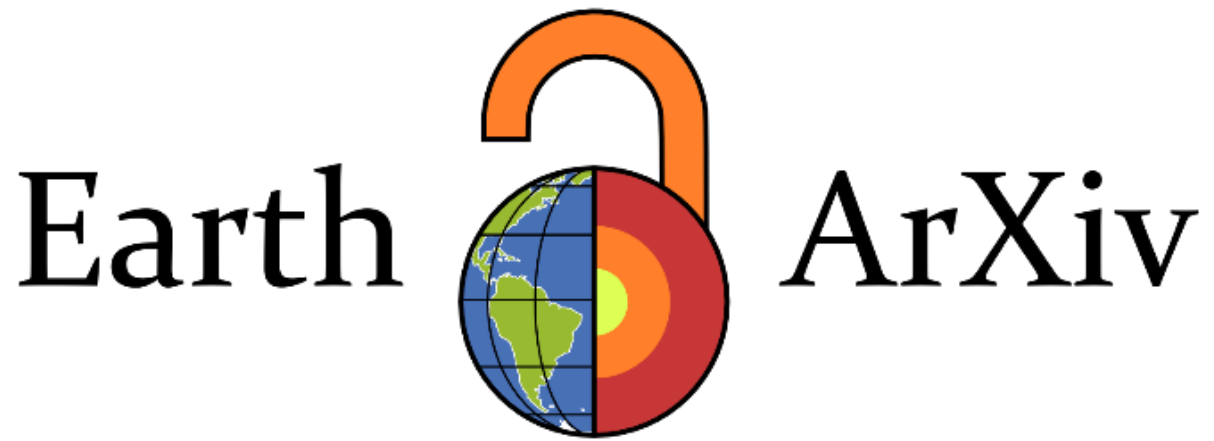




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The ocean's gravity-driven carbon flux from serendipitous particle traps

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Abstract

Particles sinking into the ocean's interior are a food source for deep-sea ecosystems and sequester carbon from the atmosphere. Yet, measurements of the sinking flux are sparse, leaving substantial uncertainties in its magnitude and variability. We demonstrate how a fleet of Argo floats has serendipitously measured the sinking flux for the last decade because particles settled onto the floats while adrift deep below the surface and were resuspended during ascent. With these new-found particle "traps", we estimate a global sinking flux of 790 TgC yr⁻¹ (95% C.I. 470–1,120 TgC yr⁻¹) at 1,000 m depth, where carbon is sequestered on timescales of centuries. This set of unanticipated flux observations offers a new way to investigate the biological carbon pump at the relevant scales and frequencies. Such observations will be valuable for addressing how the sinking particle flux responds to climate change and potential initiatives aimed at sequestering atmospheric carbon.

Keywords: BGC-Argo, parking hook, particle backscatter, export

Main

The biological carbon pump is a mechanism for the biologically mediated sequestration of carbon in the ocean's interior and sediments, where it is isolated from direct exchange with the atmosphere (1, 2). Carbon storage by the biological carbon pump is effectively a balance between the organic carbon exported from the euphotic zone into the deep ocean (through gravity, animal migration, subduction, mixing) (3, 4) and the respired carbon lost to the atmosphere once circulation brings it back to the surface (2). The dominant pathway for organic carbon to arrive in the ocean's interior is gravitational settling of particles (3–6). While also sustaining the majority of deep-sea life (7, 8), the gravity pump is the primary contributor to the long-term ocean inventory of respired carbon (3–5), making it an important process for explaining changes in Earth's climate (9, 10). There are large uncertainties in our ability to quantify the gravitational carbon pump (3, 4, 11–14). Previous global estimates of the sinking flux from the euphotic zone range by a factor of ~7 from 1.8 to 12.4 PgC yr⁻¹ (15, 16). The flux of sinking particles is even more uncertain deeper in the ocean's interior (13), although the carbon they transport becomes more relevant for long-term sequestration (17–19). At 1,000 m depth, past estimates range by a factor of ~9 from 0.25 to 2.2 PgC yr⁻¹ (5, 15) (Table S1). Furthermore, state-of-the-art Earth System Models (ESMs) from the Coupled Model Intercomparison Project phase 6 (CMIP6) do not come to a clear consensus as to how this major carbon flux will change in the future in response to climate change (11, 12) because of insufficient mechanistic understanding of its drivers (13).

Standard measurements of sinking flux are made using either naturally occurring, radiochemical tracers, like ²³⁴Th, from water samples, or by deploying funnel-shaped traps that capture sinking particles over a period of several days (20). While valuable, these observations are sparse, because their collection requires research vessels, trained scientists, and good weather, making them expensive and time-consuming. They also are biased towards the Northern Hemisphere, more biologically productive regions/seasons, and the pre-satellite era (14, 21). Nevertheless, these ship-based methods are the standard among sinking flux observations and are critical for calibrating and validating global-scale flux estimates (e.g., numerical models and satellite algorithms).

Here, we demonstrate how robotic profiling floats from the Biogeochemical-Argo (BGC-Argo) program (22) have inadvertently acted like particle traps for the last decade and thus can be calibrated to estimate the sinking particle flux globally. BGC-Argo floats are freely drifting platforms that profile the water column measuring several physical, biological, and chemical parameters, including particle backscatter (bbp), a proxy observation for particulate organic carbon (POC). Between collecting these profiles, a float parks at a depth of ~1,000 m, where it drifts for several days. During these parking phases, sinking particles settle onto the top flat surface of the float (see Fig. S1). When a float begins to ascend after the parking period ends, the settled particles are swept off and returned into suspension. The newly resuspended particles are detected by the float's bbp sensor located directly below the top flat surface. This process causes a transient anomaly in bbp at the beginning of the profile, which has been referred to as the “parking hook” in technical documentation (23).

Parking hooks as particle trap signals

The idea that the parking hook is a result of resuspended material that settled onto the float has been previously suggested in BGC-Argo quality-control procedures (23–25). We explicitly treat it as a proxy for the sinking particle flux. Two decades of research using optical sensors as sediment traps, also known as optical sediment traps (OSTs), show that it is possible to derive a flux proxy from material that had settled onto optical sensors (26–34). These OSTs involve an upward-looking transmissometer or camera that, during the float's park phase, accumulates sinking material onto the light detector, absorbing and scattering the incoming light signal. The

rate of change in measured light attenuation over the float's parking period, which is directly proportional to the rate at which particles settle onto the optical window, serves as a proxy for the sinking particle flux. This optical flux proxy is then validated and calibrated against coincident observations from traditional sediment traps to provide estimates of the sinking particle flux (29–31, 34). After the drifting period ends, the rapid vertical motion of the float creates hydrodynamic forces strong enough to resuspend the settled material and “reset” the OST. In our case, rather than detecting particles as they settle onto the optical window, resuspended particles previously settled onto the float itself are measured.

A bbp-profile with a parking hook is shown for a BGC-Argo float deployed in the northwest North Atlantic (Fig. 1A), illustrating the typical rapid decay of bbp to background conditions. Profiles from this float begin sampling on the ascent immediately after the parking phase, allowing for bbp from resuspended particles (bbp_r) to be detected by the optical sensor (Fig. S2). We derive our particle flux proxy from the parking hook as depth-integrated bbp_r ($\int bbp_r$) divided by the time the float spent parked. This proxy represents a portion of POC settled onto the float over the parking period. We estimate the bbp_r profile by first offsetting each profile by the ambient bbp and then fitting an exponential function to the difference (see *Methods*; Fig. 1B). The curve fit allows us to approximate the bbp_r profile and avoid unaccounted noise caused by, for example, the transient presence of large background or resuspended particles and changes in the float's tilt. The choice of an exponential decay function is justified when treating the resuspension rate of settled particles as a first-order kinetics process (see *Supporting Information*). Applying this calculation to the float in Fig. 1C yields seasonal patterns consistent with the expected seasonal cycle in the sinking flux as well as the sinking flux derived for the same float following a different method (35). The smoothed bbp flux proxy lags the mean bbp in the top 100 m of water-column bbp by ~13 d ($r^2 = 0.51$; $P < 0.01$), which is an indicator of phytoplankton biomass and, presumably, primary productivity.

With a large data set of BGC-Argo profiles collected over the past decade, it is possible to determine bbp flux over large spatial scales in the depth range of 900 to 1,100 m (19,445 profiles; from 201 floats; Fig. S3). However, expanding this flux proxy to the full array could introduce errors due to differences in float design (i.e., surfaces where particles can settle and the positioning of the bbp sensor). Fortunately, most of the floats with parking hook observations (99%) were from the same manufacturer and model (NKE PROVOR). Calculating bbp flux from individual profiles, as done in Fig. 1, can introduce uncertainty due to the presence of large ambient particles (or bbp spikes), that, at lower vertical resolutions, are not easily distinguishable from bbp anomalies caused by resuspended particles. To account for these large ambient particles, we can calculate bbp flux from aggregated profiles instead that provide enough information about the average contribution of bbp from large particles. Before combining profiles, bbp profiles are described as a function of the distance from the profile depth (rather than depth below the sea surface) and bbp is offset by the median bbp between 20 and 100 m from the profile depth. The bbp “anomaly” is then divided by the parking time. These steps account for varying parking depths, ambient small-particle bbp, and parking times, respectively (see *Methods*; Fig. S3–4). The resulting average profile has a non-zero asymptote because spikes positively skew the distribution of bbp. Thus, a secondary offset is applied, correcting for the average contribution of large ambient particles and providing a more accurate profile of bbp_r . This step removes the effect of large ambient particles, but not large particles settled onto the float, which are still encapsulated in the hook portion of the profile. We demonstrate the calculation of the average hook profile over large scales using all Northern Hemisphere profiles (Fig. 2A,B). Applying this process for both hemispheres for every month shows variations in bbp flux representative of the sinking flux over large scales (Fig. 2C).

If the bbp-flux proxy is a result of sinking particles, then it should be possible to calibrate bbp flux with sediment trap measurements of sinking POC, the standard for quantitative measures of the flux of sinking particles, as is done in the calibration of OSTs (29–31, 34). Using historical records

of sediment traps (21, 36, 37), we obtained 2,214 observations within the 900 to 1,100 m depth range spanning from 1982 to 2022 (see *Methods*; Fig. S5). Although 1,000 m is a relatively common depth to deploy traps (21), little overlap with the time and location of floats prevents a direct comparison with traps, as has been done with OSTs in previous work (30, 34). Instead, we compared sediment traps by aggregating parking hook profiles for various seasons and biogeochemical provinces (38, 39).

We obtained a total of 37 seasonal averages across 10 biogeochemical provinces (Fig. 3; $n_{\text{traps}} = 1,425$; $n_{\text{profiles}} = 13,170$). Despite the large differences in when and where both types of measurements were collected, bbp flux significantly correlates with the sinking flux from traps across a wide range of ocean ecosystems, excluding two outliers (Type II linear regression: weighted $r^2 = 0.83$, $P < 0.05$, $n = 35$; with outliers: weighted $r^2 = 0.55$, $P < 0.05$, $n = 37$). The provinces with the most comprehensive records are the Mediterranean Sea (619 traps from 1987 to 2005; 3,994 profiles from 2012 to 2024) and the Subantarctic water ring (355 traps from 1996 to 2022; 2,970 profiles from 2013 to 2024). In both, the seasonal patterns of bbp flux and sinking flux follow similar cycles (Fig. 3C,D). This is the case for the other provinces used in the calibration dataset too (Fig. S6). The strong correlation supports the notion that the bbp flux proxy is directly related to sinking-particle fluxes.

