Improving oceanic mesoscale eddy parameterization using high-resolution simulations and Machine Learning

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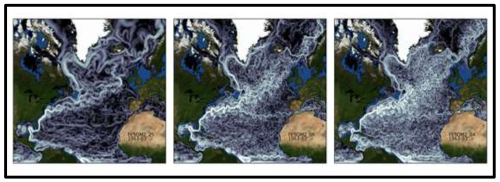
Problem

- Earth system models cannot resolve subscale structures

→ We need **parameterizations**!

- Example: **mesoscale eddies** advect tracers and affect mean circulation



FESOM2 velocity field at 100 m depth for 25, 8 and 5 km resolution. [fesom.de]

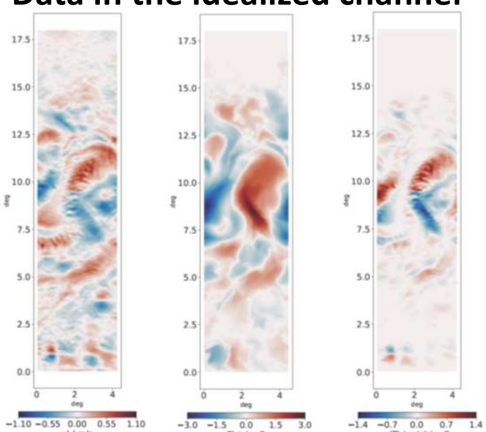
Mission

- Improve the **Gent-McWilliams** (GM) mesoscale eddy parameterization in the **FESOM2 ocean model**

How?

- Coarse-grained high-resolution ocean model data as input for a **neural network**
- Network estimates coefficient in the GM parameterization
- Test procedure in **idealized channel**, later move on to more complex setups

Data in the idealized channel



I calculate **flow diagnostics** in an **idealized rectangular channel** to **improve mesoscale eddy parameterization**

Abstract

This presentation participates in OSPP

Outstanding Student & PhD candidate Presentation contest

Sharing is encouraged

Mesoscale eddy parameterization with Gent-McWilliams

- GM parameterization adds a term to the momentum equation – the eddy-induced velocity $\vec{v}^* = (\vec{u}^*, w^*)$ which depends on the **horizontal and vertical density gradient** (isoneutral density)
- This eddy-induced velocity is expressed as a streamfunction $\vec{\psi}$:

$$\vec{v}^* = \nabla_3 \times \vec{\psi}$$

- $\vec{\psi}$ is parameterized using $\vec{\psi} = \kappa_{GM}\, \vec{S}$, where κ_{GM} is the **GM coefficient** to be optimized and $\vec{S}$ the **slope vector** of the isopycnals:

$$\vec{S} = -\frac{\nabla_h \sigma}{\nabla_z \sigma}$$

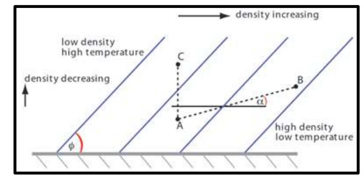
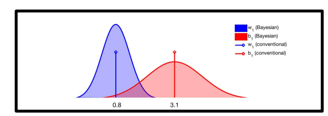


Illustration of baroclinic instability – isopycnal gradient. [Vallis 2019]

Data processing

1. Calculate **GM coefficient κ_{GM} from high-res** data (from velocities and fluxes)
2. **Coarse-grain** the high-res data
3. **Train a Bayesian neural network** with coarse-grained data
4. Have **neural network estimate κ_{GM} from low-res data** and compare to coarse-grained high-res reference to evaluate performance



Parameter estimation with a Bayesian vs. a conventional network. [Medium.com]

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