* Evaluating the evidence for environmental drivers of marine organic carbon flux via hierarchical Bayesian analysis
* Evaluating the evidence for environmental drivers of marine organic carbon flux
* XX best explains marine organic carbon flux observations

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**Abstract**

The balance of carbon between the ocean and atmosphere is sensitive to the shape of the ocean’s organic carbon flux profile, yet direct observations have poorly constrained fluxes due to large regional and temporal variability. Here we model a global compilation of organic carbon flux observations via hierarchical Bayesian methods to evaluate the empirical evidence for environmental drivers of flux profile parameters. We test… We find ….

**Introduction**

The sinking flux and subsequent remineralization of organic carbon at depth maintains a depth gradient in dissolved inorganic carbon that acts to sequester carbon from the atmosphere [*Kwon et al.*, 2009].

The sinking flux is a net effect of many interacting processes. Important factors thought to control organic matter flux include: net primary productivity, temperature, oxygen, viscosity, among others. Details …

**Methods**

We utilize a recently published global compilation of organic matter flux observations via *in-situ* sediment traps [*Mouw et al.*, 2016].

We model the vertical flux profile of organic matter via the Martin curve [*Martin et al.*, 1987]

The model is linearized by taking the log

We also test functional forms for the depth dependence of carbon flux.

We model the parameters and observations hierarchically via the following Bayesian hierarchical model

where superscript indicates an individual observed flux profile at a particular location and at a particular time, matrix is the regression ‘design matrix’ which contains the environmental data for the regression as columns and a vector of ones for the intercept. Probabilistically, and are distributed Normally, with mean given by the regression and error variance and , respectively.

The models are fit in the probabilistic programming language Stan [*Carpenter et al.*, 2016] which performs highly efficient Markov Chain Monte Carlo (MCMC) to infer the posterior of the unknown model parameters, given the data and prior distributions on the parameters.

Table: Summary of environmental variables tested in this study

|  |  |
| --- | --- |
| **Variable** | **Hypothesis** |
| Net primary productivity | **: high rates of organic matter production in the euphotic zone will drive a larger flux at the base of euphotic zone**  : Higher productivity may indicate larger diatom-like cells that may sink more quickly |
| Sea surface temperature | : As a proxy for temperature in the euphotic zone  : |
| Surface nutrient concentration | : Export is related to surface nutrient  : |
| Mineral ballast | :  : |
| Phytoplankton cell size | :  : |
| Subsurface temperature | : No direct interaction  : Higher subsurface temperature increases viscosity leads to deeper remineralization. |
| Subsurface oxygen concentration | :  : |

*Bayesian model selection*

We compare the fits of the models via a Bayesian hypothesis testing framework.

**Results**

**Discussion**

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**References**

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**Figures**

Figure: Trap data distribution

Figure: Environmental data distribution

Figure/Table: Model selection results

Figure: Analysis of best fitting relationships