

1 Global estimates of particulate organic carbon from the surface ocean to the base of the
2 mesopelagic

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8 **Key Points:**

- 9 • Float profiles of POC concentration reveal globally consistent trends in attenuation for
10 depths below an isolume of 0.427 mol d^{-1} .
- 11 • A semi-mechanistic modeling approach can be used to accurately predict POC from the
12 surface ocean to the base of the mesopelagic (1000m).
- 13 • The new approach enables the assessment of remineralization trends and standing stocks
14 of POC across the global ocean.
15

16 **Abstract**

17 The gravitational settling of organic particles from the surface to the deep ocean is an important
18 export pathway and one of the largest components of the marine biological carbon pump (BCP).
19 The strength and efficiency of the gravitational pump is often measured using metrics reliant on
20 reference depths and empirical formulations that parameterize the relationship between depth and
21 flux or concentration. Here, BGC-Argo profiles were used to identify the isolume where POC
22 concentration starts to decline, revealing attenuation trends below this isolume that are remarkably
23 consistent across the global ocean. We developed a semi-mechanistic approach that uses
24 observations from the first optical depth to predict POC concentration from the surface ocean to
25 the base of the mesopelagic (1000 m), allowing assessments of spatial and temporal variability in
26 BCP efficiencies. We find that rates of POC attenuation are high in areas of high biomass and low
27 in areas of low biomass, supporting the view that bloom events sometimes result in a relatively
28 weak deep biological pump characterized by low transfer efficiency to the base of the mesopelagic.
29 Our isolume-based attenuation model was applied to satellite data to yield the first remote sensing-
30 based estimate of integrated global POC stock of 3.02 Pg C for the upper 1000 m, with 1.27 Pg C
31 of this global carbon stock located above the reference isolume where POC begins to attenuate.

32 **1. Introduction**

33 The biological carbon pump (BCP) is a collection of biological and physical processes that
34 facilitate carbon sequestration in the deep ocean. Active transfer pathways can be physically (e.g.
35 subduction) or biologically (e.g. mesopelagic migrators) mediated and are collectively termed
36 particle-injection pumps (Boyd *et al.*, 2019). The biological gravitational pump (BGP) represents
37 the amount of organic carbon that is passively transferred from sunlit surface waters to the ocean
38 interior through particle sinking and is strongly influenced by the complexity of upper ocean
39 food webs (Siegel *et al.*, 2014; Boyd *et al.*, 2019). Particulate organic carbon (POC) is produced
40 by phytoplankton in the sunlit epipelagic at rates that vary spatially and temporally depending on
41 light and nutrient availability (Westberry *et al.*, 2023). Near the base of the epipelagic zone,
42 sunlight has been sufficiently attenuated that phytoplankton growth and particle production is
43 outweighed by losses through remineralization and grazing, leading to decreases in POC
44 concentration and flux (Henson *et al.*, 2012). Further remineralization of sinking particles occurs
45 through the mesopelagic (~200 – 1000 m), resulting in a distinct vertical attenuation profile that

46 can be measured using a variety of *in situ* approaches ranging from traps and pumps to sensors
47 on autonomous vehicles (Baker *et al.*, 2020; Briggs *et al.*, 2020). These field observations are
48 often combined with empirical formulations (e.g. the “Martin Curve”) to estimate vertical POC
49 profiles and calculate attenuation metrics that reflect the strength and efficiency of the BGP
50 (Martin *et al.*, 1987; Buesseler and Boyd, 2009).

51 The relative change in POC concentration or flux between two depth horizons can be used to
52 calculate the transfer efficiency from the surface to the deep ocean (Buesseler *et al.*, 2020). A
53 lower transfer efficiency indicates faster attenuation through depth and vice versa, but the
54 mechanisms that control BGP efficiencies are not fully understood and are a subject of debate
55 (Armstrong *et al.*, 2001; Lam *et al.*, 2011; Henson *et al.*, 2019). The efficiency of vertical
56 transfer controls the fate of carbon fixed at the surface, dictating whether it is partitioned into
57 short or long-term storage pools. The transfer of carbon out of the primary production zone to the
58 upper mesopelagic (often termed export flux) is typically viewed as short-term storage and often
59 results in the removal of carbon from the atmosphere on timescales that span months to decades
60 (DeVries and Weber, 2017). Long-term marine carbon storage is defined as carbon removal from
61 the atmosphere for timescales of centuries to millennia and is estimated to occur when carbon is
62 transported below 1000 m (IPCC 2007). The relative change in POC flux or concentration
63 between the base of the euphotic zone and the base of the mesopelagic is referred to as flux
64 attenuation (Passow and Carlson, 2012). The efficiency of flux attenuation varies in time and
65 space, but it is generally observed that more than 90% of export flux is lost before the 1000 m
66 depth threshold for long-term sequestration (Nelson *et al.*, 2002; Marsay *et al.*, 2015).

67 Given the importance of the BCP in modulating Earth’s biogeochemical cycles, it is critical to
68 improve our understanding of marine carbon sequestration pathways to better predict how they
69 will change in response to climate variability (Henson *et al.*, 2019). Satellite remote sensing is a
70 powerful tool for monitoring marine carbon stocks at global scales, but is currently limited to
71 surface observations (Brewin *et al.*, 2023; but see Behrenfeld *et al.*, 2023). *In situ* sampling
72 campaigns and autonomous platforms are more significantly constrained in horizontal spatial
73 resolution, but can be used to provide detailed insight into regional sub-surface carbon cycling
74 dynamics (Dall’Olmo *et al.*, 2016; Boyd *et al.*, 2019; Briggs *et al.*, 2020). Creating an effective
75 framework to quantify important BCP processes at a global scale requires *in situ* observations of
76 spatial and temporal resolution comparable to satellite data, thereby enabling effective

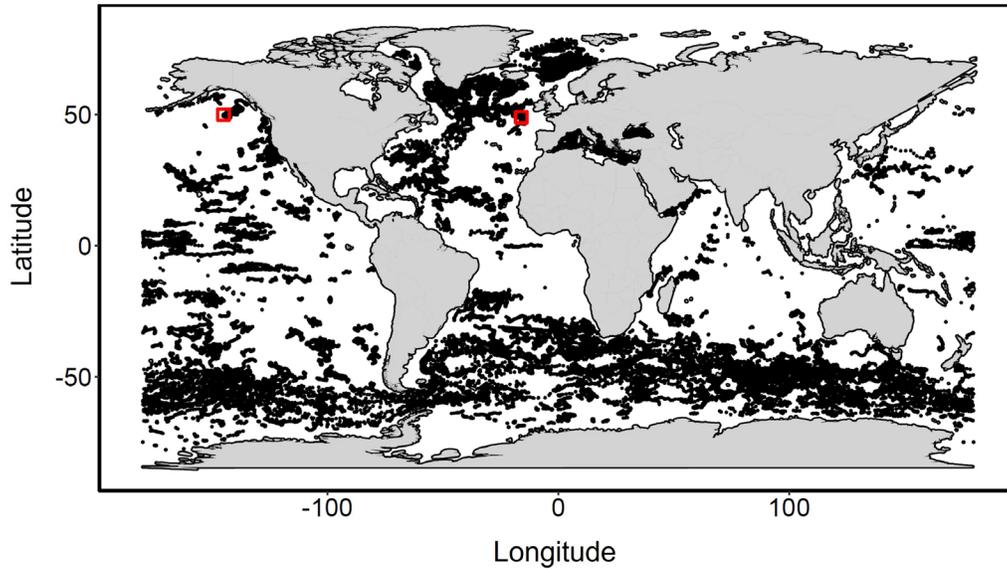
77 extrapolation of surface satellite data to depth. To this end, a multifaceted approach is desirable
78 that involves the integration of data from ship-based observations and autonomous underwater
79 vehicles, satellite remote sensing, and numerical modeling, but programs of such scale are costly
80 and therefore rare (Siegel *et al.*, 2016; Brewin *et al.*, 2021). As a result, there have been limited
81 efforts to combine multi-platform observations and assess global-scale, vertically-resolved
82 profiles of POC. To address this gap, we utilized profiling Biogeochemical-Argo (BGC-Argo)
83 data to: (i) determine an isolume-based reference depth for the point where POC concentration
84 begins to decline; and (ii) formulate a concentration-dependent algorithm to define attenuation
85 trends through the water column. This semi-mechanistic approach can be used with remotely
86 detectable properties of the first optical depth to predict POC concentrations from the surface
87 layer to the base of the mesopelagic zone and assess spatial and temporal variations in BGP
88 efficiencies at regional to global scales.

