Estimating the air-sea gas transfer velocity from a statistical reconstruction of ocean turbulence observations

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The air-sea gas exchange of climate-critical gases (e.g. CO2) is a fundamental component of our climate and of the biogeochemical systems within the oceans

• Lack of representation of the importance of processes controlling the efficiency of the air-sea gas transfer

• The air-sea gas transfer velocity (*k*) is typically parametrized as a function of wind only (e.g. Wanninkhof, 2014)

 Measurements of k are sparse and difficult (experimental uncertainty, variability in forcing, other parameters influence air-sea gas transfer)





k can also be parametrized as a function of the dissipation rate of ocean turbulent kinetic energy (TKE) at the surface from profilers

$$k_{660} = A \ 660^{-n} \ (\varepsilon_0 \ \nu)^{1/4}$$

where

- *A* is a proportionality constant that can be derived theoretically (Lamont and Scott, 1970) or measured experimentally (Esters et al., 2017)
- ν is the kinematic viscosity of water and can be derived from surface temperature and salinity (EN4)
- n varies between 1/2 for a wavy, surfactant-free water surface and 2/3 for a flat surface





Can we develop an empirical model for ε to estimate k? And what for?

- 1. Colocate ε profiles with atmospheric and ocean surface hourly fields (wind, evaporation, waves, sensible heat transfer) from ERA5
- 2. Develop a data-driven (aka empirical) model of ε as a function on depth and surface fluxes from ERA5
- 3. Using the developed model to estimate ε at the surface and compute a climatology for *k* via its TKE parametrization

Improving estimates of air-sea gas exchange (CO2, O2, DMS, CH4, N2O) and diapycnal fluxes



TKE data (and challenges)

• TKE profiles were obtained from microstructure.ucsd.edu and PANGEA (Fischer et al., 2013) data





TKE data (and challenges)



 $Var(\varepsilon)$ per depth bin and cruise



TKE data (and challenges)

• Sparse spatial sampling which does not cover all possible conditions of surface fluxes

• Upper 15 m are less well sampled and have larger unstructured noise (e.g. ship-induced turbulence)

 Sampling is very unbalanced between different cruises and therefore different conditions of surface fluxes





Empirical model

To model ϵ as a function of depth and surface fluxed we adopted a depth-varying Gaussian Process (GP) model

$$\varepsilon(z)^{1/4} \sim f(z) + \sum_j f_j(z) X_j$$

where $f, f_j \mapsto \text{zero mean GPs}$

 $X_j \mapsto \text{first 4 PC scores from ERA5 hourly data (} \sim 80\% \text{ of explained variance})$

- Inference in done in the Bayesian framework using the Integrated Nested Laplace Approximation (INLA) and the Stochastic Partial Differential Equation Approach (SPDE)
- ✓ Final predictions are obtained using Bayesian Model Averaging to account for sampling uncertainties
- ✓ The model is validated using a 5 fold cross-validation scheme based on the sampling week with random downsampling of selected cruises (many observations, fixed location)
- ✓ Model benchmark: Extreme Gradient Boosting (XGB)



Model Selection

- The GP model has superior cross validation performances based on all selections of cross-validation folds (e.g the label Atlantic-RoW implies training the model on data in the Atlantic and testing the model on data in the remaining ocean basins)
- Extending the model to account for any monthly or spatial residual autocorrelation does not improve the model performance
- Large unstructured noise and poor spatial sampling lead to a low explained variance







Posterior estimates







Given the posterior estimates for *k*, the dependence on specific drivers in different regions can be investigated and compared to existing parametrizations



Takeaways

- The model is able to recover the expected physical dependencies
- Compared to existing parametrizations of *k*, the wind dependence is weaker and other drivers emerge
- Large uncertainties due to large unstructured noise in the data and poor spatial sampling

Next steps

- Build an empirical model of the mixed layer depth using model outputs from NEMO to better understand the impact of sampling on the results
- Get more data! If you are aware of existing data sources that were not considered in this study, **please get in touch**!



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