Supporting Information for "Open ocean particle flux variability from surface to seafloor"

B. B. Cael[1], Kelsey Bisson[2], Maureen Conte[3,4], Manon T. Duret[5], Christopher L. Follett[6], Stephanie A. Henson[1], Makio C. Honda[7], Morten H. Iversen[8,9], David M. Karl[10], Richard S. Lampitt[1], Colleen B. Mouw[11], Frank Muller-Karger[12], Corinne A. Pebody[1], Kenneth L. Smith Jr.[13], David Talmy[14]

[1]National Oceanography Centre, Southampton, UK

[2]Oregon State University, Corvallis, OR, USA

[3]Bermuda Institute of Ocean Sciences, St Georges, Bermuda

[4]Marine Biological Laboratory, Woods Hole, MA, USA

[5]University of Southampton, UK

[6]Massachusetts Institute of Technology, Cambridge, MA, USA

[7]Japan Agency for Marine-Earth Science and Technology, Yokosuka, Kanagawa, Japan

[8]Alfred Wegener Institute, Bremerhaven, Germany

[9]MARUM and University of Bremen, Bremen, Germany

[10]Unversity of Hawai'i at Manoa, HI, USA

[11]University of Rhode Island, Narragansett, RI, United States

[12]University of South Florida, St. Petersburg, FL, USA

[13]Monterey Bay Aquarium Research Institute, Moss Landing, CA, USA

[14]University of Tennessee-Knoxville, TN, USA

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Enumerated Supplemental Text:

1. Note also that NPP is typically measured on a timescale of a day, shallow particle fluxes are typically measured on timescales of a few days, and deep particle fluxes are typically measured on timescales of a week or weeks, which complicates their pointwise comparison; we will return to this point later.

2. n.b. throughout the text we mean distribution in the probability sense, not the spatial/temporal sense, unless explicitly specified otherwise.

3. i.e. if the density of these minerals increases sinking speed within aggregates, or if ballast minerals are all that remain after labile POC flux is remineralized.

4. Though differences between the variability of different observation types are also affected by these observations' measurement temporal and spatial scales.

5. Note that this is a heuristic argument that ignores many of the subtleties and complexities of particle fluxes (see §Discussion) and that we discuss the link between seafloor flux and NPP (see §Dampening).

6. Note that these global data are distinct from the time-series data analyzed separately, and that herein we only analyze the near-seafloor (i.e. within 1km of reported

bottom depth) bathypelagic (i.e. greater than 1km sampling depth) data within the Mouw, Barnett, McKinley, Gloege, and Pilcher (2016) compilation.

7. This 30% benchmark uncertainty was developed for upper-ocean drifting traps and is not necessarily applicable to deep traps. However, it appears to apply equally well to the deep trap data here; the median uncertainty for the bathypelagic near-seafloor POC fluxes from the Mouw et al. (2016) database used here is 36%, while the median uncertainty for all the POC fluxes in the Mouw et al. (2016) database is 29%. Note that the conspicuous deviations in the lower tail of F_{IC} can be explained by a constant offset; the percentiles of a log-normal with the same parameters (1.26,0.97) plotted versus those of the same distribution with 0.2 subtracted results in a similar deviation in the lowest 5 percentiles (Figure S1). This deviation therefore could possibly be the result of e.g. a small underestimation by $\mathcal{F}_{IC}$ measurements, and would also be exacerbated by any additive measurement errors – though may instead be indicative of a concentration-independent calcium carbonate dissolution mechanism, or even dissolution within sediment traps. This is similarly the case for the low tails of the time-series' distributions. The deviations in the upper tails are small in relative terms but appreciable in absolute terms; these are however the result of using a fitting statistic that emphasizes the median of the distribution; if instead we use a fitting statistic that emphasizes the tails we see excellent agreement (e.g. Figure S2 shows the same as the bottom-left panel of Figure 1 but using the Anderson-Darling statistic, in which case the highest and lowest percentiles are matched within a few percent.)