89 **2. Data and Methods**

90 **2.1. Float Data and Derived Proxies**

91 We used data collected by an array of 603 floats deployed at different times between 2010 and
92 2023 across several regions of the global ocean (Figure 1). Each float was equipped with a
93 conductivity-temperature-depth sensor (SBE 41N, Seabird Scientific) and a combination bio-
94 optical sensor (ECOTRIplet, FLBB, MCOMS, Seabird-WetLABS). In total, these floats
95 acquired 51,322 vertical profiles (0 – 2000 m) of salinity, temperature, pressure, chlorophyll
96 fluorescence, and the angular scattering function at 700 nm. The raw data from each sensor were
97 calibrated according to manufacturer guidelines by the ARGO data management team before
98 undergoing quality control following the adjustment procedures described in Johnson *et al.*
99 (2017). Chlorophyll fluorescence is then converted to chlorophyll concentration (Chl) using a
100 linear calibration slope provided by the sensor manufacturer while backscattering is derived from
101 the angular scattering function at 700 nm. Values of backscattering are then converted to the
102 backscattering coefficient of particles (b_{bp_float}) by removing the scattering function of seawater
103 using local salinity and temperature data (Zhang *et al.*, 2009). All processed data products were
104 downloaded from ARGO Global Data Assembly Center servers in September 2023 using the
105 BGC-Argo-R toolbox (Cornec *et al.*, 2021). Data flagged as poor quality were removed, along
106 with outliers ($> 98.5^{\text{th}}$ percentile), before profiles were interpolated to 1 m vertical resolution
107 through the upper 1000 m. Mixed layer depth (MLD) was calculated for each float profile as the

108 depth where density was $\geq 0.03 \text{ kg m}^{-3}$ than the density at 10 m (de Boyer Montégut *et al.*,
109 2004).



110

111 **Figure 1.** The global distribution of all float profiles ($n = 51,322$) used in this study that were collected as
112 part of the BGC-Argo program between 2010 and 2023. Red squares show the location of sites analyzed
113 for interannual variability.

114 Profiles of b_{bp_float} were smoothed with a 7-point median filter (Briggs *et al.*, 2011) before being
115 used to estimate particulate organic carbon (POC_{float}) though depth (z) following the methods
116 described in Gali *et al.* (2022):

$$POC_{float}(z) = b_{bp_float} \cdot a, \text{ if } z \leq \text{MLD} \quad \text{Equation (1a)}$$

and

$$POC_{float}(z) = b_{bp_float} \cdot 12100 + (a - 12100) \cdot e^{-0.00657 \cdot (z - \text{MLD})}, \quad \text{Equation (1b)}$$

if $z > \text{MLD}$,

117 where $a = 43,256 \text{ mg C m}^{-3}$ and is the average $POC/b_{bp}(700)$ ratio in the euphotic zone calculated
118 using regression coefficients from several previous studies [see Table A1 in Gali *et al.*, (2022)].

119 Fluorescence derived measurements of Chl were corrected for daytime non-photochemical
120 quenching (NPQ) following Xing *et al.* (2012). The average Chl in the first optical depth (OD1)
121 was then used to calculate the diffuse attenuation coefficient at 490 nm [$k_d(490)$; units = m^{-1}]
122 following Morel & Maritorena (2001):

$$k_d(490) = 0.0166 + 0.07242 \cdot \text{Chl}^{0.68955}. \quad \text{Equation (2)}$$

123 Values of $k_d(490)$ were converted to the diffuse attenuation coefficient for Photosynthetically
 124 Available Radiation (PAR), k_{PAR} , following Morel et al. (2007):

$$k_{\text{PAR}} = 0.0864 + 0.884 \cdot k_d(490) - 0.00137 \cdot [k_d(490)]^{-1}, \text{ if MLD} \leq [k_d(490)]^{-1} \quad \text{Equation (3a)}$$

and

$$k_{\text{PAR}} = 0.0665 + 0.874 \cdot k_d(490) - 0.00121 \cdot [k_d(490)]^{-1}, \text{ if MLD} > [k_d(490)]^{-1}. \quad \text{Equation (3b)}$$

125 This approach accounts for changes in spectral irradiance through depth and the subsequent
 126 impact on estimations of light attenuation. It assumes that for a homogeneously mixed surface
 127 layer, attenuation coefficients for individual wavelengths in the blue-green domain (e.g. $\lambda_i \sim 443$,
 128 $\lambda_i \sim 490$, and $\lambda_i \sim 510$ nm) are only weakly dependent on the depth of that layer because these
 129 medium wavelengths typically penetrate deeper into the water column. In contrast, diffuse
 130 attenuation coefficients for the full visible spectrum (e.g. k_{PAR}) must account for the
 131 polychromatic nature of PAR and the rapid attenuation of longer wavelengths, which narrows the
 132 PAR domain at depth. As such, for a given $k_d(490)$, k_{PAR} will decrease significantly with mixed
 133 layer depth, thus warranting different relationships for shallow, homogenous layers (Equation
 134 3a) and deeply mixed waters (3b).

135 Finally, the 0.1% light depth ($E_{Z_{0.1}}$) was calculated using k_{PAR} :

$$E_{Z_{0.1}} = -\ln(0.001) / k_{\text{PAR}}. \quad \text{Equation (4)}$$

136 **2.2. Satellite Data and Derived Proxies**

137 Ocean color products from the Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua
 138 satellite used for this analysis included 9 km resolution, 8-day Chl (OCI algorithm), b_{bp} at 443
 139 nm [$b_{\text{bp_sat}}(443)$], derived from the Generalized Inherent Optical Property algorithm (Werdell *et*
 140 *al.*, 2013), the diffuse attenuation coefficient [$k_{d_sat}(490)$], and incident PAR (PAR_0). Values of
 141 $b_{\text{bp_sat}}(443)$ were converted to 700 nm using a power law model of the particulate backscattering
 142 coefficient spectral dependency with an exponent of -1 (Morel and Maritorena, 2001) to make
 143 them comparable with $b_{\text{bp_float}}$:

$$b_{\text{bbp_sat}}(700) = b_{\text{bbp_sat}}(443) \cdot \left(\frac{700}{443}\right)^{-1} \quad \text{Equation (5)}$$

144 Global estimates of MLD were calculated from salinity, temperature, and pressure data
 145 converted to density (sigma-theta) and based on daily, multi-layer products from the HYbrid
 146 Coordinate Ocean Model (HYCOM). Net primary production (NPP) for the MODIS Aqua
 147 record was estimated using the absorption-based productivity model of Silsbe et al. (2016). NPP
 148 and MLD data are available at <https://sites.science.oregonstate.edu/ocean.productivity/index.php>.
 149 Satellite based estimates of POC (POC_{sat}) were calculated following Equations 1a and 1b (i.e.,
 150 replacing $b_{\text{bp_float}}$ with $b_{\text{bp_sat}}$). Similarly, $k_{\text{PAR_sat}}$ values were calculated using $k_{\text{d_sat}}(490)$ and
 151 equations 3a and 3b.