Several factors contribute to the uncertainty in the sinking flux from the parking hook, many paralleling those from sediment traps (40). One specific to the parking hook lies in possible seasonal or regional variation in the bbp efficiency of sinking particles (41). Another uncertainty is that the settled particles are not protected from microbial degradation or grazing, which could influence bbp strength. Samples from traditional traps are preserved typically with HgCl_2 or buffered formalin to prevent particles from disintegration and degradation. During the parking phase, zooplankton may also be attracted to the sensor's LEDs, causing some of the spikes in the vicinity of the parking hook (42, 43). Like with traditional sediment traps, this “swimmer” effect may lead to overestimates in bbp flux. The trapping efficiency of both traditional and optical traps is also influenced by hydrodynamics (e.g., strong current velocities resuspend particles or tilt traps), which will vary with the specific design of the float, its surface area, and the relative position of the bbp sensor. The accuracy of the exponential fit used to explain the parking hook relies on the assumption of a constant ascent speed, which may be slower at the start of the profile, but otherwise does explain the average parking hook well (e.g., Fig. 2). We minimized uncertainties arising from differences in design by using only PROVOR-type floats here. However, structural differences still exist between these floats depending on what sensors they are equipped with and how they are attached to the float. Such uncertainties could be corrected for in the future by standardizing parking hooks to a well-characterized OST sensor (30, 34).

Global gravitational carbon pump

The global annual sinking flux of POC at 1,000 m depth estimated from the parking hook is 790 TgC yr^{-1} , with a 95% confidence interval of 470–1,120 TgC yr^{-1} (Fig. 4). The area-specific sinking flux suggests fluxes peak at equatorial and subpolar latitudes, with a global area-weighted average ($\pm \text{SE}$) flux of $6.8 \pm 1.4 \text{ mgC m}^{-2} \text{ d}^{-1}$. The global estimate represents a wide range of spatial and temporal scales because the floats are in a globally distributed array and typically spend >90% of their lifespan parked in the deep ocean. This means that conditions hard to observe with traditional methods are included in the hook average (e.g., rare, episodic events of high flux; seasons excluded from satellite detection or polar night). The global hook-based estimate is also robust to excluding any single province from the calibration dataset, including outliers, and with alternative quality-control parameters (Table S3).

To place the hook-based fluxes in the context of existing global estimates, we compared them with those from 14 CMIP6 ESMs, and 80 permutations of satellite-based estimates (see *Methods*; Fig. 4). None of the three approaches constitutes the true flux, so the discrepancies between

169 them are best read as a measure of collective uncertainty, rather than the performance of any
170 one estimate. The hook-based flux (790 TgC yr^{-1} , 95% C.I. $470\text{--}1,120 \text{ TgC yr}^{-1}$) overlaps most
171 ESMs and satellite-based estimates ($480\text{--}1,780 \text{ TgC yr}^{-1}$ and $240\text{--}2,230 \text{ TgC yr}^{-1}$), but sits 25%
172 below the mean of both ($1,080 \text{ TgC yr}^{-1}$ and $1,050 \text{ TgC yr}^{-1}$). Our approximation is close to the
173 first estimate (830 TgC yr^{-1}) made by Martin et al. in 1987 (44; see Table S1) and within range of
174 those reported in the literature (average of $\sim 1,000 \text{ TgC yr}^{-1}$ and range of 250 to $2,200 \text{ TgC yr}^{-1}$).
175 Previous work comparing Argo- and satellite-based primary productivity found stronger
176 productivity at equatorial latitudes relative to subtropical ones (45), a pattern consistent with our
177 hook-based observations. In contrast, the average ESM follows a reasonably similar latitudinal
178 pattern to the hook-based estimate. Individual ESMs and satellite estimates covary with hook-
179 based fluxes to varying degrees (r^2 range of $0.26\text{--}0.84$ and $0.07\text{--}0.60$; multi-model averages of
180 0.49 and 0.36 , respectively). Seasonal sampling biases in the hook estimate are unlikely because
181 the floats collect profiles year-round. While the spatial coverage is still much greater than that of
182 traditional traps (Fig. 3A), biases may be present due to the geographic clustering of available
183 profiles. We tested for this by matching the profile locations with each ESM and satellite estimate
184 and calculating global fluxes from the average latitudinal transect, as done with the hook method.
185 The average global fluxes from ESMs ($1,090 \text{ TgC yr}^{-1}$) and satellites ($1,080 \text{ TgC yr}^{-1}$) computed
186 this way were close to the full field estimates, suggesting that the geographic distribution of hook
187 observations and the latitudinal extrapolation are not major sources of bias.

188 Serendipitously, BGC-Argo floats have observed a decade's worth of sinking particle fluxes
189 through the parking hook. With BGC-Argo already collecting data autonomously across the globe,
190 the parking hook signal, alongside dedicated OSTs, can rapidly expand observations at the
191 scales needed to monitor the sinking carbon flux. Optical estimates of flux could offer insights into
192 long-standing questions about the magnitude and spatial variability of export efficiency and flux
193 attenuation in the ocean. Currently, only $\sim 20\%$ of bbp profiles are suitable for bbp flux
194 calculations. Highly constrained, annual estimates of global flux could be possible with only
195 $\sim 10,000$ profiles collected each year (14). Such a system would offer a means of tracking
196 changes in the sinking flux due to climate change and could contribute to assessing technologies
197 intended to sequester atmospheric carbon by enhancing export (i.e., ocean fertilization or artificial
198 upwelling).

Methods

Biogeochemical-Argo float data

BGC-Argo float data were downloaded from the Argo Global Data Assembly Centers on October 20, 2024. We obtained bbp data from 1,074 floats with CTD (conductivity, temperature, and depth) and bbp sensors. Only float data with the parking depth information were used (i.e., Rtraj files). For quality control, the temperature, salinity, and pressure data are subject to potential calibration errors (e.g., sensor drift) over the float's lifetime, so only data associated with quality-control flags equivalent to "good" (equal to flags 1, 2, 5, and 8) (46) were used in the analysis. Similarly, good quality-control flags were applied for time and location data. For bbp, data were independently quality-controlled, as the parking hook is flagged as "bad" in the latest quality-control procedure (25). Minimal quality control is needed for bbp data as problems associated with sensor drift or bio-fouling are typically uncommon or non-apparent (47). Therefore, we applied a simple procedure that discards bbp outside of the range of 0 and 0.01 m^{-1} and any bbp data not associated with good quality-control flags from the CTD data (which is needed to calculate bbp).

We identified parking hook profiles as profiles where the float began its ascent within 20 m of its recorded parking depth. Downcast profiles were not used. We chose data profiles that began close to the parking depth because otherwise, if the float begins measuring too late in its ascent, any particles settled onto the float during the parking phase may have already been lost by the time the sensor turns on. Our analysis focuses on hook profiles at $\sim 1,000 \text{ m}$, since this is the most common float parking depth ($\sim 67\%$ of quality-controlled profiles with parking depth recorded; Fig. S3A). There is often meaningful variability between the actual parking depth and the targeted parking depth (i.e. $1,000 \text{ m}$), so profiles were used if the recorded parking depth was between 900 and $1,100 \text{ m}$ depth.

The parking time is recorded by the floats when they descend to or ascend from their parking depth. In some cases ($<1\%$ of the final dataset), the exact parking time was unavailable so instead we used the time stamps collected when the float completed its profile (at the surface) and subtracted the time it takes to ascend/descend by assuming a vertical velocity of 0.1 m s^{-1} . We limited parking times from 1 to 15 d (Fig. S3B). Without knowing the limit of detection for the parking hook, we decided to take a more cautious approach and apply the lower limit of 1 d to allow time for particles to accumulate onto the float, presumably increasing the signal-to-noise ratio of the hook. The upper limit was chosen to reduce the possibility of hydrodynamic forces removing particles from the float and to limit any bio-optical changes during the parking time as the particles are respired.

After identifying these profiles, we applied four additional steps. During the initial investigation for this analysis, we found that the bbp measurements near the first meter of the start of the profile were generally closer to background values of bbp. We suspect that this is the case because the float has not yet accelerated to a speed at which the settled particles begin to fall off. To limit biases on the exponential curve fit, we removed bbp measurements within the first meter traveled by the float. Following this step, we then only retained profiles that had collected at least two bbp measurements within the first 20 m of the profile. The aim of this was to ensure that profiles contained some information on the parking hook. With these profiles, we applied an additional step to remove profiles with possible biofouling or sensor drift. In the mesopelagic, bbp is generally low, so only profiles where the median bbp (20 m to 100 m from the start of the profile) was less than 0.002 m^{-1} were retained. Lastly, bbp data were binned and averaged to a 2-m

resolution to ensure consistent spacing of measurements. The resulting 19,445 profiles from 201 floats are used for this analysis.

Determining bbp flux from BGC-Argo profiles

We use two complementary approaches to calculate bbp flux. Calculations from individual profiles, presented here as a proof-of-concept, preserve high-frequency temporal variability but are more sensitive to outliers resulting from ambient large particles. Calculations based on aggregated profiles, used for large-scale calculations, sacrifice temporal resolution in exchange for improved robustness and minimal sensitivity to spikes associated with the background particle assemblage. The approaches mainly differ in their treatment of background bbp but otherwise the calculations of bbp flux are effectively equivalent.

Distance travelled from start. The vertical distance the float has travelled is calculated for each profile as the difference between the depth and the profile's maximum depth. This step is needed when aggregating profiles, as most settled particles are likely resuspended during the first 20 m of the float's ascent and therefore require a similar reference depth to account for profile-to-profile variability in parking depth (Fig. S3–4).

Background bbp correction. With both approaches, background bbp is removed by applying a two-sided least-squares linear regression to data between 20 and 100 m above the profile's maximum depth. Over this range in depth, bbp varies little so we believe it is reasonable to assume a linear response with depth. For individual profiles in Fig. 1, bbp data are pre-processed by smoothing with a five-point rolling median filter over the 20–100 m distance range to limit the effects of bbp spikes (from large particles) which otherwise could greatly influence the linear fit. This step could introduce some biases in bbp flux since the smoothing is not applied across the whole profile. For aggregated profiles, pre-processing of each bbp profile, prior to combining, involves subtracting the median bbp value between 20 and 100 m and then by dividing the difference in bbp by the parking time. The offsetting step reduces variability between profiles, while dividing the anomaly by the parking time ensures all profiles are comparable due to varying parking periods. Once profiles are combined into various regions/seasons, the average bbp_r profile (in m⁻¹ d⁻¹) exhibits an asymptote >0 m⁻¹ d⁻¹ as bbp is positively skewed due to the presence of large (particle) spikes. The final detrending step is applied using the regression step described above. This detrending step re-centers the profile to 0 m⁻¹ d⁻¹ while, unlike with individual profiles, removing the effects of large background spikes both in and outside of the parking hook and thus isolating the resuspended particle signal. All steps are illustrated in Fig. S7.