8. We note that we apply a constant depth attenuation factor (b) to $\mathcal{F}_{OC}$ but not $\mathcal{F}_{IC}$ or $\mathcal{F}_{Si}$. For simplicity and for consistency with the original formulation of the ballast hypothesis (Armstrong et al., 2001), we assume mineral fluxes are constant with depth below 1km depth, i.e. neglect dissolution of calcium carbonate or opal. This power-law depth correction has an established empirical basis and may be rationalized as the result of increasing sinking speeds and/or decreasing organic carbon remineralization rates with depth (Cael & Bisson, 2018). A 3500m depth was chosen because the median depth of the 2,798 measurements considered was 3530m. This choice of a normalization depth is arbitrary and has no impact on our results as the 3500^b term can be incorporated into the κ parameter. Note that the power-law renormalization appears be effective for this dataset as we do not see any statistically significant differences in the parameter values when regressing data from $z < 2$km, 2-3km, 3-4km, or >4km compared to the total dataset.

9. Note this includes variance accounted for of both the x and y variables, unlike a standard r^2 which only includes the latter. There is some remaining behavior in the residuals not captured by this model; it can be seen in Figure 3 that when $\mathcal{F}_{IC} + \beta\mathcal{F}_{Si}$ is small, depth-normalized $\mathcal{F}_{OC}$ tends to sit above the regression line. This may be because significant calcium carbonate dissolution has occurred in these cases, so this mineral's organic carbon associated per unit mass is underestimated. The model we present here does not consider lysocline depth and the impact of calcium carbonate dissolution below this depth, the incorporation of which might explain some of the remaining variability in depth-normalized $\mathcal{F}_{OC}$.

10. Compared to global sediment trap-based estimates (e.g. $b = 0.84 \pm 0.14$ from Gloege, McKinley, Mouw, and Ciochetto (2017)), though as most other b-value estimates consider much shallower measurements they are not directly comparable with this value.

11. We unfortunately are not aware of sufficient NPP measurements at or near K2 to characterize σ_{NPP} there. Note also that the CARIACO σ values in Figure 4 differ slightly from those in Figure 8 of Cael, Bisson, and Follett (2018) because of the inclusion of new data for that time-series here.

12. This method and its relationship with NPP is discussed comprehensively elsewhere (Marra, 2009; Peterson, 1980; Pei & Laws, 2013); the principal issues discussed in the literature are the interpretation of metabolic terms and the accuracy with which *in vitro* measurements reflect *in situ* conditions.

13. The joint ratio is only one of many potential metrics by which episodicity can be quantified (others include the Gini index or the flux stability index (Lampitt & Antia, 1997)) but is preferred because of its comparative insensitivity to noise in the extreme values and its broad use in many contexts.

14. Figure S5 shows some representative log-normal distributions with σ values yielding 80/20, 71/29, and 60/40 joint ratios for reference.

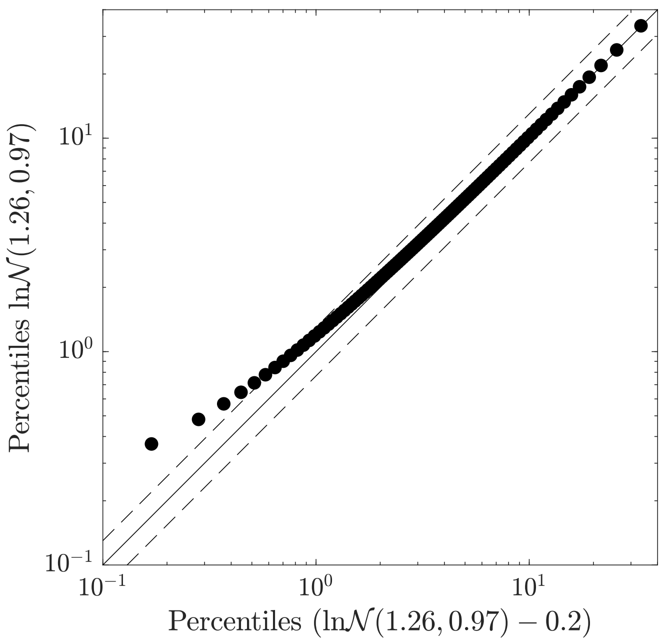

Figure S1. Percentiles of a(n arbitrary) log-normally distributed random variable with $\mu = 1.26$ and $\sigma = 0.97$, versus percentiles of the same distribution with 0.2 subtracted (note this particular value of 0.2 is an ad hoc choice). Dashed lines indicate 30% deviations from the 1:1 (solid) line.

