 Our study is the first to evaluate structural uncertainty in the ocean’s biological  
316 pump. Although previous studies have compared individual, or a subset, of the alter-  
317 native remineralization curves used here (e.g., Yamanaka & Tajika, 1996; Gehlen et al.,  
318 2006; Kriest & Oschlies, 2008; Gloege et al., 2017) with a focus on minimizing model-  
319 observational differences, none has attempted to evaluate this structural uncertainty, which  
320 we do here by comparing six alternative functional forms fit to a reference power-law pro-  
321 file.

322 As Earth System Models continue to rely on simple biological pump parameter-  
323 izations, our estimate of structural uncertainty underscores the importance of research  
324 aimed at improving the basic mechanistic characterization of the biological pump (Boyd  
325 et al., 2019), and particularly the depth-dependence or evolution of these mechanisms.  
326 A better process-based understanding is critical to choosing between these parameter-  
327 izations based on their mechanistic underpinnings and thus reducing structural uncer-

328 tainty, because empirical fits to flux measurements alone cannot currently do so (Cael  
329 & Bisson, 2018). This is even more the case for modeling past climate or projections of  
330 future change. In our simulations, the parameterizations were forced to be as similar as  
331 possible, but functional forms based on different processes will have different sensitiv-  
332 ities to temperature and other phenomena, and therefore will produce divergent projec-  
333 tions and different climate feedbacks. It would therefore be valuable to compare these  
334 different functional forms within state-of-the-art Earth System Models to improve con-  
335 fidence in projections involving biosphere-climate interactions.

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346 **Data availability:** Preliminary model input, code, and output processing routines can  
347 be accessed via GitHub ([https://github.com/seamanticscience/Lauderdale\\_and\\_Cael\\_Exports](https://github.com/seamanticscience/Lauderdale_and_Cael_Exports),  
348 to be updated and uploaded to *Zenodo.org* open science archive).

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Figure 1.