152 **2.3. Estimating the particle compensation depth**

153 To determine an ecologically relevant reference depth corresponding to the point at which POC
 154 begins attenuating in the upper ocean, we first identified the absolute light level where POC
 155 losses to remineralization and grazing outweigh accumulation through primary production in the
 156 epipelagic zone (this isolume is henceforth referred to as the particle compensation depth, PCD).
 157 A smoothing function and a local maximum filter were first applied to each BGC-Argo profile of
 158 $\text{POC}_{\text{float}}$ to detect sub-surface peaks in POC concentration (Supp. Figure 1). The depth of the
 159 largest peak (z_{peak}) below the mixed layer, but above the euphotic depth (defined here as the 0.01
 160 mol d^{-1} isolume), was considered the PCD. For profiles where the MLD was deeper than the
 161 euphotic depth, z_{peak} was defined as the base of the MLD. The absolute photon flux at the PCD
 162 was then calculated as:

$$\text{PAR}_{\text{PCD}} = \text{PAR}_0 \cdot e^{(k_{\text{PAR}} \cdot z_{\text{peak}})}. \quad \text{Equation (6)}$$

163 Estimates of PAR_{PCD} showed a unimodal distribution with a positive skew (Supp. Figure 2), so a
 164 square root transformation was applied before the median (0.427 mol d^{-1} , Inter Quartile Range =
 165 0.09-1.37) was taken as the global isolume for the PCD. Estimates of PAR_0 and k_{PAR} were then
 166 used to calculate the PCD for all profiles in the global dataset using this isolume:

$$z_{\text{PCD}} = -\ln\left(\frac{0.427}{\text{PAR}_0}\right) / k_{\text{PAR}}. \quad \text{Equation (7)}$$

167 For equation 7, the PCD was defined as MLD when $z_{\text{PCD}} \leq \text{MLD}$.

168

2.4. Assessing attenuation trends in POC below the PCD

169

Profiles of $\text{POC}_{\text{float}}$ (e.g., Figure 2a) were used to investigate the spatial and temporal variability

170 in attenuation trends below the PCD. First, $\text{POC}_{\text{float}}$ data from depths shallower than the PCD

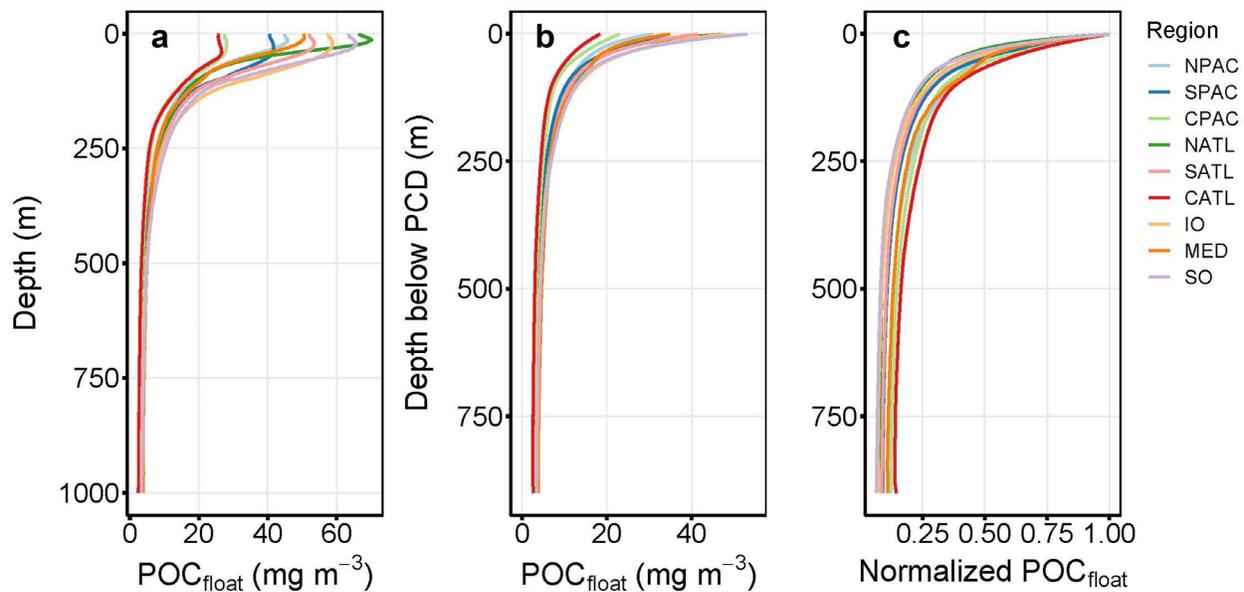
171 were removed from all profiles in the global dataset. The remaining data of each profile were

172 then adjusted such that the PCD depth = 0 m (e.g. $z_{\text{norm}} = z - z_{\text{PCD}}$; Figure 2b) before being fitted

173 to a cumulative distribution function (i.e. stretched exponential model). The coefficients from all

174 model fits were used to parameterize an algorithm to predict POC concentration below the PCD,

175 as described in the following section.



176

177 **Figure 2.** Regionally averaged vertical profiles of (a) particulate organic carbon derived from float
178 observations of particulate backscatter ($\text{POC}_{\text{float}}$), (b) $\text{POC}_{\text{float}}$ versus depth after removing data shallower
179 than the particle compensation depth (PCD) and then normalizing each profile to zero depth at the PCD,
180 and (c) data from panel b normalized to the maximum value of $\text{POC}_{\text{float}}$ at the PCD. The regional bins are
181 NPAC = North Pacific, NATL= North Atlantic, CPAC = Central Pacific, CATL = Central Atlantic, SPAC
182 = South Pacific, SATL = South Atlantic, SO = Southern Ocean, IO = Indian Ocean, and MED =
183 Mediterranean.

184

2.5. Modeling particulate organic carbon concentration and attenuation trends

185

Using the coefficients from the model fits described in section 2.4, together with surface

186 estimates of b_{bp} , we developed an isolume-based model to predict POC concentration through the

187 water column at 1m resolution. The first step of the approach calculates POC from the surface to

188 the PCD using Equations 1a and 1b, and the average b_{bp} value over the first optical depth

189 [b_{bp}(OD1)], with the assumption that b_{bp}(OD1) is vertically constant from the surface to the
 190 PCD. Estimates of POC below the PCD are then calculated as follows:

$$\text{POC}(z) = \text{POC}_{\text{PCD}} \cdot e^{-\left(\frac{z_{\text{norm}}}{c_1}\right)^{c_2}}, \quad \text{Equation (8)}$$

191 where POC at the PCD (POC_{PCD}) is calculated using Equations 1a or 1b and b_{bp}(OD1) when z =
 192 z_{PCD}, c₂ = 0.325, and c₁ is a concentration dependent scaling parameter calculated as:

$$c_1 = 19 + 450.29 \cdot e^{-0.0708 \cdot \text{POC}_{\text{PCD}}}. \quad \text{Equation (9)}$$

193 For comparison to the isolume-based attenuation model developed here, depth resolved POC
 194 concentrations were also estimated using a modified version of the ‘Martin Curve’ (hereafter
 195 referred to as the B20 method) where POC values at the 0.1% light depth (POC_{Ez_{0.1}}) are fitted to
 196 a power law function following the approach described in Buesseler *et al.* (2020):

$$\text{POC}_{\text{B20}}(z) = \text{POC}_{\text{Ez}_{0.1}} \cdot \left(\frac{z}{\text{Ez}_{0.1}}\right)^{-b}, \quad \text{Equation (10)}$$

197 where *b* is the power law exponent of 0.858, and POC_{Ez_{0.1}} is calculated using Equation 1b when *z*
 198 = Ez_{0.1} or Equation 1a if MLD > Ez_{0.1}.