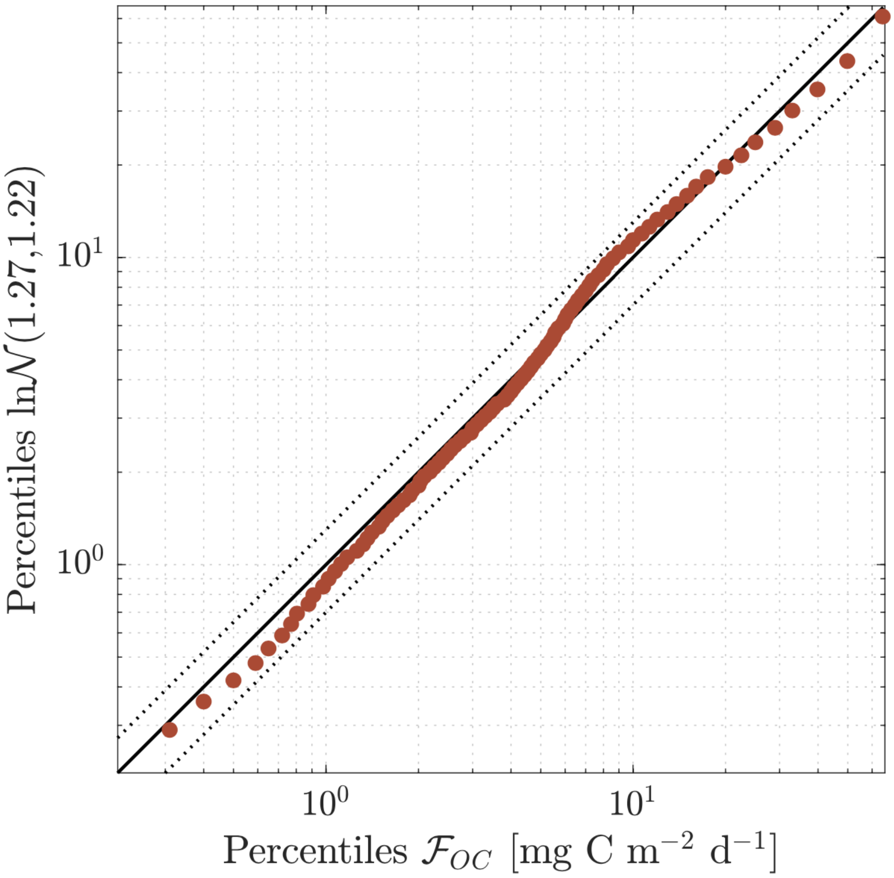

Figure S2. Same as the bottom left panel of Figure 1 but using the Anderson-Darling statistic, which emphasizes distributions' tails relative to the median-emphasizing Kolmogorov-Smirnov statistic, to estimate (μ, σ).