CO<sub>2</sub> fluxes



production

$C_{pre}$

mixed layer

sinking

$C_{bio}$

remin

$C_{pre} + C_{bio}$

$C_{bio}$

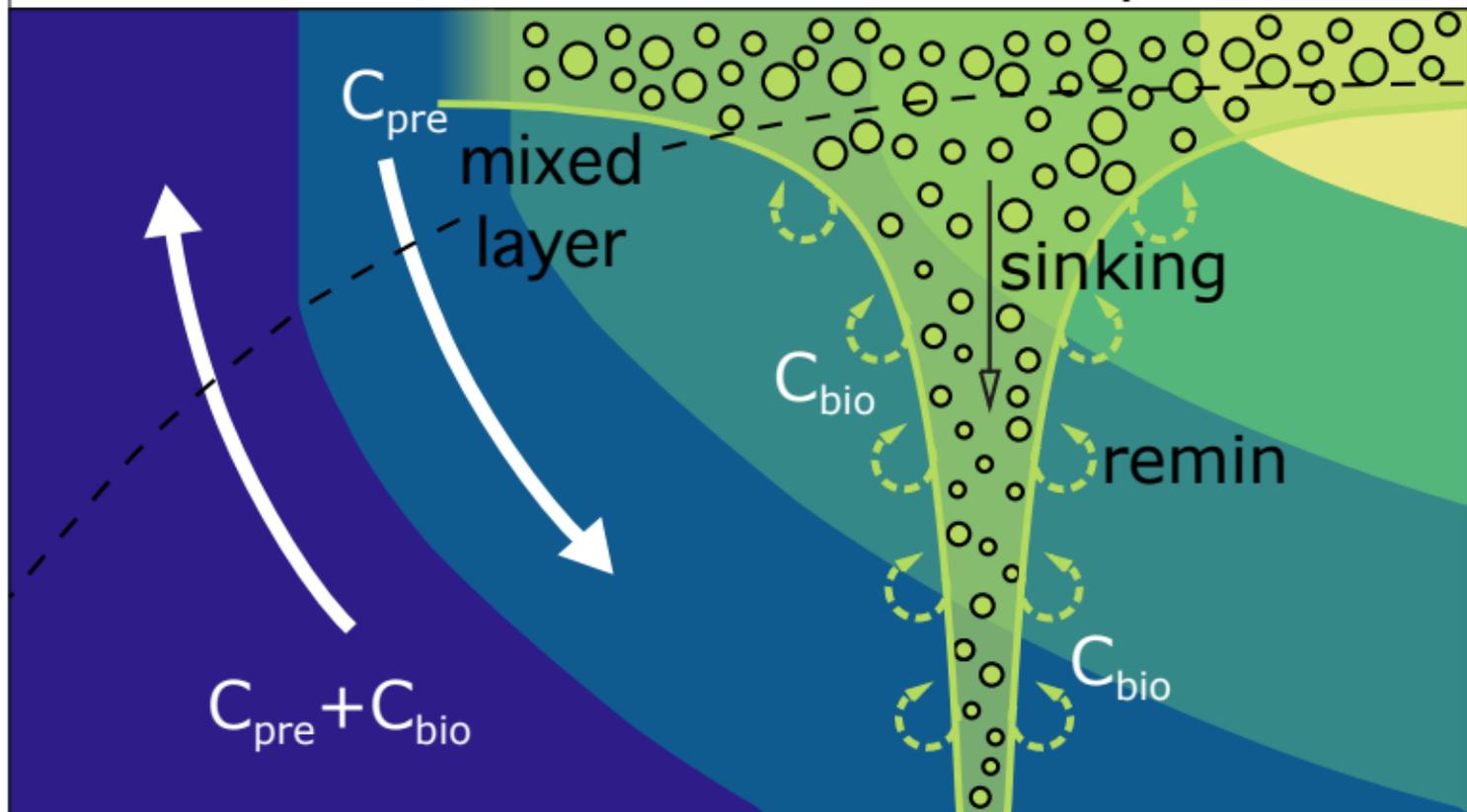


Figure 2.