199 Depth-resolved POC estimates from the isolume-based POC attenuation model (Equations 8 &
 200 9) and the B20 method (Equation 10) were used to calculate attenuation metrics to assess the
 201 strength and efficiency of the biological carbon pump. One of these metrics was a concentration
 202 ratio (λ₁₀₀) which describes the change in POC between the PCD and the upper mesopelagic and
 203 is comparable to the transfer efficiency parameter derived from particle flux measurements:

$$\lambda_{100} = \frac{\text{POC}_{\text{PCD}+100}}{\text{POC}_{\text{PCD}}}, \quad \text{Equation (11)}$$

204 where POC_{PCD+100} is the POC concentration 100 m below the PCD reference depth. The second
 205 attenuation metric evaluated is comparable to the flux attenuation coefficient and was calculated
 206 as the difference in POC concentration between the PCD and the base of the mesopelagic
 207 (λ₁₀₀₀):

$$\lambda_{1000} = \frac{\text{POC}_{1000}}{\text{POC}_{\text{PCD}}}, \quad \text{Equation (12)}$$

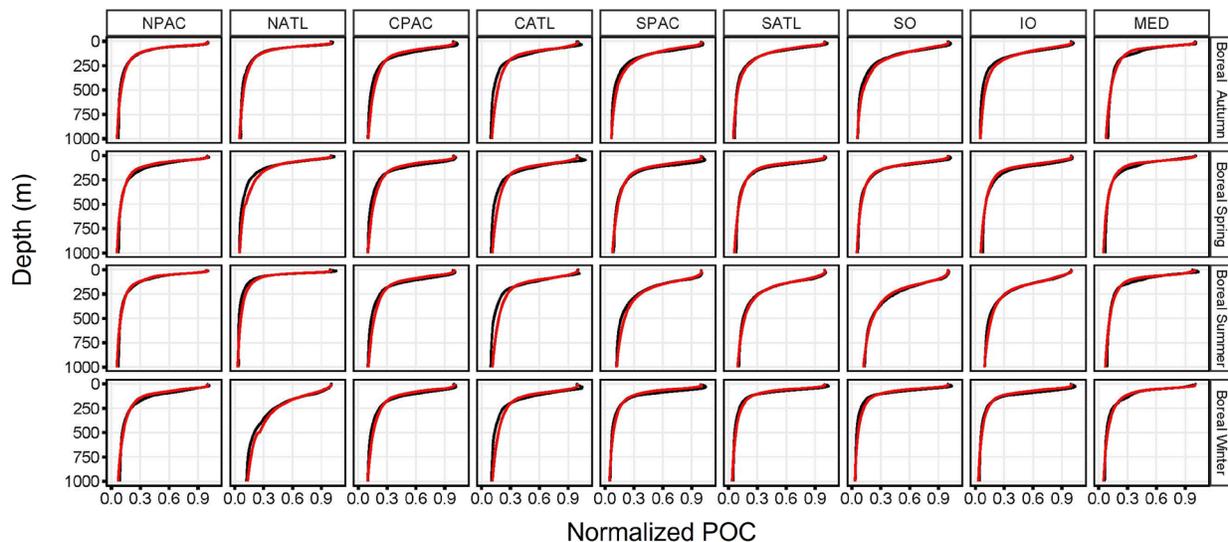
208 where POC_{1000} is the POC concentration at 1000 m. It is important to note that the
209 concentration-based attenuation metrics defined here are analogous but not equivalent to
210 traditional flux-based metrics. We nonetheless use similar terminology to emphasize the
211 parallels, in keeping with previous studies (Lam *et al.*, 2011; Rosengard *et al.*, 2015).

212 Finally, global and regional depth-resolved POC were estimated using the isolume-based
213 attenuation model (Equations 8 and 9) and the B20 method (Equation 10) with satellite retrievals
214 of PAR, k_{PAR} , bbp, and MLD. In addition, two sites were selected to assess the interannual
215 variability in high latitude areas of the Northeast Atlantic (49°N, 16.5°W) and the subarctic
216 North Pacific (50°N, 145°W).

217 **3. Results**

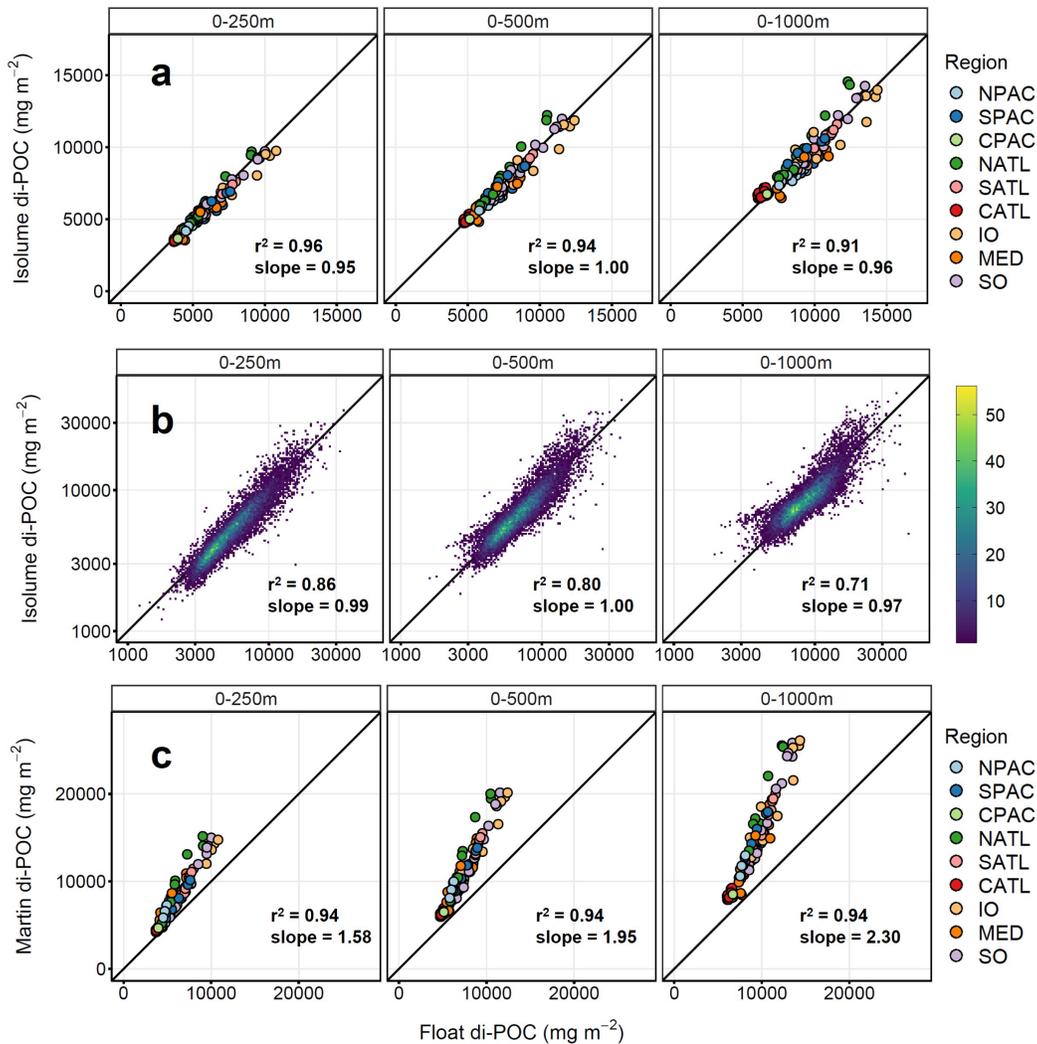
218 **3.1. Estimations of Depth Resolved POC**

219 Regionally averaged profiles of POC_{float} from the particle compensation depth (PCD) down to
220 1000 m showed a two-fold range in POC concentration at the point of attenuation (Figure 2b).
221 When these data are normalized to the POC concentration at the PCD, a consistent exponential
222 decay profile is revealed with varying degrees of vertical compression (Figure 2c). Regions with
223 the lowest POC concentration at the PCD (e.g. Central Pacific and Central Atlantic) typically
224 have the most “stretched” profile, reflecting a slower rate of carbon attenuation. In contrast, high
225 latitude regions (e.g. Southern Ocean and North Atlantic) where POC concentration is high at
226 the PCD have steeper, more compressed profiles. The isolume-based attenuation model (red lines
227 in Figure 3) effectively reproduces float-measured POC profiles (black lines in Figure 3) for all
228 regions of the global ocean across all seasons ($r^2 = 0.98$, RMSE = 1.319; Figure 5). In
229 comparison, the B20 method struggled to capture seasonal trends in attenuation profiles across
230 all regions and underestimated the rate of attenuation leading to overestimates of POC through
231 the mesopelagic (Supp. Figure 3).