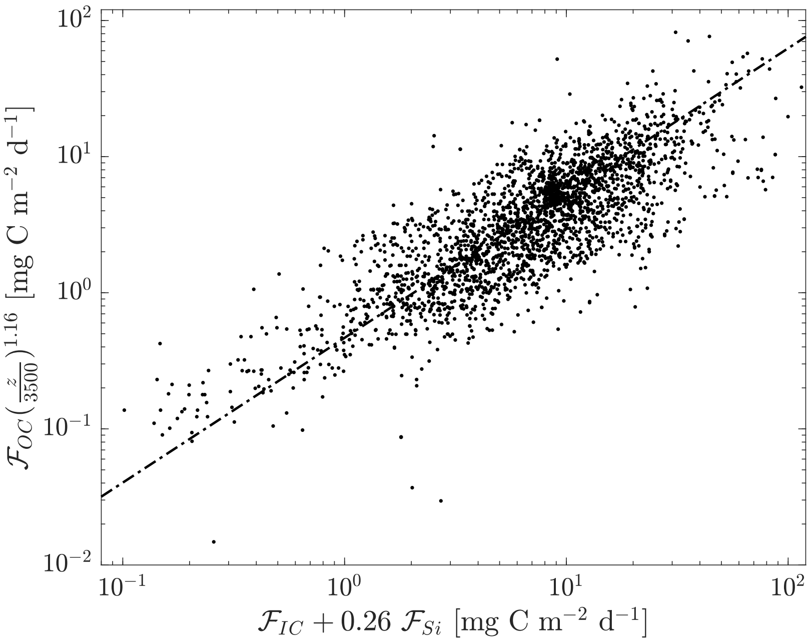

Figure S3. Same as Figure 3 but with smaller scatterpoints to show density of data.

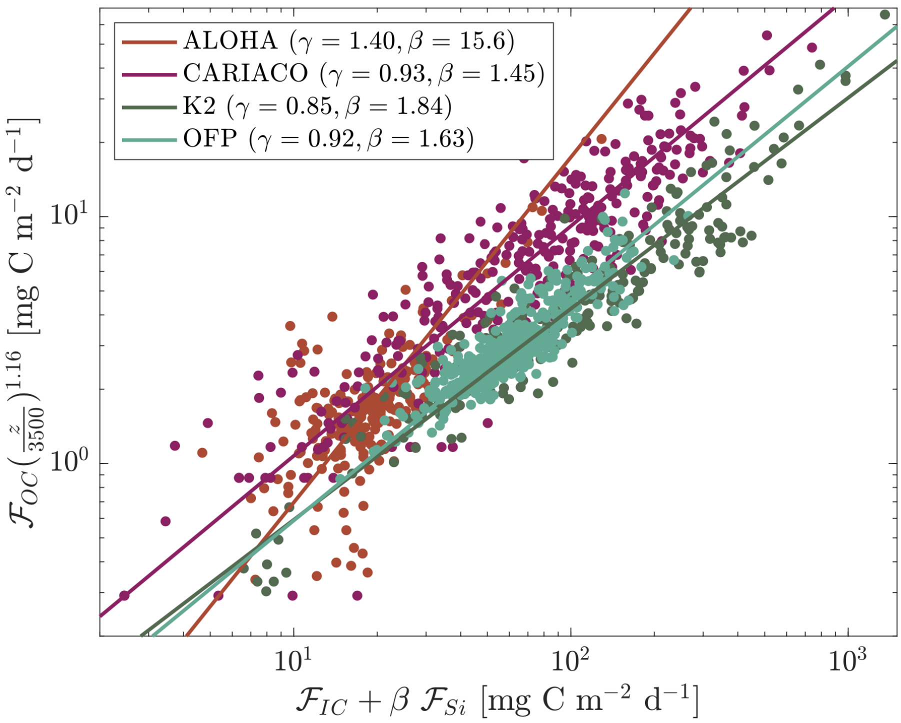

Figure S4. Same as Figure 3 but for the time-series ALOHA, CARIACO, K2, and OFP.