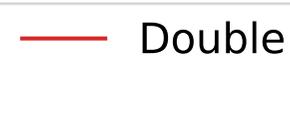
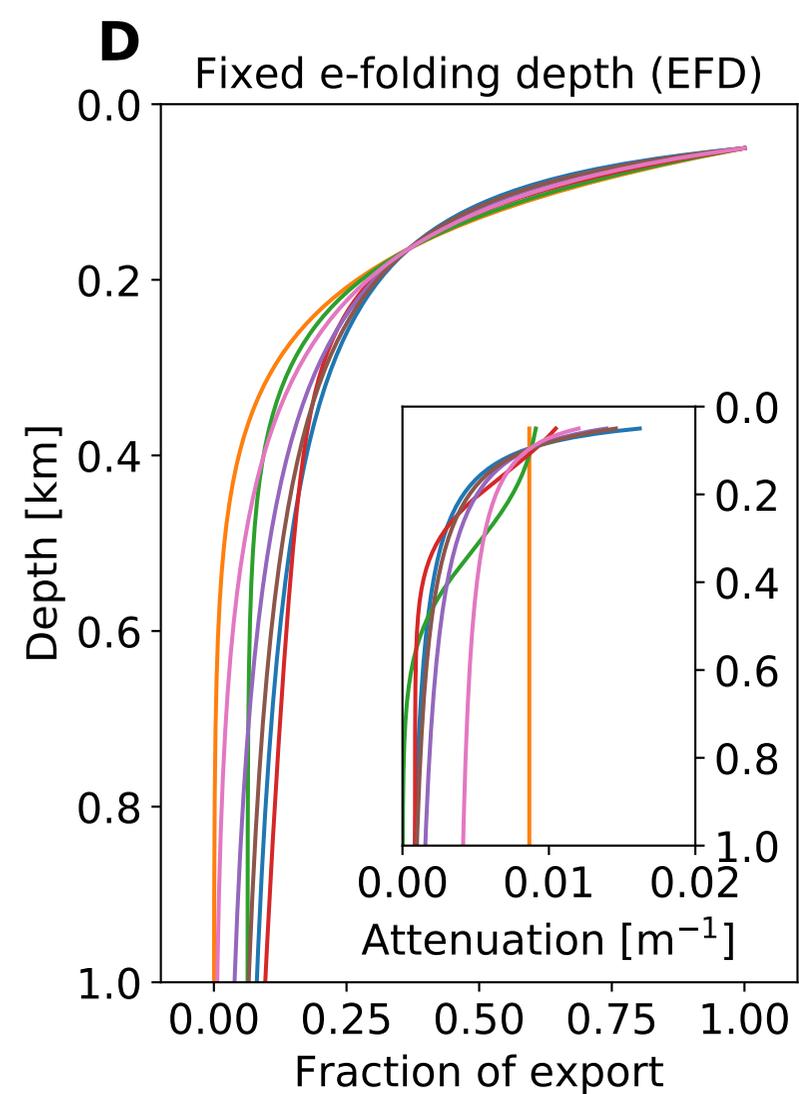
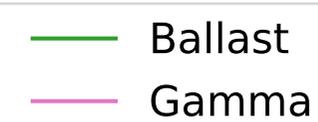
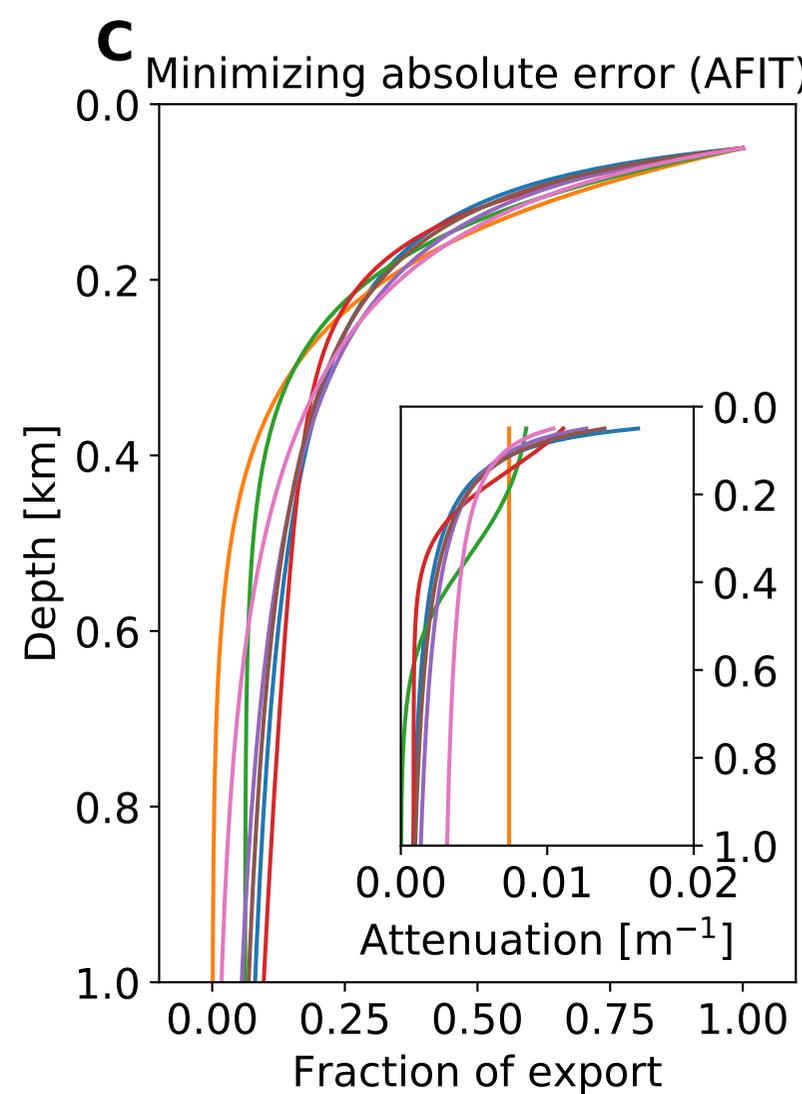
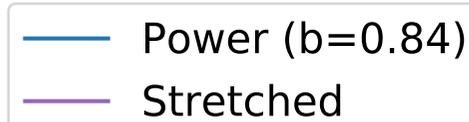