232
 233 **Figure 3.** Seasonal variability in particulate organic carbon (POC) profiles across the global ocean. Depth
 234 resolved POC are derived from float profiles of particulate backscatter (POC_{float} , black line) and the
 235 isolume-based attenuation model approach (red line) following normalization to the POC_{float}
 236 concentration at one optical depth. The regional bins are NPAC = North Pacific, NATL= North Atlantic,
 237 CPAC = Central Pacific, CATL = Central Atlantic, SPAC = South Pacific, SATL = South Atlantic, SO =
 238 Southern Ocean, IO = Indian Ocean, and MED = Mediterranean.

239 Values of POC estimated using the isolume-based attenuation model and the B20 method were
 240 integrated over the top 250 m, 500 m, and 1000 m of the water column to quantify upper ocean
 241 carbon stocks. Integrated stocks predicted using the isolume-based model were averaged by
 242 region and month and showed excellent agreement with float-based observations over all depth
 243 horizons (Figure 4a). Comparisons between the isolume model and float observations averaged
 244 at finer resolution reveal the approach still performs well across all depth horizons (Figure 4b).
 245 The B20 method also showed a strong correlation with regionally averaged float observations
 246 but the slope of the regression ranged from 1.58 - 2.3, highlighting the overestimation of POC at
 247 depth due to the inability of the method to capture the correct attenuation gradient (Figure 4c).

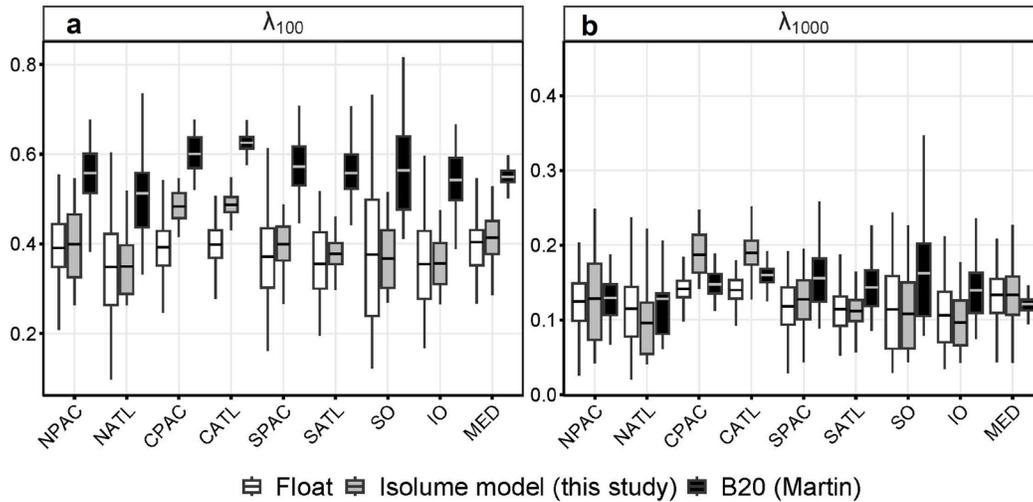


248
 249 **Figure 4.** Particulate organic carbon (POC) values from float profiles of particulate backscatter versus
 250 model predictions integrated over the top 250m, 500m, and 1000m of the water column (left to right). (a)
 251 POC estimated using the isolume-based attenuation model and averaged by region and month ($n = 108$),
 252 (b) a bivariate histogram showing POC estimated using the isolume-based attenuation model averaged by
 253 float, year, region and month ($n = 13,020$), and (c) POC estimated using the modified Martin (B20) method
 254 and averaged by region and month ($n = 108$). Note the change in axis range between each plot. Color
 255 scheme for regions in (a) and (c) follows that of Figure 2.

256 3.2. Global Observations of POC Attenuation Metrics

257 Comparisons between float and model estimates of λ_{100} and λ_{1000} showed the isolume-based
 258 attenuation model performed well across the nine global ocean regions of the float database
 259 (Figure 5). Float-based measurements of POC attenuation through the upper mesopelagic reveal
 260 extensive global variability, with values ranging from $\sim 10\%$ to 75% (Figure 5a). Estimates of
 261 λ_{100} and λ_{1000} from the isolume-based model are generally within 10% of the float values, with
 262 slight overestimations in the Central Pacific and Central Atlantic (Figure 5). In contrast, the B20

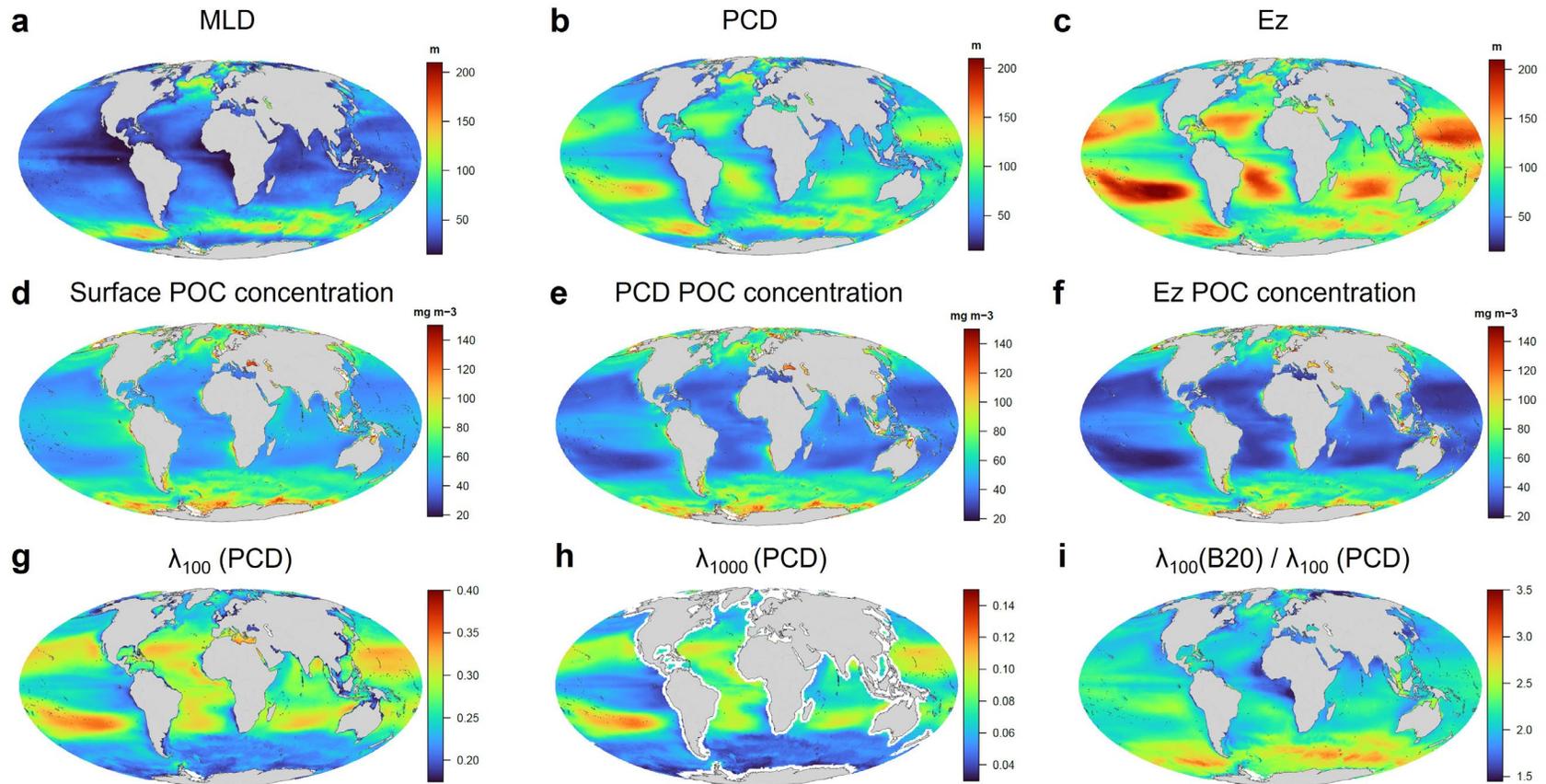
263 method significantly overestimates λ_{100} in all regions due to the underestimation of POC
 264 attenuation through depth. The two different approaches are closer in performance when
 265 predicting λ_{1000} , which ranged from ~ 3 to 20% when calculated using float observations (Figure
 266 5b).