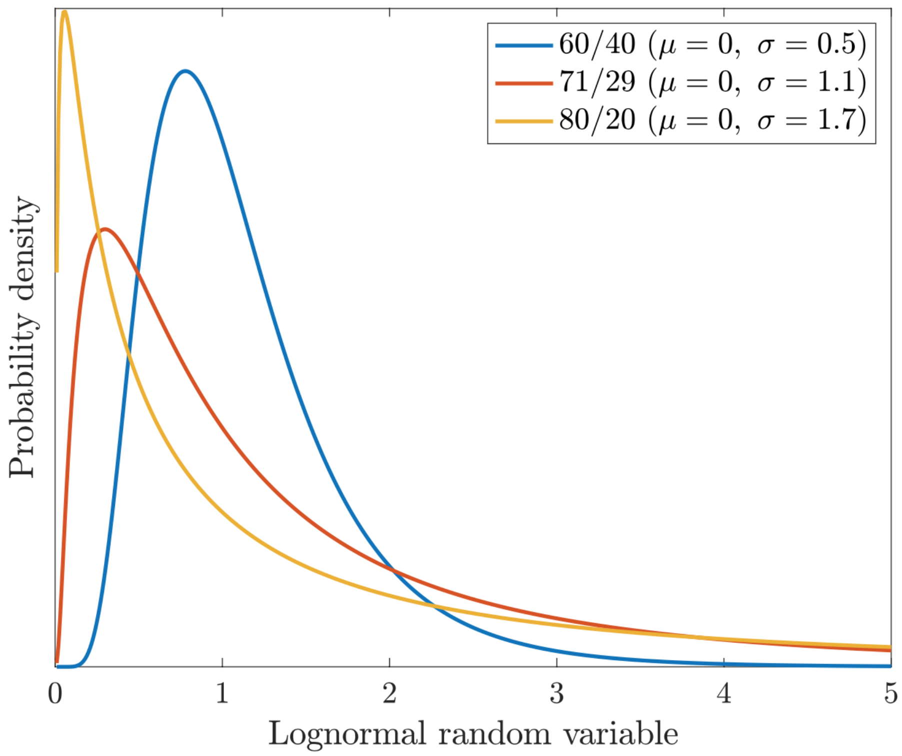

Figure S5. Log-normal probability density functions with different σ values and $\mu = 0$, corresponding to different joint ratios (see legend). μ is irrelevant for the joint ratio. The 50/50 case would be a delta function, which would be visualized as a vertical line at e.g. $x = 1$.

References

Armstrong, R. A., Lee, C., Hedges, J. I., Honjo, S., & Wakeham, S. G. (2001). A new, mechanistic model for organic carbon fluxes in the ocean based on the quantitative association of POC with ballast minerals. *Deep Sea Research Part II: Topical Studies in Oceanography*, *49*(1-3), 219–236.

Cael, B., & Bisson, K. (2018). Particle flux parameterizations: Quantitative and mechanistic similarities and differences. *Frontiers in Marine Science*, *5*, 395.

Cael, B., Bisson, K., & Follett, C. L. (2018). Can rates of ocean primary production and biological carbon export be related through their probability distributions? *Global biogeochemical cycles*, *32*(6), 954–970.

Gloege, L., McKinley, G. A., Mouw, C. B., & Ciochetto, A. B. (2017). Global evaluation of particulate organic carbon flux parameterizations and implications for atmospheric pCO2. *Global Biogeochemical Cycles*, *31*(7), 1192–1215.

Lampitt, R., & Antia, A. (1997). Particle flux in deep seas: regional characteristics and temporal variability. *Deep Sea Research Part I: Oceanographic Research Papers*, *44*(8), 1377–1403.

Marra, J. (2009). Net and gross productivity: weighing in with 14C. *Aquatic Microbial Ecology*, *56*(2-3), 123–131.

Mouw, C. B., Barnett, A., McKinley, G. A., Gloege, L., & Pilcher, D. (2016). Global ocean particulate organic carbon flux merged with satellite parameters. *Earth System Science Data*, *8*, 531–541.

Pei, S., & Laws, E. A. (2013). Does the 14C method estimate net photosynthesis? Implications from batch and continuous culture studies of marine phytoplankton. *Deep Sea Research Part I: Oceanographic Research Papers*, *82*, 1–9.

Peterson, B. J. (1980). Aquatic primary productivity and the 14C-CO2 method: a history of the productivity problem. *Annual Review of Ecology and Systematics*, *11*(1), 359–385.