Exponential model and bbp flux. We then fit an exponential model to the bbp_r profile:

$$bbp_r(x) = ae^{-bx} \quad (1)$$

where x is distance (m) from the start of the profile, b is the decay constant (m⁻¹), and a is the bbp anomaly (m⁻¹) at $x = 0$ m. This model is supported by our theoretical explanation of the parking hook, where the resuspension rate follows first-order kinetics and is proportional to the particles remaining on the float (see *Supporting Information*).

The bbp_r fit was then integrated from 0 to 100 m above the profile's maximum depth. For individual profiles, bbp flux was determined by dividing depth-integrated bbp_r by the parking time, whereas pre-processing of aggregated profiles already accounts for parking time. The model fit

function returns the best-fit parameters (a , b) and their covariance matrix $\text{cov}(a, b)$, which are used to calculate the error in bbp flux via Jacobian error propagation:

$$\frac{\partial \text{bbp flux}}{\partial a} = \frac{a}{b} (1 - e^{-b^{100}}) \quad (2)$$

$$\frac{\partial \text{bbp flux}}{\partial b} = \frac{a(100be^{-100b} - (1 - e^{-100b}))}{b^2} \quad (3)$$

$$\sigma_{\text{bbp flux}}^2 = \left(\frac{\partial \text{bbp flux}}{\partial a}\right)^2 \sigma_a^2 + \left(\frac{\partial \text{bbp flux}}{\partial b}\right)^2 \sigma_b^2 + 2 \left(\frac{\partial \text{bbp flux}}{\partial a}\right) \left(\frac{\partial \text{bbp flux}}{\partial b}\right) \text{cov}(a, b) \quad (4)$$

$$\sigma_{\text{bbp flux}} = \sqrt{(\sigma_{\text{bbp flux}}^2)} \quad (5)$$

where $\sigma_{\text{bbp flux}}$ is the standard error in bbp flux.

Calculating bbp flux from individual profiles, as shown with float #6901486 in Fig. 1, makes the proxy more susceptible to outliers, leading to occasionally extremely high and negative values (although slightly negative values may simply suggest a very low sinking flux). To smooth the time series in Fig. 1C, we interpolated values to a daily resolution and then found the residuals between the calculated bbp flux and a smoothed version (60 d rolling median followed by a 60 d rolling mean), removing values whose residual was greater than 0.001 m^{-1} . For the smoothed version of bbp flux, we applied a 30 d rolling median followed by a 30 d rolling mean to the bbp flux data without outliers.

Sediment trap observations and calibration of bbp flux

Sediment trap observations were combined from three sources. The majority are from the global compilation by Mouw et al. (21). The second largest source is from the Southern Ocean Time Series (37) and the third from the DYFAMED site (36). While trap observations are a standard oceanographic measurement, it is well known that they contain biases (40, 48, 49). Low trapping efficiencies are an issue for traps deployed in the upper 1,500 m, due to stronger hydrodynamic biases (e.g., trap tilting) in this depth range, whereas traps deployed at greater depths are more efficient at trapping sinking particles (e.g., 100%) (40, 49). In the trap dataset we compiled, a low trapping efficiency is apparent when comparing fluxes at $1,000 \pm 100$ m (mean: $5.5 \text{ mgC m}^{-2} \text{ d}^{-1}$) with those at $2,000 \pm 100$ m (mean: $5.7 \text{ mgC m}^{-2} \text{ d}^{-1}$). Assuming exponential, Martin-type decay with an exponent of 0.86 (44), we expect the flux at 1,000 m to be about twice as high as the flux at 2,000 m.

Therefore, prior to calibration, we approximated a correction factor to account for poor trapping efficiencies at 1,000 m. We grouped sediment trap observations in 500 m bins and 5° latitude/longitude grid cells and fit a Martin curve to the flux values for all observations deeper than 1,500 m at each grid cell. Assuming an efficiency of 100% for traps deeper than 1,500 m, we compared the predicted flux at 1,000 m with the actual flux, when possible (Fig. S5). We found that the predicted flux in the 500–1,500 m bin is, on average ($\pm \text{SE}$), $\sim 2.4 \pm 0.5$ times higher than

the observed flux, which is equivalent to a ~40% trapping efficiency. This correction factor is similar to those implied by ^{230}Th and ^{231}Pa validation studies (40).

Estimating POC flux from bbp flux

We calibrated bbp flux to the sinking POC flux by comparing seasonal averages among various biogeochemical provinces in the depth range of 900 to 1,100 m. We determined bbp flux using aggregated profiles. For a valid climatological bbp flux, we required the average number of bbp data points per 2-m bin between 0 and 100 m above the profile's starting depth to be greater than 50. Initial investigations found this to be an important threshold to reduce the occurrence of anomalous bbp flux values and improve the calibration. Using the Mahalanobis distance (95% confidence threshold), we identified two data points as outliers and excluded them from the main regression analysis. We used least-squares bivariate (York) regression (50), which explicitly accounts for analytical errors in both the independent and dependent variables and finds the line that minimizes the weighted sum of squares residuals in both x- and y- directions. Regression analyses were performed on the seasonal averages and standard errors of bbp flux and trap-based sinking POC flux (see Table S3 for sensitivity analysis):

$$F_{POC} = 10954(\pm 1154) \times bbp\ flux - 0.01(\pm 0.25) \quad (6)$$

The uncertainty in F_{POC} ($\sigma_{F_{POC}}$) is determined by propagating the slope (σ_s) and intercept (σ_i), their covariance ($cov(s, i)$), the residual variance (σ_r^2), the uncertainty in bbp flux ($\sigma_{bbp\ flux}$), and the uncertainty in trap efficiency (σ_{corr}):

$$\sigma_{F_{POC}}^2 = \sigma_r^2 + bbp\ flux^2 + \sigma_s^2 + \sigma_i^2 + 2bbp\ flux \cdot cov(s, i) + s^2 + m^2 \sigma_{bbp\ flux}^2 + \left(\frac{F_{POC} \times \sigma_{corr}}{2.45} \right)^2 \quad (7)$$

$$\sigma_{F_{POC}} = \sqrt{\sigma_{F_{POC}}^2} \quad (8)$$

Calculations of bbp flux are made by combining profiles into 6° latitudinal bands. Area-integrated fluxes and their errors are calculated as the product of surface area at 1,000 m depth and sinking POC flux predicted from the hook. The global flux is the sum of area-weighted bbp fluxes multiplied by the total ocean area and regression coefficients (Equation 6). For error in the global flux, the independent error sources also are weighted by area and summed in quadrature, while systematic errors (σ_s , σ_i , and σ_{corr}) are propagated using an area-weighted bbp flux.

Satellite-based estimates

Satellite estimates of sinking POC flux at 1,000 m were based on various combinations of algorithms available in the literature, rather than relying on any single combination. This process first involves estimating export near or at the base of the euphotic zone from depth-integrated net primary productivity (NPP). The empirical relationships we applied predict export efficiency (equal to the ratio of export to net primary productivity) from estimates of NPP, sea surface temperature (SST), the concentration of chlorophyll-a at the surface (sChla) or its average concentration within

the euphotic zone ($Chla_{zeu}$; 51, 52), and the depth of the euphotic zone (z_{eu} ; 52). We used five export efficiency algorithms (16, 53–56):

$$export\ efficiency = 10^{-0.67+0.30 \times \log_{10}(Chla_{zeu})} \quad (9)$$

$$export\ efficiency = -0.0101 \times SST + \frac{0.0582 \times \log(NPP)}{z_{eu}} \quad (10)$$

$$export\ efficiency = 0.23 \times e^{-0.08 \times SST} \quad (11)$$

$$export\ efficiency = 0.62 - 0.02 \times SST \quad (12)$$

$$export\ efficiency = \frac{(0.5857 - 0.0165 \times SST) \times NPP}{51.7 + NPP} \quad (13)$$

Data for SST and sChla are from the Moderate Resolution Imaging Spectroradiometer Aqua and were downloaded from the Oregon State University website. For Equation 9, we estimated the depth-integrated Chla from Morel et al. (51) and estimated z_{eu} based on the relationship reported with sChla by Lee et al. (52). Estimates of NPP relied on four satellite-based models, including the Vertically-Generalized Productivity Model (57), the Carbon-based Productivity Model (58, 59), the Carbon, Absorption, and Fluorescence Euphotic-resolving model (60), and a simple empirical relationship between sChla and NPP by Eppley et al. (61). With export efficiency, we estimated carbon export with the four estimates of NPP:

$$carbon\ export = export\ efficiency \times NPP \quad (14)$$

Following the Martin curve (44), the sinking flux at a specified depth (in this case 1,000 m) below z_{eu} is estimated from Martin's b in the form of the equation:

$$sinking\ POC\ flux\ at\ 1,000\ m = carbon\ export \left(\frac{1000}{z_{eu}} \right)^{-b} \quad (15)$$

Four estimates of the b coefficient were used (44, 62–64). For one set of estimates, we assumed a constant and commonly used b of 0.86 from Martin et al. (44). We obtained two other sets of estimates specific to biogeochemical provinces (62, 63; values taken from Guidi et al.'s Table 2). A final set of b estimates was obtained using the temperature-based relationship reported by Marsay et al. (64):

$$b = 0.062 \times T_{0-500\ m} + 0.303 \quad (16)$$

where $T_{0-500\ m}$ is the median water temperature in the upper 500 m of the water column (calculated from World Ocean Atlas 2023, 2015-2022 objectively-analyzed annual mean $\frac{1}{4}^\circ$ resolution; 65). Using all possible unique combinations of NPP, carbon export, and the b exponent, we calculated 80 global distributions of POC flux at 1,000 m to compare against the BGC-Argo parking hook estimate.

Earth System Model estimates

The simulated sinking flux of POC was obtained from 14 Earth System Models as part of the Coupled Model Intercomparison Project Phase 6 (CMIP6). For each ESM, the sinking flux was

downloaded from the “historical” simulations and a single ensemble member (r1i1p1f1) during 2000–2014. Differences in the simulated POC flux between models are due to differences in model physics and model biogeochemistry. Details of the 14 ESMs used and their representations of the gravitational carbon pump are described in ref. (13).