267 \square Float \square Isolume model (this study) \blacksquare B20 (Martin)

268 **Figure 5.** Values of the POC concentration gradient between the particle compensation depth (PCD) and
 269 (a) 100m below the PCD (λ_{100}), and (b) 1000 m (λ_{1000}). The estimates were made using monthly float
 270 observations (white boxes), the new isolume-based attenuation approach (grey boxes), and the modified
 271 Martin approach (B20 method; black boxes). The regional bins are the same as described in Figure 3. Note
 272 changing y-axis scales, values are unitless.

273 Satellite-based estimates of POC differed significantly between the PCD and the $Ez_{0.1}$,
 274 sometimes resulting in a 60% reduction in concentration between the two depth horizons (Figure
 275 6). Global-scale attenuation metrics calculated using satellite retrievals with the B20 method and
 276 the new isolume-based attenuation model differed substantially, with the former yielding values
 277 over three-fold higher in some parts of the ocean (Figure 6i; Supp. Figure 4h-i). The isolume-
 278 based attenuation model showed more muted variability in λ_{100} estimates with most values
 279 falling between ~ 15 -40 % (Figure 6g), and the highest efficiencies were found in the South
 280 Pacific gyre where light penetrates deepest and surface POC concentrations are incredibly low
 281 (Figure 6). High production areas, particularly areas with shallow mixed layers and high surface
 282 POC concentrations, typically had lower concentration ratios reflecting higher rates of
 283 remineralization and lower efficiencies of transfer from the surface to the mesopelagic. Annual
 284 averages of λ_{1000} largely mirrored the spatial dynamics of the λ_{100} estimates and ranged from ~ 3 -
 285 15% (Figure 6h).

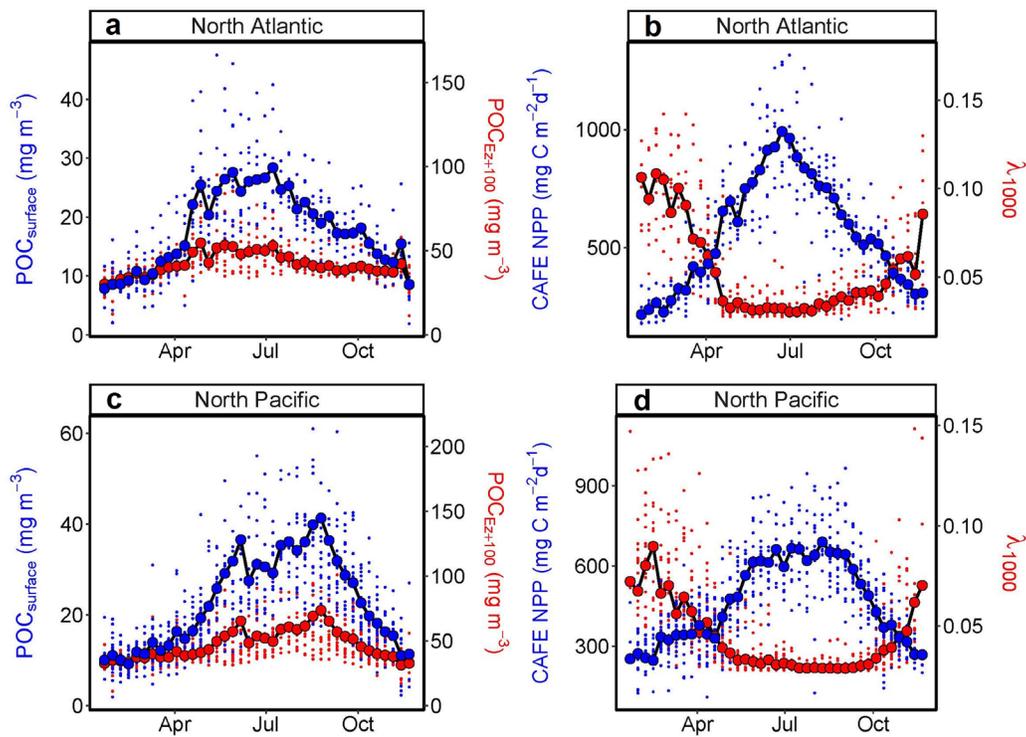


286

287 **Figure 6.** Satellite observations of (a) mixed layer depth (MLD, units = m), (b) the particle compensation depth (PCD, units = m), (c) the 0.1%
 288 light depth ($Ez_{0.1\%}$, units = m), (d) particulate organic carbon (POC, units mg C m^{-3}) concentration at the surface, (e) POC concentration at the
 289 PCD, (f) POC concentration at $Ez_{0.1\%}$, (g) the POC concentration ratio for the PCD and 100 m below the PCD (λ_{100}) made using the new isolume-
 290 based model, (g) the POC concentration ratio for the PCD and 1000 m (λ_{1000}) made using the new isolume-based model, (h) the difference
 291 between λ_{100} calculated using the modified Martin approach (B20) and the new isolume-based model.

292 **3.3. Regional Interannual Variability in Carbon Dynamics**

293 Annual cycles of NPP and POC for two Northern Hemisphere subpolar regions were assessed
 294 using satellite climatologies (Figure 7). The highest values of λ_{100} and λ_{1000} at both sites occurred
 295 in the winter months (December – February) when surface POC concentration is lowest and
 296 strong advective mixing results in deep mixed layers. Despite the ~ 3.5 -fold change in surface
 297 POC at both sites over the annual cycle the coincident increase in attenuation rates often results
 298 in similar POC concentrations below the euphotic zone (Figure 7a and Figure 7c). Temporal
 299 trends in surface POC concentration and NPP were notably different between the two regions. In
 300 the North Atlantic, the maximum surface POC concentration occurs in spring and corresponds
 301 with high values of NPP associated with the large phytoplankton bloom event characteristic of
 302 this region (Figure 7a-b).



303
 304 **Figure 7.** Climatological annual cycles of carbon stocks and rates at the Porcupine Abyssal Plain (PAP; top
 305 row) site in the Northeast Atlantic and the Ocean Station Papa (OSP; bottom row) site in the sub-arctic
 306 North Pacific, including (a) differences at PAP between surface particulate organic carbon (POC)
 307 concentration ($POC_{surface}$; large blue circles) and POC concentration 100 m below the euphotic zone
 308 (POC_{Ez+100} ; large red circles) which is shown on the secondary axis, (b) net primary production (large blue
 309 circles; NPP) at PAP with the concentration gradient between the particle compensation depth (PCD) and
 310 1000 m (λ_{1000} ; large red circles) shown on the secondary axis, (c) differences at OSP between $POC_{surface}$

311 (large blue circles) and POC_{Ez+100} (large red circles), and (d) values of λ_{1000} and NPP at OSP. Climatologies
 312 were constructed from weekly (8 day) composites of MODIS data over a 20-year period (2003–2022)
 313 averaged over a $0.5^\circ \times 0.5^\circ$ pixel grid centered over the PAP and OSP sites. Small circles represent all 8-day
 314 data from the 20-year study period.