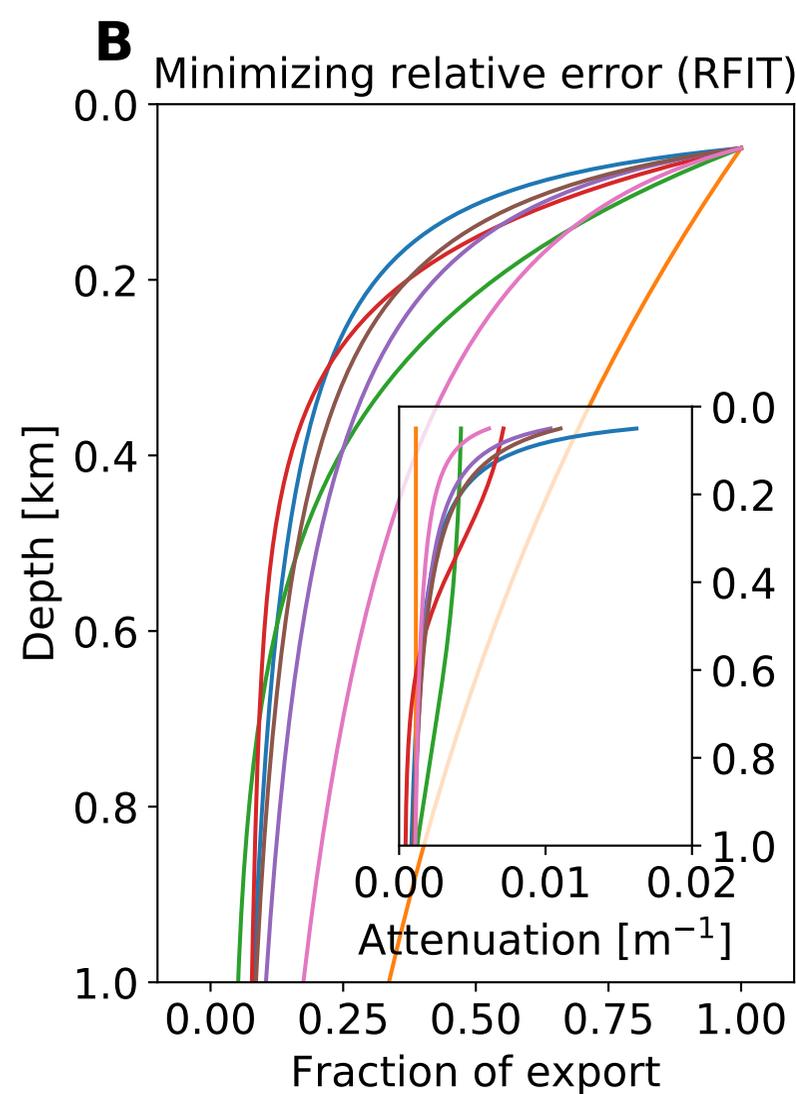
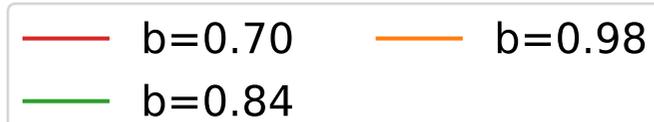
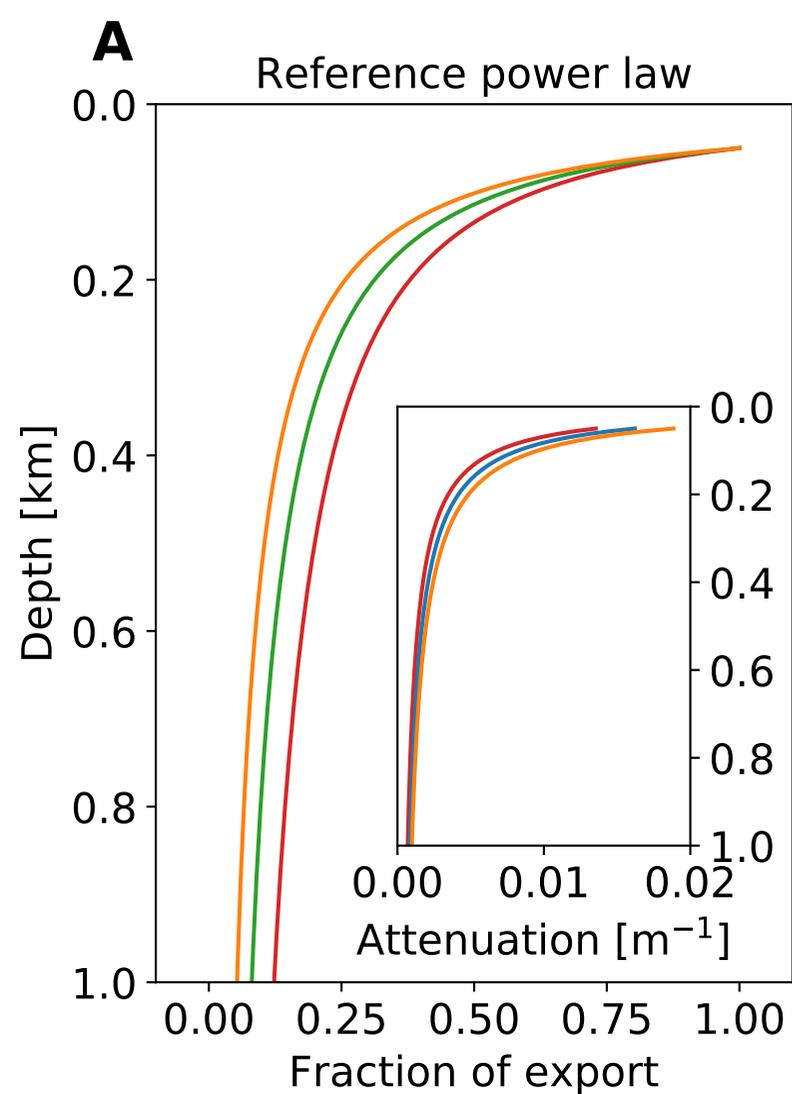
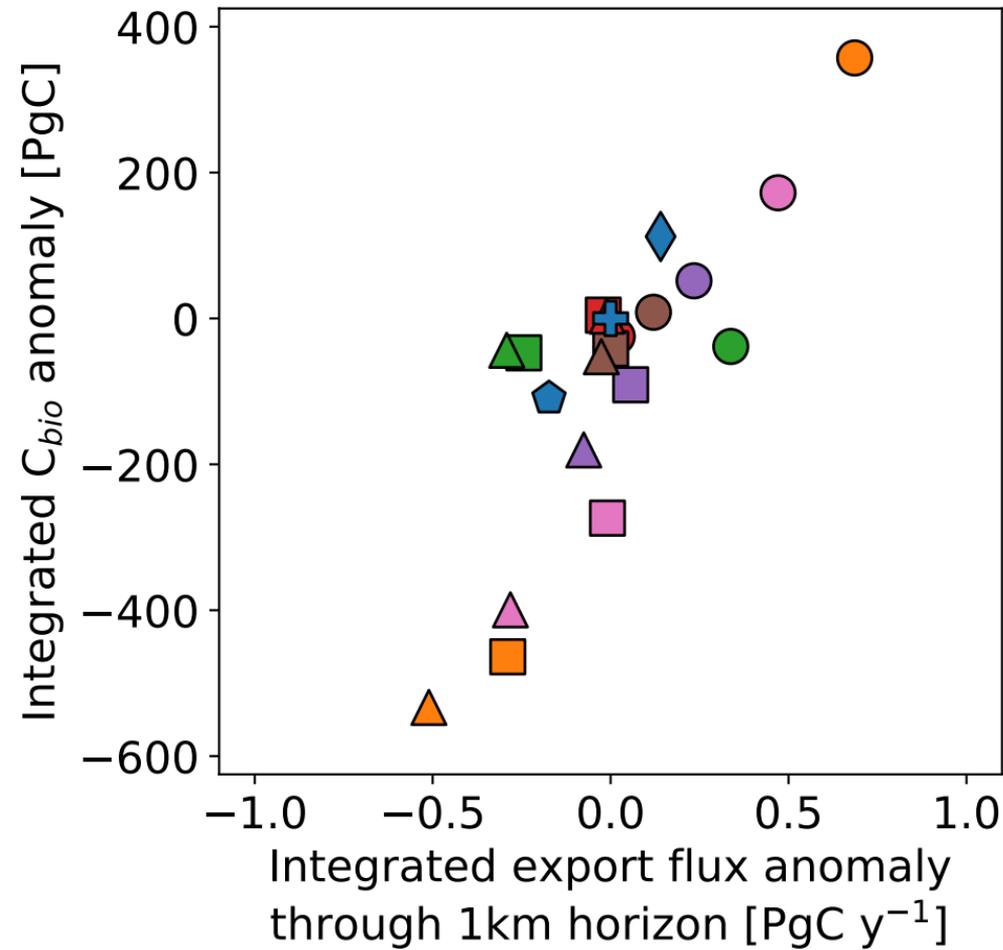


Figure 3.

R=0.819



	RFIT	AFIT	EFD
Exponential			
Ballast			
Double			
Stretched			
Rational			
Gamma			
Power			
	0.70	0.84	0.98

**Figure 4.**

Atmospheric pCO<sub>2</sub> Anomaly [ $\mu\text{atm}$ ]