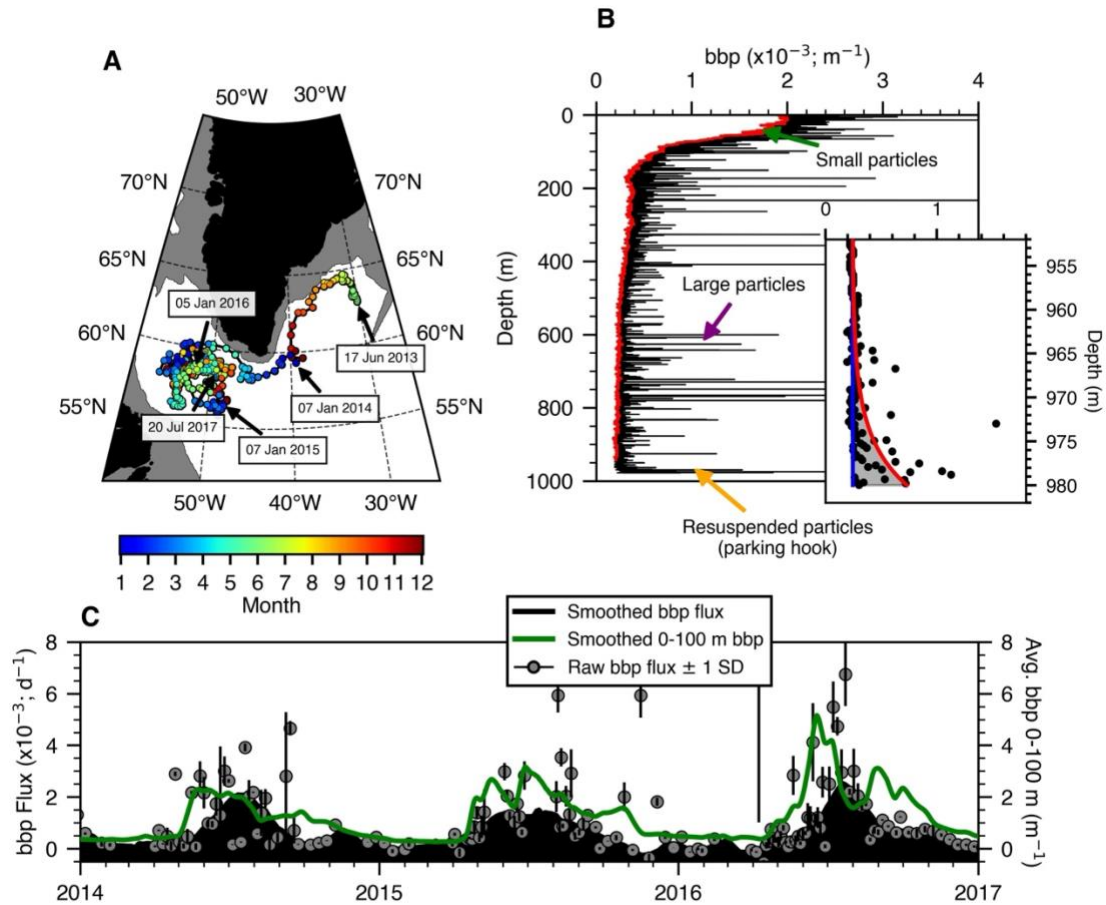
Data and Code Availability

Our processed data and software will be made publicly available on Zenodo upon acceptance. The BGC-Argo data were collected and made freely available by the International Argo Program and the national programs that contribute to it (<http://www.argo.ucsd.edu>, <http://argo.jcommops.org>; 66). For satellite estimates, surface chlorophyll-a and sea surface temperature data from the Moderate Resolution Imaging Spectroradiometer Aqua satellite are made available by the NASA Ocean Biology Distributed Active Archive Center (<https://oceancolor.gsfc.nasa.gov/>) and were obtained from the Oregon State Productivity website (<http://orca.science.oregonstate.edu/>) alongside net primary productivity estimates. CMIP6 model outputs are available from the Earth System Grid Federation data repository (<https://esgf-node.llnl.gov/search/cmip6/>; last access: September 2021). Topographic data are based on 60s ice-surface Earth TOPOgraphy Relief Model from the NOAA (accessed 1 October 2024; 67). The historical record of sediment trap observations is compiled from previous work (21, 36, 37).

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393 Main Figures and Tables



394

395 **Fig. 1. Parking hooks detect sinking POC.** (A) The path of a profiling float deployed in the
 396 Northwest Atlantic with bbp profiles starting near the parking depth. (B) High-resolution profile of
 397 bbp (thin black line) taken on June 9, 2015, shown as a representative example. Three categories
 398 of particles can drive the bbp signal in the profile: 1) small particles, highlighted as the smoothed,
 399 'background' profile (red line; 68), 2) large particles, which are detected as spikes in the bbp
 400 profile (purple arrow; 68), and 3) resuspended particles, which cause the parking hook at the
 401 bottom of the profile (orange arrow; 25). The inset panel is zoomed into the bottom 30 m of the
 402 profile where the parking hook is present. In the inset, bbp measurements are shown as black
 403 dots. bbp from the POC resuspended during the ascent (bbp_r) is isolated by subtracting a
 404 background signal (blue line) based on a linear regression applied to a smoothed version of the
 405 profile (see Methods). An exponential curve fit is applied to the isolated bbp signal to approximate
 406 a profile of bbp_r . The flux proxy termed bbp flux is equal to the depth-integrated bbp_r signal (grey
 407 area) divided by the time the float spent in the parking phase. (C) The seasonal patterns in bbp
 408 flux for individual profiles (grey points). Error bars represent one standard deviation. Maxima in
 409 the smoothed bbp flux (black area) lag behind maxima in the smoothed average bbp in the upper
 410 100 m of the water column (green line) (see Methods).

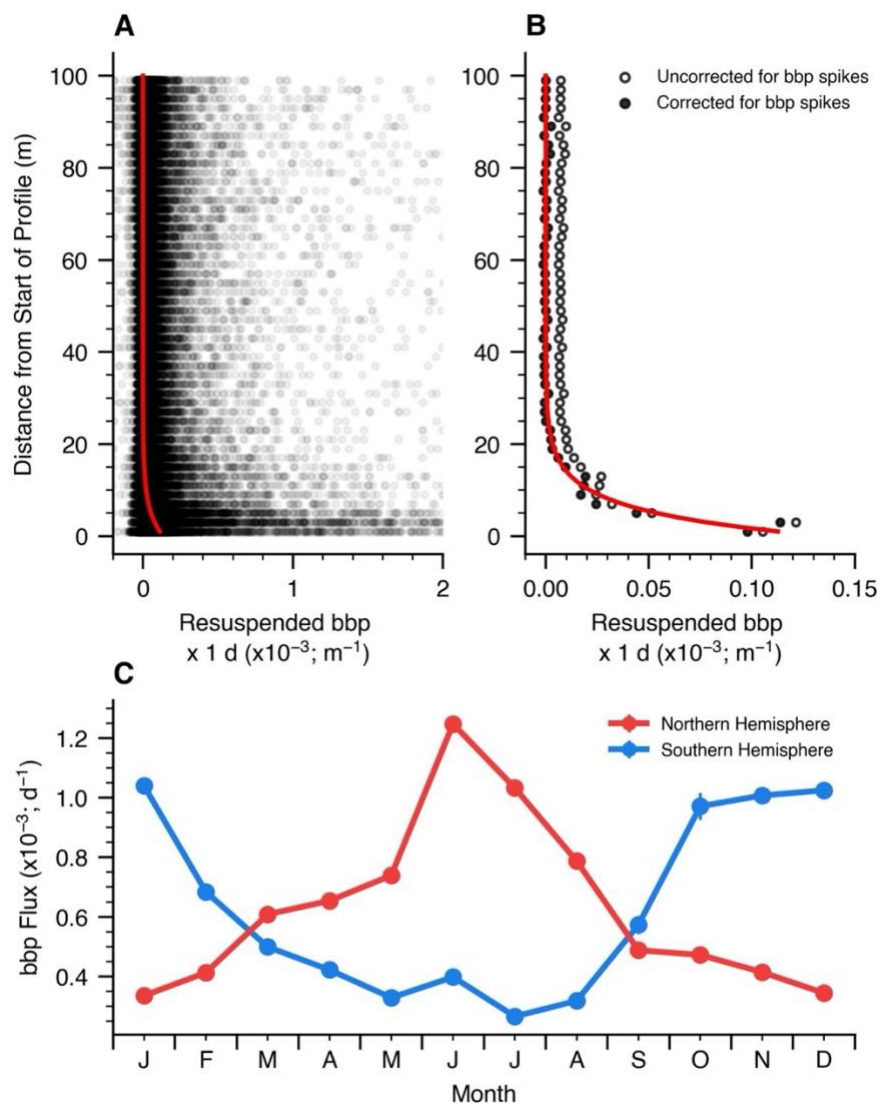


Fig. 2. Large-scale seasonality in the parking hook. (A) All profiles of bbp from resuspended particles in the Northern Hemisphere aggregated to create a composite profile. (B) The average profile from panel A with exponential fit demonstrates that this model is appropriate to describe the parking hook. Panel (B) also highlights the secondary correction applied to the merged profile, which removes the effects of large ambient particles from the entire profile. (C) Monthly variation in bbp flux calculated from profiles aggregated by hemisphere. Error bars in panel C, representing one standard deviation, are plotted but are small and not always visible.

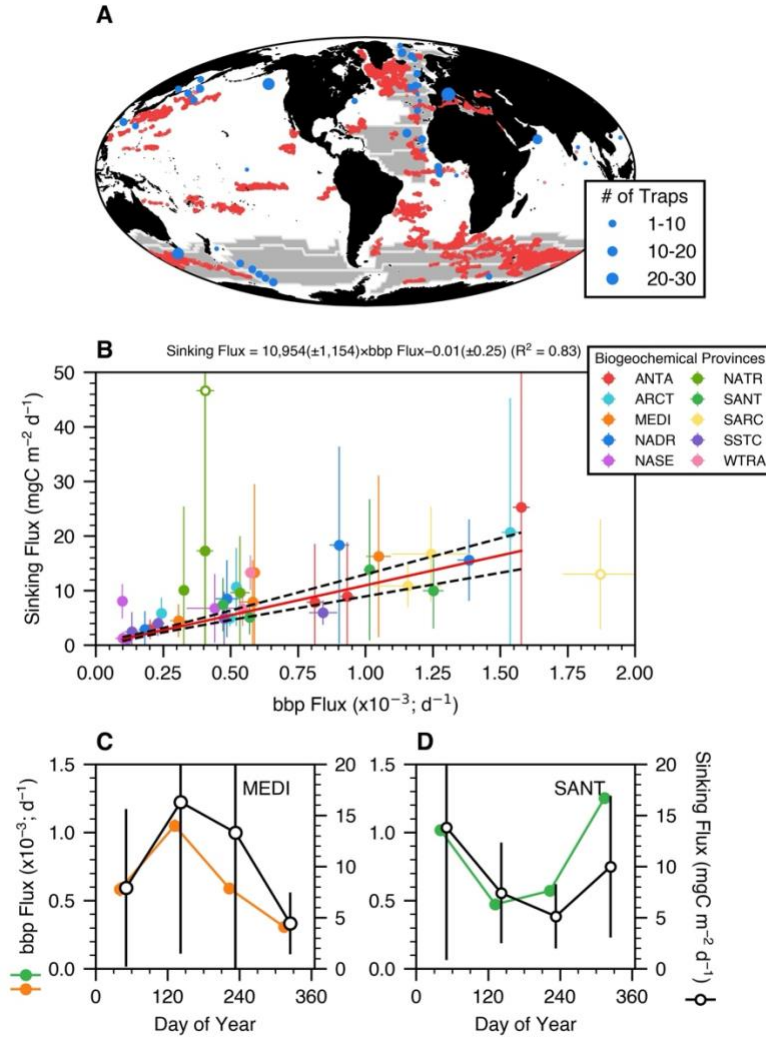
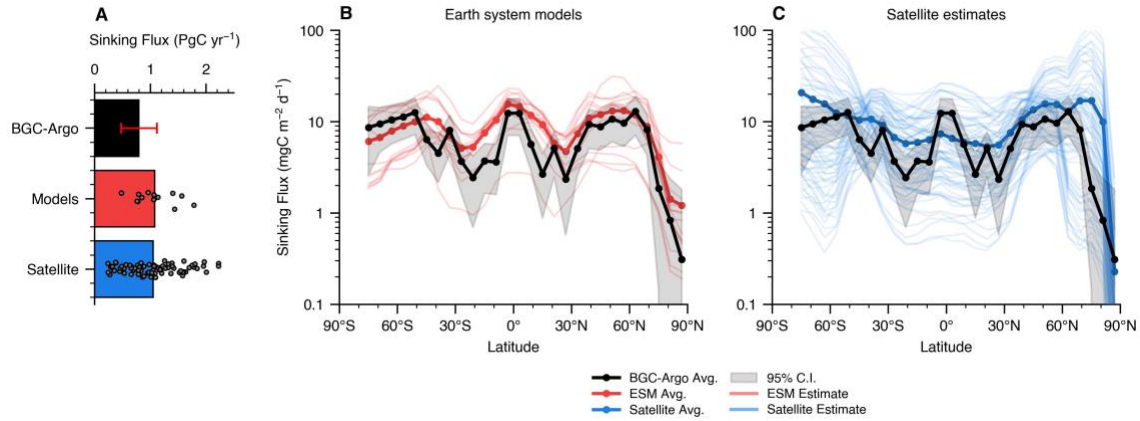