315 Following this spring peak, POC concentration slowly declines through summer and autumn
 316 (July – November), leading to a corresponding decrease in the rate of POC attenuation and
 317 higher values of λ_{100} and λ_{1000} . In contrast, NPP and surface POC concentration both peak
 318 markedly later in the North Pacific, following a steady increase during spring and summer (April
 319 – August) (Westberry *et al.*, 2016). These peaks are immediately followed by a sharp and
 320 continuous decrease in concentration through autumn (September – November), corresponding
 321 with a lower rate of attenuation and higher concentration ratios.

322 4. Discussion

323 Satellite remote sensing is the most effective approach for monitoring marine carbon dynamics at
 324 global scales, but satellite-detected signals are largely restricted to the uppermost layer of the
 325 surface ocean (<1 optical depth) (Brewin *et al.*, 2023). Autonomous *in situ* platforms are more
 326 restricted in their horizontal spatial resolution but can provide important information on sub-
 327 surface carbon-cycling dynamics (Dall’Olmo *et al.*, 2016; Boyd *et al.*, 2019; Briggs *et al.*, 2020).
 328 Thus, surface observations of ocean color must be coupled with *in situ* observations, as well as
 329 empirical and mechanistic models, to vertically resolve the major reservoirs of marine carbon
 330 pools and understand the fluxes between different pools (Siegel *et al.*, 2016). Marine POC is
 331 estimated to constitute ~80% of the organic matter exported to the deep ocean through the BCP.
 332 POC cycling in the upper 1000 m therefore plays an outsized role in defining the strength and

Table 1. POC stocks for the global ocean integrated over different depth horizons. All values are calculated using the full mission composites of MODIS AQUA data over a 20-year period (2003–2023). Coastal regions were removed from the estimates (see Figure 8). Units are Pg C.

	PACIFIC	ATLANTIC	SOUTHERN	INDIAN	Global
Surface - PCD	0.48	0.19	0.40	0.12	1.27
PCD – 500 m	0.50	0.20	0.32	0.13	1.21
500 m – 1000 m	0.23	0.10	0.12	0.06	0.54
Total	1.21	0.49	0.84	0.31	3.02

333 efficiency of the BCP and, in turn, is a key factor defining the magnitude of CO₂ exchange
334 between the ocean and atmosphere. Here we introduce an isolume-based attenuation model that
335 provides the first global estimate of POC stocks in the top 1000 m based on observations from
336 satellite remote sensing (Figure 8; Table 1). Our method also permits estimation of POC
337 concentrations through the water column at highly resolved resolution, thereby allowing
338 calculation of key metrics used to assess the gravitational component of the BCP.

339 4.1. Predicting vertical POC using satellite observations

340 Remineralization of carbon through the water column is commonly parameterized as an
341 empirical function of depth, often referred to as a ‘Martin curve’, which has been revised and
342 modified in the decades since its origination (Martin *et al.*, 1987; Buesseler and Boyd, 2009,
343 Buesseler *et al.*, 2020). Two key
344 considerations in applying the Martin curve
345 are the choice of reference depth from which
346 the curve pivots and the value of the power
347 law exponent that defines the rate of
348 attenuation. The former is taken as the point
349 in the water column where POC flux or
350 concentration begins to decline, while the
351 latter reflects the intensity of
352 remineralization through the water column.
353 Recently, the $E_{z_{0.1\%}}$ light level was proposed
354 as a mechanistic reference depth (Buesseler
355 *et al.*, 2020), as opposed to the fixed point at
356 100 m originally used by Martin *et al.*
357 (1987). In their study, Buesseler *et al.* (2020)
358 found that the fixed-depth approach
359 underestimates BCP efficiencies when the
360 euphotic zone is shallow, and vice versa.
361 Our results support these findings but
362 suggest an absolute light level, or isolume,

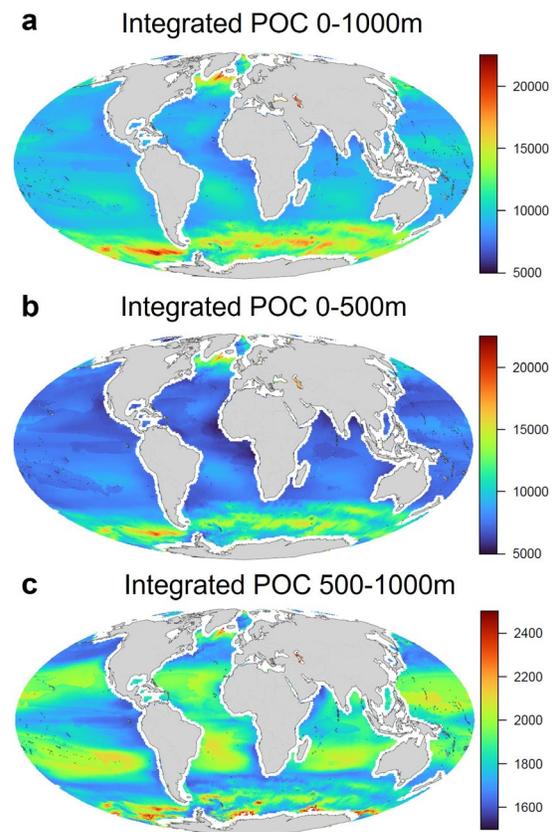


Figure 8. Global stocks of particulate organic carbon (POC) integrated over 1000 m. Input data for the new model are mission composites from MODIS AQUA at 9km resolution. Coastal waters are masked removed from the calculation of global stock estimates. Units are mg C m⁻².

363 is more suitable than a percentage when predicting the depth where particle losses outweigh
364 gains (i.e. the PCD).

365 Despite the assumption that b_{bp} at OD1 will remain constant from the surface to the PCD, the
366 isolume-based attenuation approach still predicts POC accurately through the upper water
367 column. This result suggests that for large areas of the global ocean the concentration of POC,
368 despite significant horizontal variability, is sufficiently homogeneous between the surface ocean
369 and the PCD to permit extrapolation using observations from the first optical depth. One
370 exception is the central regions of the Pacific and Atlantic where sub-surface peaks in POC result
371 in significant variance in surface POC compared to the PCD, resulting in poorer predictions of
372 attenuation trends. This result is consistent with a previous approach that used an empirical
373 formulation to extrapolate satellite-derived surface observations of POC to the base of the
374 euphotic zone (Duforêt-Gaurier *et al.*, 2010). In that study, integrated values of POC were shown
375 to correlate well with surface values for well-mixed regions but showed a weaker relationship in
376 stratified regions, particularly where Chl was $<0.1 \text{ mg m}^{-3}$, such as oligotrophic regions. The
377 weaker relationship between POC and Chl in oligotrophic regions was attributed to a deep POC
378 maximum that coincided with the deep Chl maximum.