Fig. 3. Comparison of bbp flux from profiling floats and sinking flux from sediment traps. (A) Map of BGC-Argo profiles of bbp (red dots) and sediment trap measurements (blue dots, whose size scales with the number of observations per location). For BGC-Argo profiles, the profile began at $1,000 \text{ m} \pm 100 \text{ m}$ ($n_{\text{profiles}} = 19,445$ profiles; see *Methods*). Sediment traps are shown for the same depth range ($n = 2,214$ sediment trap observations from 43 unique locations; 21, 36, 37). (B) The sinking flux of POC, plotted as a function of bbp flux using 37 seasonal climatologies available from 10 different Longhurst biogeochemical provinces (38, 39), is shown in different colors (inliers as solid colors, outliers with white center). A significant relationship was found with a Type II linear regression (red line, excluding outliers, weighted $r^2 = 0.83$; $P < 0.05$; $n = 35$ constructed from 1,382 traps and 12,944 profiles; 95% confidence intervals are shown as black dashed lines). (C and D), The two BGC provinces with the largest number of sediment trap observations are good representatives of the seasonality in trap-based and float-based POC flux. (C) Seasonally averaged POC flux for the Mediterranean Sea compared with bbp flux from BGC-Argo floats. (D) as in (C), for the Subantarctic water ring. Error bars represent one standard deviation.



435

436 **Fig. 4. Global estimates of sinking flux.** (A) The globally integrated sinking particle flux based
437 on BGC-Argo floats (black bar), an average of 14 CMIP6 Earth System models (red bar), and an
438 average of 80 satellite-based estimates (blue bar). Individual model and satellite estimates are
439 shown as gray dots. (B and C) The zonally averaged sinking flux from profiling floats (black line)
440 compared with the CMIP6 ESMs (B, red lines) and satellite-based (C, blue lines) estimates.
441 Model and satellite values are area-weighted averages for a 6° latitudinal resolution. Error bars
442 (A–C) represent one standard deviation. Hook-based flux estimates are presented in Table S2,
443 and alternative global estimates are shown in Table S3.

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608

1 **Supporting Information**

2 **Theoretical Model for the Parking Hook**

3 The parking hook signal typically decays exponentially as the float ascends and fewer settled
4 particles remain on the float (e.g., as in Fig. 1B inset and Fig. 2A,B). This exponential decay
5 pattern can be explained with first-order kinetics as follows. We define the mass of particles
6 settled onto the float, and later resuspended, as $S(t)$ (mgC, mass of particulate organic carbon)
7 where t is time in days (d) and $t = 0$ d marks the start of the float's ascent from the parking
8 depth. Assuming a first-order loss of particles on the float, the instantaneous rate at which particle
9 mass is lost ($\frac{dS}{dt}$, mgC d⁻¹) is proportional to $S(t)$:

$$\frac{dS}{dt} = -kS(t) \quad (1)$$

10 where k is a positive decay constant (d⁻¹). Equation 1 can be rearranged by grouping variables S
11 and t (Equation 2), integrating (Equation 3), and solving for $S(t)$ (Equations 4–6):

$$\frac{1}{S(t)} dS = -k dt \quad (2)$$

$$\int \frac{1}{S(t)} dS = \int -k dt \quad (3)$$

$$\ln|S(t)| = -kt + C \quad (4)$$

$$S(t) = e^{-kt+C} \quad (5)$$

$$S(t) = e^C e^{-kt} \quad (6)$$

12 After defining e^C as constant A , we solve for the initial mass of settled particles (S_0 , mgC at $t = 0$
13 d):

$$S(t) = Ae^{-kt} \quad (7)$$

$$S_0 = Ae^{-k0} \quad (8)$$

$$S_0 = A \quad (9)$$

14 Substituting Equation 9 into Equation 6 yields the final solution for the exponential decline of
15 particle mass on the float:

$$S(t) = S_0 e^{-kt}. \quad (10)$$

16 Now knowing the evolution of particle mass remaining on the float, $S(t)$, we obtain the volumetric
17 concentration of resuspended particles, $P(t)$ (mg m⁻³). In a continuous flow system under steady
18 state, the volumetric concentration of mass (c , mg m⁻³) can be known in the general form as the
19 mass release rate (m , mg d⁻¹) and volumetric flow rate (q , m³ d⁻¹):

$$c = \frac{m}{q}. \quad (11)$$

20 In our case, m is equal to the resuspension rate of particles entering the detection volume of the
21 sensor ($L(t)$, mg d^{-1}), and q is equal to the volumetric flow rate within the detection volume (Q , m^3
22 d^{-1}), which we assume to be constant. Therefore, $P(t)$ is:

$$P(t) = \frac{L(t)}{Q} \quad (12)$$

23 where $L(t)$ is the resuspension rate of particle mass and equal to $R(t)$ multiplied by the fraction of
24 particle mass entering the sensor volume (f , unitless):

$$L(t) = fR(t) \quad (13)$$

25 $R(t)$ is equal to the negative derivative of Equation 10, which yields a positive resuspension rate:

$$R(t) = kS_0 e^{-kt}. \quad (14)$$

26 Additionally, Q is equal to the product of the ascent speed (v , m d^{-1}) and the effective cross-
27 sectional area of the detection volume (A_{sens} , m^2):

$$Q = vA_{\text{sens}} \quad (15)$$

28 Equation 12 can be rewritten to find $P(t)$:

$$P(t) = \frac{fR(t)}{vA_{\text{sens}}} \quad (16)$$

$$P(t) = \frac{fkS_0}{vA_{\text{sens}}} e^{-kt} \quad (17)$$

29 Since the parking hook is a function of the parking depth (x , m), we substitute t for x in Equation
30 17 using the formula for velocity:

$$v = \frac{x}{t} \quad (18)$$

$$t = \frac{x}{v} \quad (19)$$

31 We can therefore describe P as a function of distance by substituting Equation 19 into Equation
32 17:

$$P(x) = \frac{fkS_0}{vA_{\text{sens}}} e^{-\frac{k}{v}x} \quad (20)$$

33 The sensor is reporting particle backscattering (bbp , m^{-1}), a proxy observation for the
34 concentration of resuspended particle mass, P . We must multiply P by the carbon-specific
35 backscattering coefficient (bbp^* , $\text{m}^2 \text{mgC}^{-1}$) to describe the idealized depth-profile of resuspended
36 particle mass as a function of distance from the parking depth:

$$bbp_r(x) = bbp^* \frac{fkS_0}{vA_{sens}} e^{-\frac{k}{v}x} \quad (21)$$

Equation 21 serves as the basis for describing the parking hook observed in the depth-profiles of bbp . Our justification for fitting an exponential equation in a generalized form is based on the derived model assuming first-order kinetics. Equation 21 can be simplified to the generalized form we use for the curve fit:

$$bbp_r(x) = ae^{-bx} \quad (22)$$

where $a = bbp^* \frac{fkS_0}{vA_{sens}}$ and $b = \frac{k}{v}$.

We can use this model to also understand possible sources of unexplained variability. The variable bbp^* is affected by optical characteristics of the resuspended particles like their size and shape. The float's ascent speed, which we assume constant, may vary and therefore alter the expected decay pattern as a function of distance. With varying float speed, the minimum velocity needed to cause resuspension for individual particles may not be met. The fraction of detected particle mass (f) is affected by factors like horizontal/vertical currents directing material into the sensor's detection volume and the float's tilt. The effective cross-sectional area (A_{sens}) of the sensor may also be affected by the float wobbling during the ascent.

Deriving an Optical Flux Proxy

The generalized equation for POC flux ($\text{mgC m}^{-2} \text{d}^{-1}$) measured by sediment traps is:

$$F_{POC} = \frac{M}{AT} \quad (23)$$

where M (mgC) is the mass of particulate organic carbon found within the trap, A (m^2) is the cross-sectional area where particles enter the trap, and T (d) is the duration of the trap deployment. When applying the same general equation to floats, the material settled onto the float, M is S_0 , A is the plan area of the float's top (A_{float} , m^2), and T is the time the float spent at its parking position (T_{park} , d), such that:

$$F_{POC} = \frac{S_0}{A_{float}T_{park}} \quad (24)$$

We can re-write this relationship using properties that are observed by the float. First, the constant fraction of S_0 observed by the sensor (f) over the same time interval (see Equation 13) is:

$$f = \frac{S_{obs}}{S_0} \quad (25)$$

where S_{obs} (mgC) is the mass of resuspended particles observed by the float. Equation 25 can be re-arranged to solve for S_{obs} :

$$S_{obs} = fS_0 \quad (26)$$

Dividing both sides of Equation 26 by the cross-sectional-area of the sensor (A_{sens}) and the time spent parked (T_{park}) yields the observed flux of resuspended particles (F_{obs} , $\text{mgC m}^{-2} \text{d}^{-1}$) on the left-hand side and:

$$F_{obs} = \frac{f S_0}{A_{sens} T_{park}} \quad (27)$$

65 Re-arranging Equation 24 to solve for S_0 and substituting it into Equation 26, yields the
66 relationship between F_{POC} and F_{obs} :

$$F_{obs} = \frac{f F_{POC} A_{float} T_{park}}{A_{sens} T_{park}} \quad (28)$$

$$F_{obs} = \frac{f F_{POC} A_{float}}{A_{sens}} \quad (29)$$

67 or, if re-arranged, to solve for F_{POC} :

$$F_{POC} = \frac{F_{obs} A_{sens}}{f A_{float}} \quad (30)$$

68 Our proxy observation for F_{POC} is termed bbp flux (d^{-1}). We obtain the bbp flux by first integrating
69 Equation 21, the equation representing the theoretical parking hook, to obtain the proxy $\frac{f S_0}{A_{sens}}$,
70 and then dividing by the time spent parked (T_{park}). The integral of Equation 21 determined with
71 bounds of 0 to 100 m is:

$$\int_0^{100} \text{bbp}(x) dx = \int_0^{100} \text{bbp}^* \frac{f k S_0}{v A_{sens}} e^{-\frac{k}{v} x} dx \quad (31)$$

$$\int_0^{100} \text{bbp}(x) dx = \text{bbp}^* \frac{f k S_0}{v A_{sens}} \left[\frac{v}{k} e^{-\frac{k}{v} x} \right]_0^{100} = \text{bbp}^* \frac{f k S_0}{v A_{sens}} \frac{v}{k} \left(e^{-\frac{k}{v} x} \right) \quad (32)$$

$$\int_0^{100} \text{bbp}(x) dx = \text{bbp}^* \frac{f S_0}{A_{sens}} \left(1 - e^{-\frac{k}{v} 100} \right) \quad (33)$$

72 Integrating from 0 to 100 m effectively eliminates the value's dependence on k and v (Equations
73 31–33). In other words, the integrated value is a proxy for the total mass of observed
74 resuspended material, regardless of how “spread out” the material is, assuming that A_{sens} , f , and
75 bbp^* are constant. Most of the resuspension occurs in the first 20-30 m of the profile, meaning that
76 $e^{-\frac{k}{v} 100}$ is approximately zero.

77 Finally, we can calculate bbp flux, our proxy for F_{obs} , as:

$$\text{bbp flux} = \frac{\int_0^{100} \text{bbp}(x) dx}{T_{park}} = \frac{\text{bbp}^* \frac{f S_0}{A_{sens}} \left(1 - e^{-\frac{k}{v} 100} \right)}{T_{park}} \quad (34)$$

78 Alternatively, as S_0 , bbp^* , A_{sens} , f , k , and v are not required for the calculation of bbp flux, the
79 integral of the generalized form used to fit to the parking hook observation, is:

$$\int_0^{100} \text{bbp}(x) dx = \frac{a}{b} (1 - e^{-b 100}) \quad (35)$$

80 with bbp flux in the generalized form calculated as:

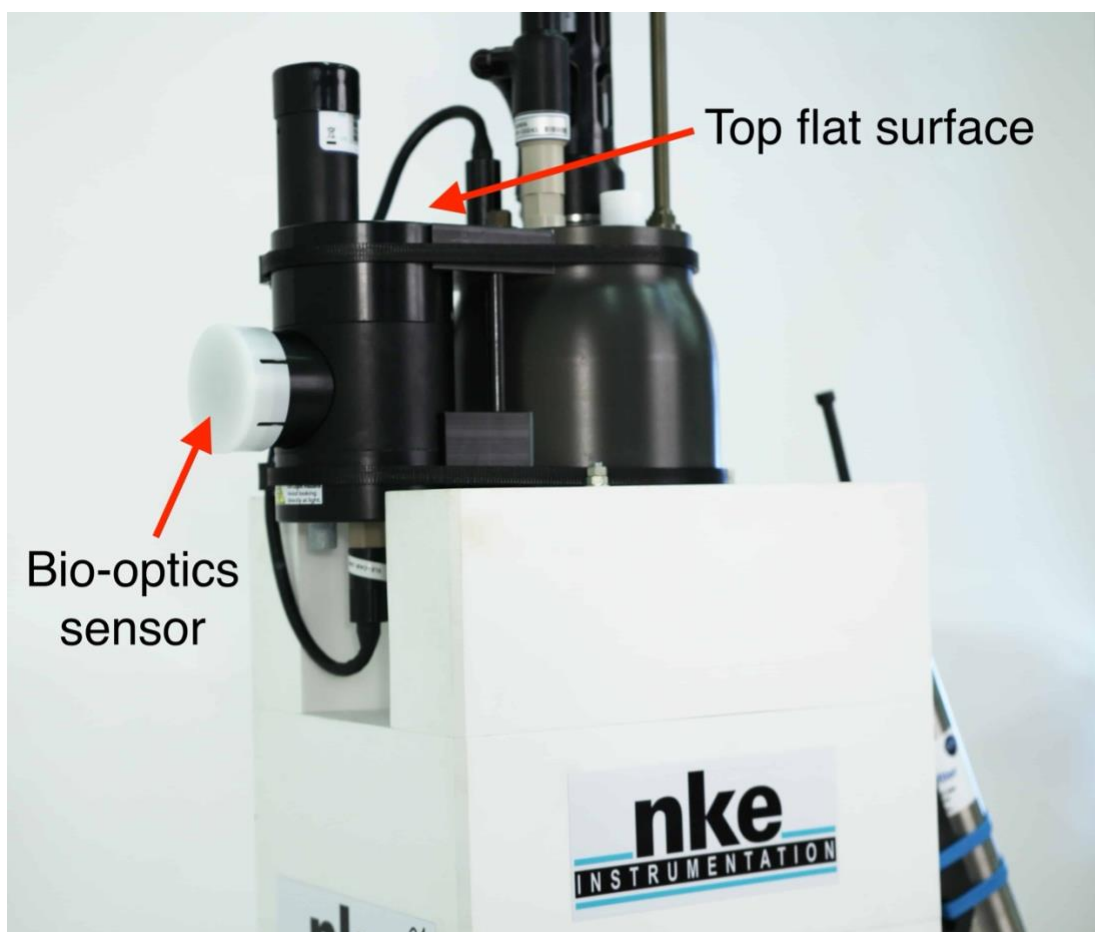
$$bbp\ flux = \frac{\int_0^{100} b_{bp}(x) dx}{T_{park}} = \frac{\frac{a}{b}(1 - e^{-b100})}{T_{park}} \quad (36)$$

81 We can express Equation 29 in a form that converts bbp (m^{-1}) to particulate organic carbon
82 concentration, or $P(x)$ ($mgC\ m^{-3}$):

$$F_{POC} = \frac{A_{sens}}{fA_{float}} bbp^* \times bbp\ flux \quad (37)$$

83

84 **Supporting Figures**



85

86 **Fig. S1. Top portion of NKE's PROVOR CTS5 Float.** This design includes the REM-A
87 configuration which combines the radiometer and bio-optics sensor into a single package. The
88 bio-optics (backscatter) sensor, located immediately below the top flat surface, has a protective
89 cap on it, which is removed prior to deployment.

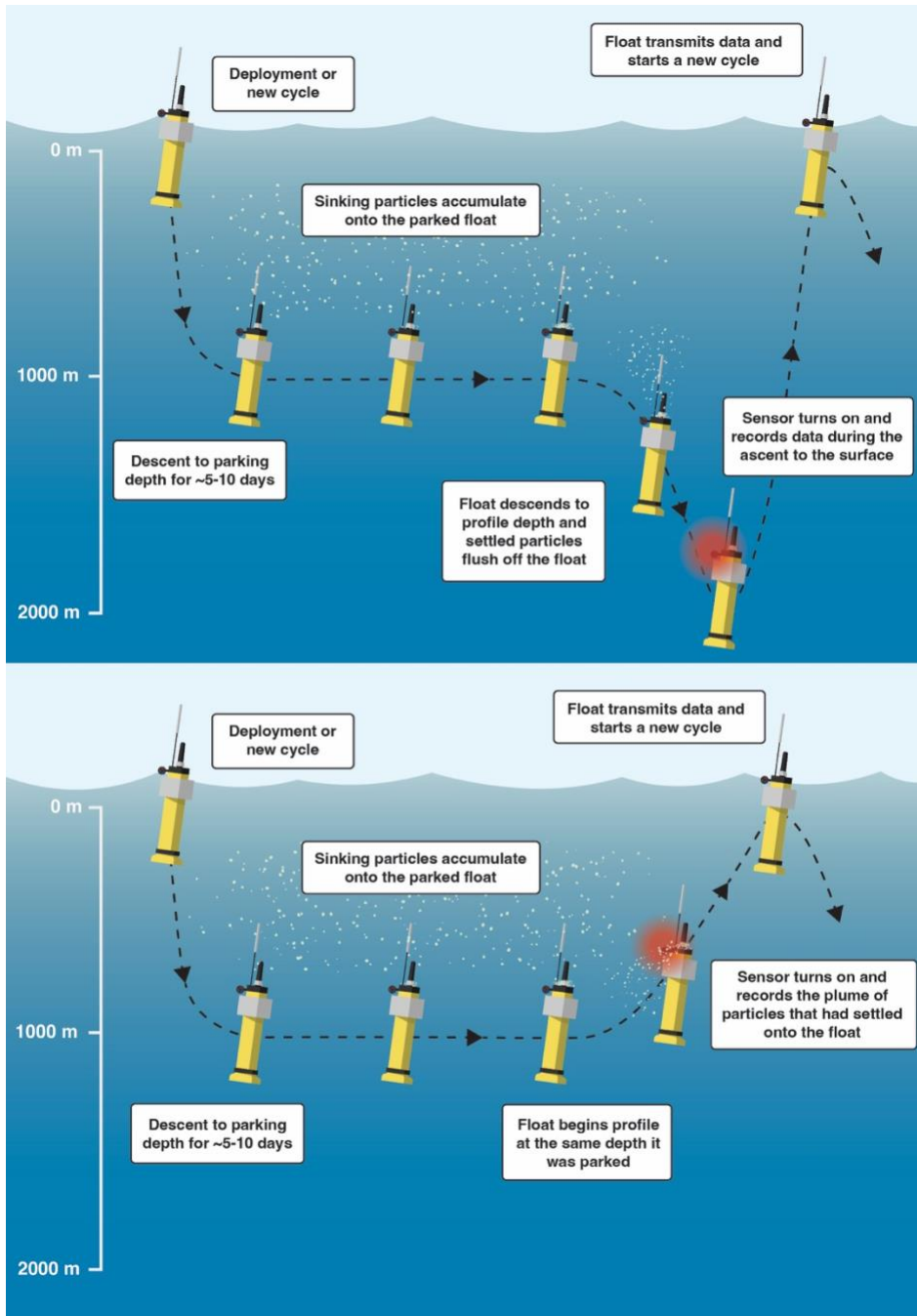


Fig. S2. Sampling strategies with BGC-Argo floats. (A) A typical BGC-Argo float sampling strategy involves the float parking at 1,000 m depth for several days before descending further to 2,000 m where the float begins its profile. During this parking phase, sinking particles accumulate on the top of the float. When the float descends to its profile depth, these particles likely flush off the float and are not detected by the float's optical sensor. (B) However, some floats do not follow this sampling protocol and instead park and start profiling at the same depth (commonly at ~1,000 m). In these cases, the float's optical sensor serendipitously observes the particles flushing off the ascending float following the parking phase. With this configuration, the "parking hook" can be observed (e.g., Fig. 1B). The diagram is not to scale.