379 In addition to a fixed reference depth, the original Martin Curve formulation also used a value of
380 0.858 for the power law exponent, as it captured the average attenuation trends of the available
381 data. Numerous studies have since shown that a fixed exponent is insufficient if the approach is
382 to be used at a global scale (Armstrong *et al.*, 2001; Cael and Bisson, 2018). Marsay *et al.*,
383 (2015) suggested that temperature can be used to explain observed variability in the strength of
384 vertical POC flux attenuation, while Lam *et al.*, (2011) observed a strong positive correlation
385 between the POC concentration at the reference depth used in the canonical Martin formulation
386 and the power law exponent coefficient, b (Lam *et al.*, 2011). The correlation identified by Lam
387 *et al.* (2011) reflects a decrease in efficiency of the BCP with increasing POC at the point of
388 attenuation, with the highest rate of attenuation observed in high latitude regions. These results
389 are consistent with the findings of the current study and are likely a significant factor in the
390 marked improvement in the isolume-based attenuation model predictions through the
391 mesopelagic compared to the B20 approach.

4.2. Defining global BCP efficiencies using the isolume-based attenuation model

The isolume-based attenuation model presented here permits the estimation of POC through the water column and can be used with satellite observations to assess global BCP efficiencies. Our results reveal the modified Martin Curve (B20 method) leads to significant overestimates of depth-resolved POC concentration and BCP efficiencies when using $E_{z_{0.1}}$ as a reference depth and a fixed exponent of 0.858. Other studies have used NPP or other satellite observations (e.g. phytoplankton biomass or Chl) along with food web models to predict export production and vertical carbon flux to the deep ocean (Schlitzer, 2002, 2004; Siegel *et al.*, 2014; DeVries and Weber, 2017). Those studies sought to define carbon flux, rather than concentration, and provided important steps towards understanding climate driven trends in global carbon dynamics (Wang *et al.*, 2023). The isolume-based attenuation approach presented here differs from those carbon export models in design and complexity but may benefit from its relative simplicity. For example, one advantage of the new approach is the availability of all base input variables (e.g. MLD, k_{par} , PAR, b_{bp}) from satellite remote sensing and a lack of reliance on derived/modeled parameters such as primary production, which have been shown to significantly alter some model outputs depending on NPP model choice (Bisson *et al.*, 2018). These model features, in combination with its improved ability to estimate BGC efficiencies and POC concentration through the mesopelagic, provide new avenues to study particle cycling through the water column (Amaral *et al.*, 2022), the microbial carbon pump (Jiao *et al.*, 2010), and energy budgets of deep-sea ecosystems that rely on the export of POC from the surface.

4.3. Drivers of variability in vertical POC attenuation

Biogeochemical mechanisms defining the transfer efficiency of POC from the surface to the deep ocean through gravitational settling remain unclear but are influenced by the local composition of phytoplankton, bacteria, and zooplankton assemblages (Passow and Carlson, 2012; Turner, 2015). Recent studies show evidence supporting the hypothesis that ecosystem structure is the primary driver controlling the efficiency of the BGP, rather than other factors such as the ballasting effect of calcium carbonate and other biogenic minerals (Lam *et al.*, 2011; Henson *et al.*, 2012; Henson *et al.*, 2012; Rosengard *et al.*, 2015). A common finding across these studies is that low transfer efficiencies are typically found in high latitude regions that are often dominated by diatoms, where the proportion of NPP exported from the euphotic zone (i.e.

422 export efficiency) is high (Henson *et al.*, 2012). The low transfer efficiency from the surface
423 ocean into the upper mesopelagic suggests that the POC produced in these conditions is highly
424 labile and susceptible to remineralization, a conclusion consistent with the parameterization of
425 the isolume-based attenuation model presented in this study. Regions where permanent or
426 seasonal stratification give rise to phytoplankton communities dominated by smaller cells and a
427 strong microbial loop are often characterized by a high mesopelagic transfer efficiency. *In situ*
428 observations at these sites show higher POC concentrations deep in the mesopelagic, suggesting
429 that the organic material exported from the surface is more resistant to remineralization at depth
430 (Lam *et al.*, 2011). These findings are consistent with the spatial and temporal observations
431 shown in Figure 6 and Figure 7, where high concentration ratios are generally found in
432 permanently-stratified, oligotrophic regions while low concentration ratios are found in high
433 latitude regions. However, we are unable to conclude whether the driver of this relationship is
434 community composition, as suggested by Lam *et al.* (2011), due to the absence of taxonomic
435 data associated with the float observations employed in our study. Our results do suggest,
436 however, that concentration alone may be the primary driver of attenuation rate [noting that while
437 high biomass events often coincide with a high proportion of diatoms, this is not always the case
438 (Bolaños *et al.*, 2021)].

439 **4.4. Summary and future directions**

440 Integrating satellite and *in situ* observations is a powerful and necessary step towards better
441 comprehension of the ocean's biological pump. Here, we utilized BGC-Argo profiles to develop
442 a semi-mechanistic modeling approach that employs observations from satellite remote sensing
443 to predict POC concentrations from the ocean's surface to the base of the mesopelagic zone. The
444 work builds on existing literature that has sought to improve empirical formulations commonly
445 used to predict carbon cycling dynamics in the epipelagic and mesopelagic zones. The PCD
446 isolume identified in this study offers a systematic reference depth for the point of POC
447 attenuation which is an important step towards the accurate prediction of attenuation gradients.
448 The new isolume based attenuation model incorporates a concentration specific scaling factor
449 which effectively varies the attenuation gradient, with the results supported by previous studies
450 that have assessed vertical POC distribution using *in situ* data. When combined, the PCD
451 isolume and the algorithm for POC attenuation enables the assessment of BGP efficiencies at a

452 global scale and the first estimation of global POC standing stock in the upper 1000 m (3.02 Pg
453 C) made using satellite remote sensing observations. While most efforts to calculate global POC
454 stocks using remote sensing have so far been limited to the surface layer or euphotic depth our
455 results are incredibly similar to previous estimates. Stramska (2009) quantified POC stocks over
456 the top 200 m using remote sensing reflectance and estimated a global average of 2.29 Pg C
457 which is incredibly close to the prediction from this study (2.32 Pg C for surface to 200 m). A
458 recent stock assessment over the top 1000 m, made using the Pelagic Interactions Scheme for
459 Carbon and Ecosystem Studies (PISCES) model, also resulted in a similar value (2.6 Pg C; Galí
460 *et al.*, 2022) to the predictions derived from our approach over the same depth horizon (3.02 Pg
461 C; Table 1).

462 The enhanced ability to predict vertical profiles of POC concentration from space could open
463 new avenues for investigating the ocean's carbon sequestration pathways. The inversion of POC
464 concentration data recently has been shown to provide a unique approach to predicting how
465 particle cycling rates are impacted by different biogeochemical properties in the upper ocean
466 (Amaral *et al.* 2022). Combining the isolume-based attenuation model with tracer-based models
467 could provide a new approach to predicting particle cycling dynamics in the upper ocean at a
468 global scale. However, additional steps should also be taken to improve the accuracy of the
469 method presented in this study. One of the simplifying assumptions in our approach is that b_{bp} at
470 OD1 is constant to the PCD isolume which permits the calculation of POC concentration at the
471 point of attenuation. While this assumption may hold for much of the global ocean, subsurface
472 POC maxima in some areas of the global ocean give rise to inaccuracies in POC_{PCD} that impact
473 predictions through depth. Significant effort has gone into predicting deep chlorophyll maxima
474 and a similar effort to estimate the equivalent phenomena for POC will permit greater accuracy
475 of POC concentration estimates through the mesopelagic. However, the rapid development of
476 satellite-based lidar may soon offer ocean-observation capabilities through the water column to
477 multiple optical depths. Other future satellite missions (e.g., NASA's Plankton, Aerosol, Cloud,
478 ocean Ecosystem) (Werdell *et al.*, 2019) will also permit the evaluation of phytoplankton
479 community composition which will help determine the relative impacts of biomass versus
480 taxonomy on the POC attenuation trends.

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483 **Open Research**

484 Raw data are available from the locations described in Section 2. Processed data and code are
485 available in the Zenodo data repository (<https://doi.org/10.5281/zenodo.10775647>), Github
486 (<https://github.com/jfox-osu/Data-and-scripts-for-publications>), and upon request.

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