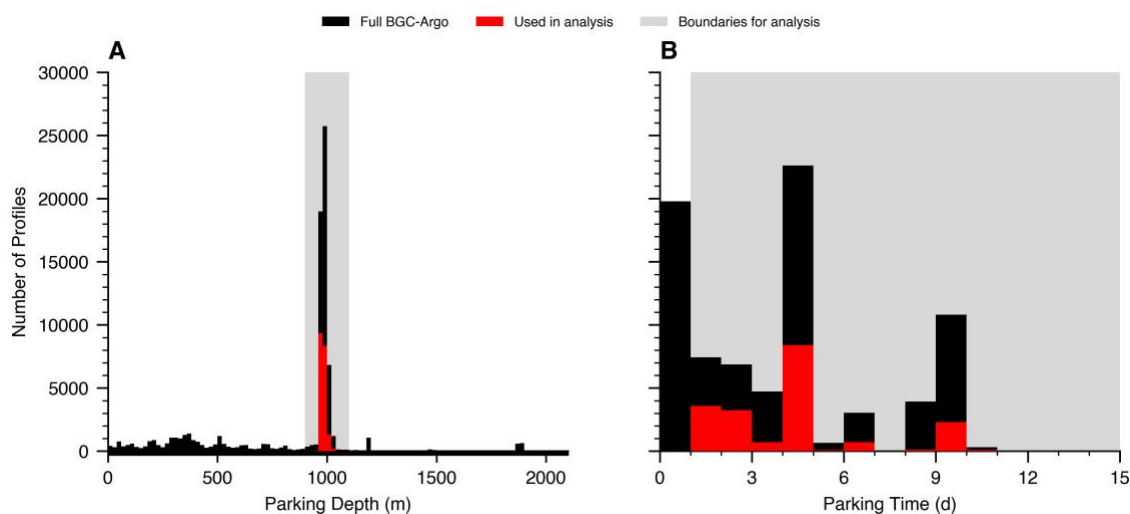


Fig. S3. Parking depths and times in BGC-Argo array. The parking depth (A) and parking times (B) of ascending profiles collected by all BGC-Argo floats with trajectory files (80,765 profiles from 459 floats) and from those used in the analysis (19,445 profiles from 201 floats). Note that only BGC-Argo floats with bbp sensors and parking depth data are reported here. The boundaries in panel A are 900 to 1,100 m, while those in panel B are 1 to 15 d.

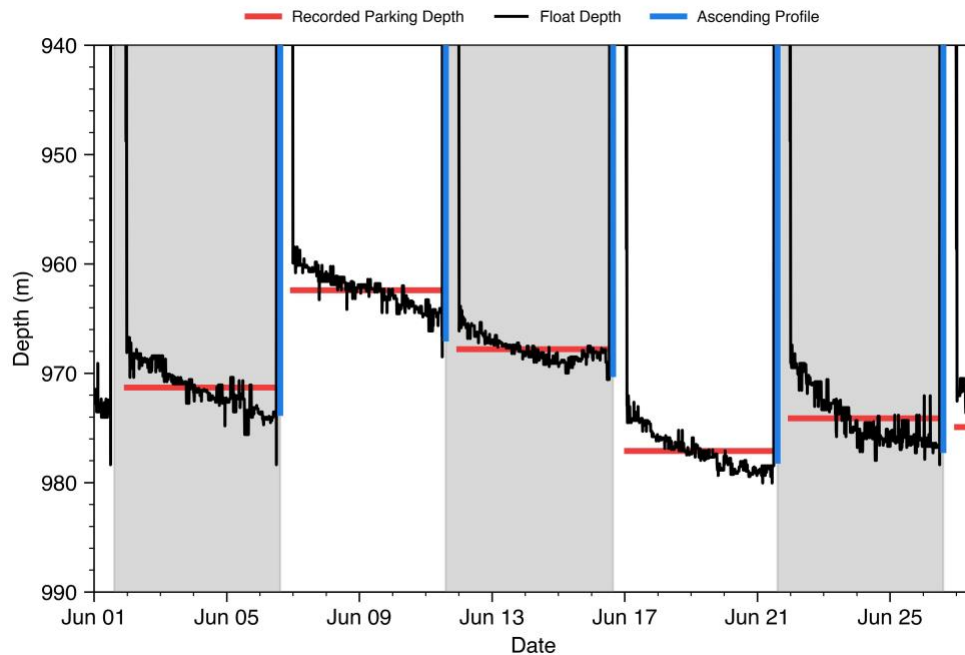


Fig. S4. Example of the variability in parking depth. The depth of the float is shown in Fig. 1 (black line) as it descends, parks for several days, and then ascends to collect biogeochemical data. The average parking depth (horizontal red line) is used to define the depth of the bbp flux measurement since the material observed in the parking hook is collected over this period. Variability in parking depth is apparent during the parking phase. The distance from the start of the profile is calculated from the profile's max depth, rather than the average parking depth.

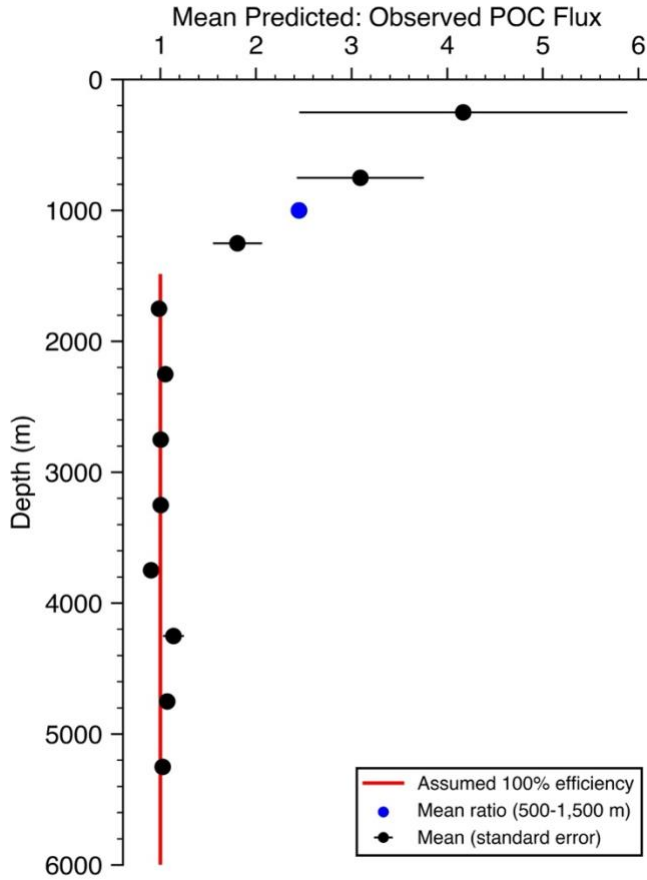


Fig. S5. Ratio of predicted:observed sinking POC flux with depth. Observed POC fluxes are from the compilation of trap records. Predicted POC fluxes are made by fitting a Martin curve to observed deep sediment traps (>1,500 m depth), assuming that these traps capture particles with 100% efficiency (red line). Observed fluxes are binned into a 5° latitude/longitude grid, by season, and 500 m depth bins prior to the curve fit. POC flux at depths <1,500 m is predicted by extrapolating the curve fitted to the deep trap data. The average of predicted:observed is calculated for all possible profiles at a 500 m resolution (black points; error bars represent one standard error). Assuming the predicted upper-layer fluxes are the “true” values and observed values suffer from trapping efficiency issues, this ratio represents the inverse of trapping efficiency. The average predicted-to-observed flux ratio at 1,000 m is ~2.4, representing an average trapping efficiency of ~40%.

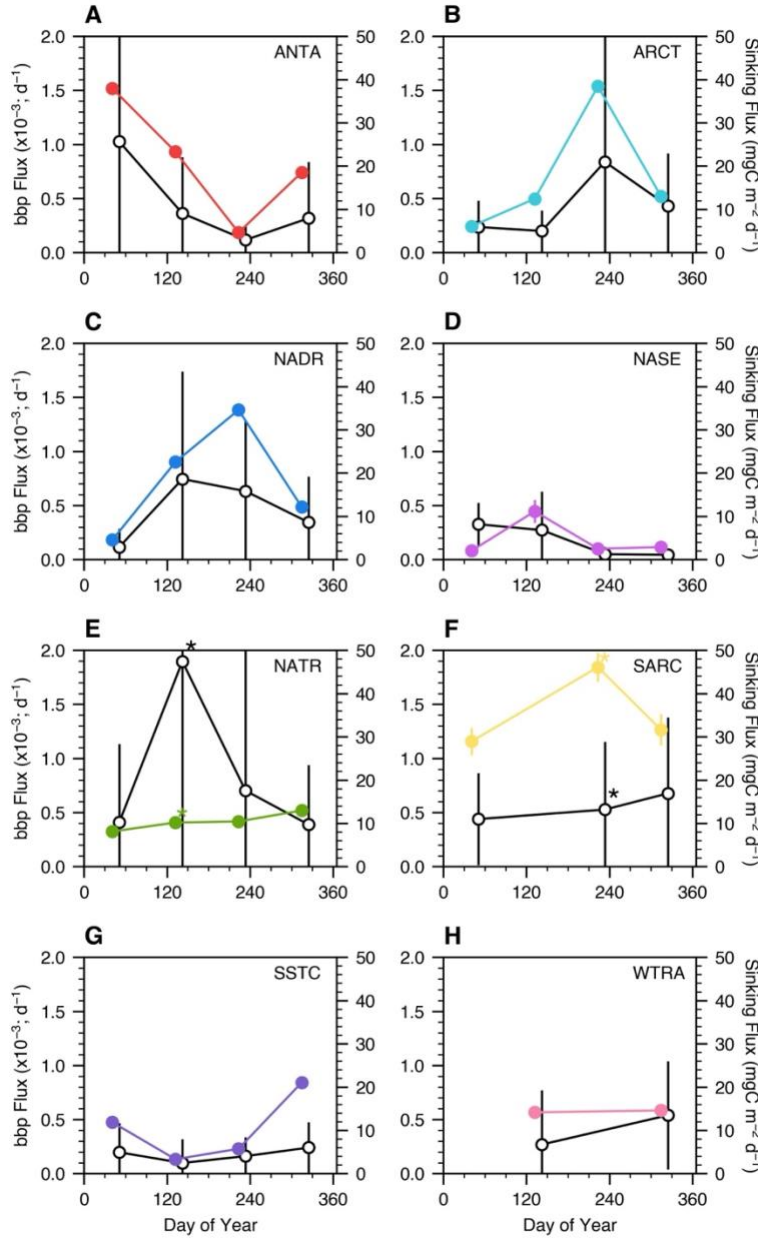


Fig. S6. Seasonality of bbp flux and sinking flux. (A–H) Eight BGC provinces with seasonal averages (and not already shown in Fig. 3). Each point represents the average bbp flux (colored points) or trap-based sinking flux (black outlined points). ANTA, $n_{\text{traps}} = 120$ from 1996 to 1999 and $n_{\text{profiles}} = 1,175$ from 2015 to 2024; ARCT, $n_{\text{traps}} = 68$ from 1987 to 1996 and $n_{\text{profiles}} = 1,908$ from 2013 to 2024; NADR, $n_{\text{traps}} = 74$ from 1989 to 2001 and $n_{\text{profiles}} = 765$ from 2013 to 2024; NASE, $n_{\text{traps}} = 22$ from 1989 to 2001 and $n_{\text{profiles}} = 217$ from 2013 to 2023; NATR, $n_{\text{traps}} = 120$ from 1991 to 1992 and $n_{\text{profiles}} = 473$ from 2012 to 2021; SARC, $n_{\text{traps}} = 32$ from 1986 to 1992 and $n_{\text{profiles}} = 211$ from 2013 to 2024; SSTC, $n_{\text{traps}} = 12$ from 2008 to 2009 and $n_{\text{profiles}} = 1,175$ from 2013 to 2024; WTRA, $n_{\text{traps}} = 3$ from 1992 to 1993 and $n_{\text{profiles}} = 282$ from 2014 to 2024. Colors correspond to those in Fig. 3. The error bars represent the standard error of the trap-based fluxes. Outliers are labeled with an asterisk.

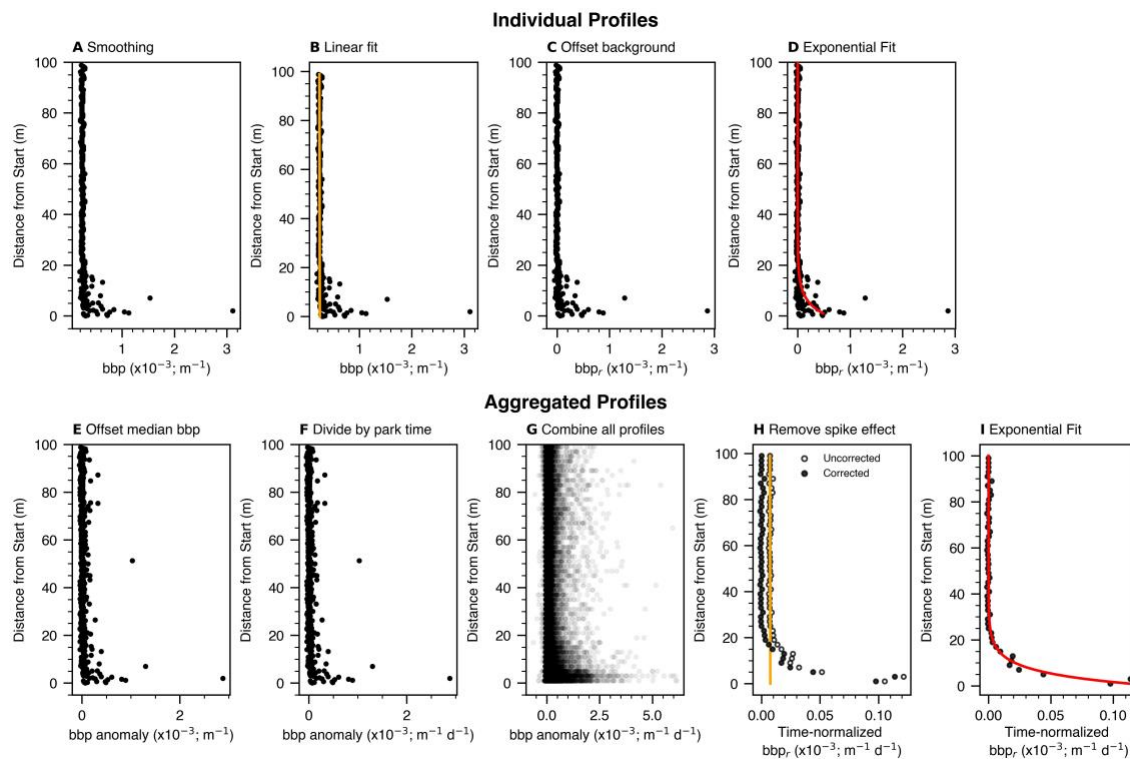


Fig. S7. Steps to remove background bbp. For both individual (A–D) and aggregated profile (E–I) methods to calculate bbp flux, pre-processing involves setting the vertical axis to distance from the start of the profile. The last step shown here involving the exponential fit is followed by integrating the curve. For individual profiles, the integrated value is divided by the time spent parked, while aggregated profiles are already time normalized. For aggregated profiles, bbp anomaly is treated as the intermediary between bbp and bbp_r .

Supporting Tables

Table S1. Various estimates of flux at 1,000 m reported in the literature.

Study	Ref. #	Flux at 1,000 m (TgC yr ⁻¹)
Martin et al. (1987)	(1)	830
Jahnke (1996)	(2)	864
Lutz et al. (2007)	(3)	880 ^a ; 2,200 ^b
Dunne et al. (2007)	(4)	630 (from 60°S to 60°N)
Guidi et al. (2015)	(5)	500 ^c ; 645 ^d
DeVries and Weber (2017)	(6)	1,100 ^e
Doney et al. (2024)	(7)	950 ^f , 650 [250–1,900] ^g

^aWithout accounting for trapping efficiency; ^bWith trapping efficiency correction; ^cbased on calibration underwater vision profilers; ^dFollowing Henson et al. (8) methods; ^eAssuming a 1,000 m transfer efficiency of 0.12; ^fExtrapolation of sediment trap observations; ^gNumerical model mean and range (based on their Fig. 3).

Table S2. Sinking flux of POC in 6°-latitude bands. Topographic data are based on 60s ice-surface Earth TOPOgraphy Relief Model (9). Errors represent the one standard error. High-latitude bands (>78°N or <66°S) contained too few, or no, observations to estimate bbp flux, and were instead estimated by linearly extrapolating the nearest three log-transformed fluxes. At 3 ± 3°N, bbp flux was estimated from the corresponding values in the Southern Hemisphere due to insufficient data.

Latitude ± 3°	Profiles	Area (10 ¹³ ; m ²)	bbp flux (10 ⁻³ ; d ⁻¹)	Sinking Flux (mgC m ⁻² d ⁻¹)	Regional Sinking Flux (TgC yr ⁻¹)
87	-	0.13	0.03 ± 0.01	0.3 ± 0.8	0.2 ± 0.4
81	-	0.2	0.08 ± 0.02	0.8 ± 0.8	0.6 ± 0.6
75	698	0.13	0.17 ± 0.03	1.9 ± 0.8	0.9 ± 0.4
69	404	0.09	0.75 ± 0.07	8.2 ± 1.2	2.8 ± 0.4
63	949	0.11	1.19 ± 0.1	13.0 ± 1.8	5.4 ± 0.7
57	1339	0.33	0.88 ± 0.05	9.7 ± 1.2	11.8 ± 1.5
51	581	0.53	0.98 ± 0.04	10.7 ± 1.3	20.7 ± 2.5
45	1165	0.75	0.81 ± 0.03	8.8 ± 1.1	24.1 ± 3.0
39	2327	1.01	0.86 ± 0.06	9.4 ± 1.3	34.4 ± 4.7
33	1562	1.14	0.47 ± 0.02	5.1 ± 0.9	21.2 ± 3.5
27	460	1.25	0.22 ± 0.02	2.4 ± 0.8	10.7 ± 3.6
21	381	1.47	0.47 ± 0.04	5.1 ± 0.9	27.5 ± 5.1
15	609	1.76	0.25 ± 0.01	2.7 ± 0.8	17.2 ± 4.9
9	648	1.77	0.52 ± 0.03	5.7 ± 0.9	36.8 ± 6.0
3	58	1.92	1.13 ± 0.03	12.4 ± 1.4	87.0 ± 9.6*
-3	90	1.83	1.13 ± 0.03	12.4 ± 1.4	83.0 ± 9.2
-9	750	1.86	0.33 ± 0.01	3.6 ± 0.8	24.6 ± 5.3
-15	488	1.85	0.34 ± 0.02	3.7 ± 0.8	25.1 ± 5.3
-21	888	1.76	0.22 ± 0.02	2.5 ± 0.8	15.8 ± 4.9
-27	154	1.78	0.34 ± 0.02	3.7 ± 0.8	24.2 ± 5.2
-33	317	1.8	0.74 ± 0.04	8.1 ± 1.1	53.4 ± 7.3
-39	1068	1.87	0.41 ± 0.03	4.5 ± 0.8	30.9 ± 5.8
-45	1470	1.74	0.58 ± 0.03	6.4 ± 1.0	40.6 ± 6.1
-51	1995	1.53	1.16 ± 0.02	12.7 ± 1.4	70.5 ± 7.7
-57	693	1.44	1.03 ± 0.03	11.3 ± 1.3	59.3 ± 6.8
-63	311	1.15	0.96 ± 0.07	10.5 ± 1.4	44.2 ± 5.9
-69	-	0.52	0.87 ± 0.12	9.5 ± 1.7	18.0 ± 3.2
-75	-	0.08	0.79 ± 0.22	8.6 ± 2.6	2.5 ± 0.7

Table S3. Sensitivity analysis of calibration and global sinking flux estimate. Global estimates were repeated with different variations of the calibration fit and quality-control parameters. The calibration equation estimates the sinking flux of POC from the optical proxy bbp flux. For each fit, sample size (n), the slope and intercept, the standard error (SE) of the slope and intercept, the weighted coefficient of determination (r^2), the statistical significance of the slope factor (P), and the re-calculated total and standard deviation of the global sinking flux, are shown.

Change Made	n	Slope $\pm$ SE	Intercept $\pm$ SE	r^2	P	Global Sinking Flux (TgC yr ⁻¹)
Original calibration	35	10,954 $\pm$ 1,154	-0.01 $\pm$ 0.25	0.83	*	790 $\pm$ 160
Original calibration (with outliers)	37	10,673 $\pm$ 1,102	0.03 $\pm$ 0.24	0.55	*	780 $\pm$ 160
Only Polar provinces (no outliers)	10	8,608 $\pm$ 1,831	1.42 $\pm$ 0.94	0.9	*	790 $\pm$ 170
Only Westerlies provinces (no outliers)	20	9,311 $\pm$ 1,516	0.11 $\pm$ 0.25	0.83	*	690 $\pm$ 160
Only Trades provinces (no outliers)	5	39,938 $\pm$ 47,123	-12.09 $\pm$ 26.12	0.18	n.s.	1,500 $\pm$ 530
Exclude ANTA (no outliers)	31	10,913 $\pm$ 1,242	-0.02 $\pm$ 0.27	0.80	*	790 $\pm$ 170
Exclude ARCT (no outliers)	31	10,923 $\pm$ 1,261	-0.02 $\pm$ 0.26	0.82	*	790 $\pm$ 170
Exclude MEDI (no outliers)	31	10,793 $\pm$ 1,228	0.00 $\pm$ 0.26	0.82	*	780 $\pm$ 170
Exclude NADR (no outliers)	31	10,807 $\pm$ 1,261	0.00 $\pm$ 0.26	0.82	*	780 $\pm$ 170
Exclude NASE (no outliers)	31	7,951 $\pm$ 1,442	1.98 $\pm$ 0.27	0.68	*	810 $\pm$ 160
Exclude NATR (no outliers)	32	10,902 $\pm$ 1,197	-0.01 $\pm$ 0.79	0.88	*	790 $\pm$ 170
Exclude SANT (no outliers)	31	11,209 $\pm$ 1,295	-0.04 $\pm$ 0.26	0.84	*	810 $\pm$ 170
Exclude SARC (no outliers)	33	10,145 $\pm$ 1,309	-0.03 $\pm$ 0.27	0.82	*	810 $\pm$ 170
Exclude SSTC (no outliers)	31	12,267 $\pm$ 1,296	-0.16 $\pm$ 0.27	0.84	*	870 $\pm$ 180
Exclude WTRA (no outliers)	33	10,036 $\pm$ 1,024	0.07 $\pm$ 0.28	0.84	*	740 $\pm$ 150
Parking times: 1 to 6 d	35	10,585 $\pm$ 973	0.21 $\pm$ 0.84	0.84	*	820 $\pm$ 170
Parking times: 1 to 6 d (with outliers)	37	10,343 $\pm$ 934	0.03 $\pm$ 0.20	0.56	*	800 $\pm$ 160
Parking/trap depth: 950 to 1,050 m	33	7,364 $\pm$ 1,352	2.26 $\pm$ 0.75	0.54	*	800 $\pm$ 160
Parking/trap depth: 950 to 1,050 m (with outliers)	35	7,082 $\pm$ 1,256	2.37 $\pm$ 0.71	0.21	*	790 $\pm$ 160

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