Deep Learning of Subgrid Fluxes in Ocean Models

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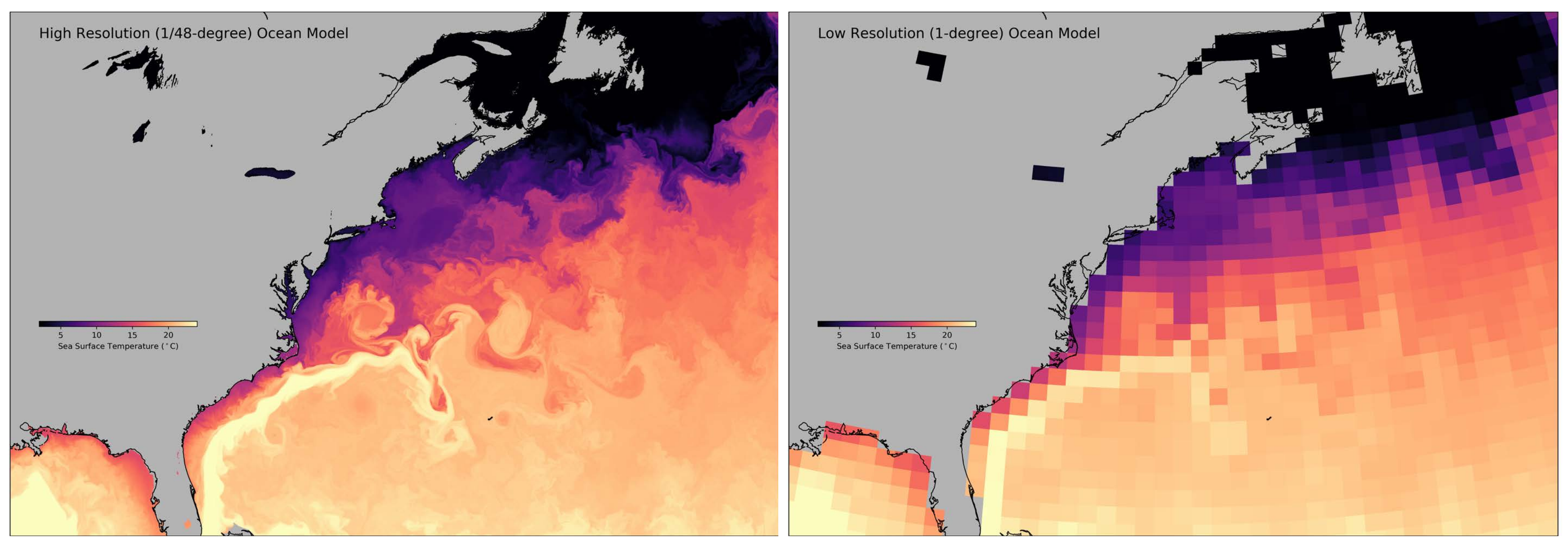
Physical Problem

Parameterization in mesoscale turbulence

The goal of turbulence parameterization is to evaluate the tendencies of physical variables including velocity, temperature, salinity et. al. due to the unresolved turbulent motions. The eddy transportation by mesoscale turbulence (e.g. heat, salt, dissolved chemicals etc.) is significant in climate model. However, the scales of eddy transportation is about 10~200 km which are barely resolved by global climate model. To predict the tendencies of eddy transportation correctly, the parameterization will be presented in subgrid scheme.



Zonal averaged tracer equation:

$$\frac{\partial \bar{c}}{\partial t} + \bar{\vec{u}} \cdot \nabla \bar{c} = \kappa \nabla^2 \bar{c} + \bar{\mathcal{F}}_c - \nabla \cdot \overline{\vec{u}' c'}$$

Unknown!

The mesoscale flux of a tracer c is parameterized through two distinct components:

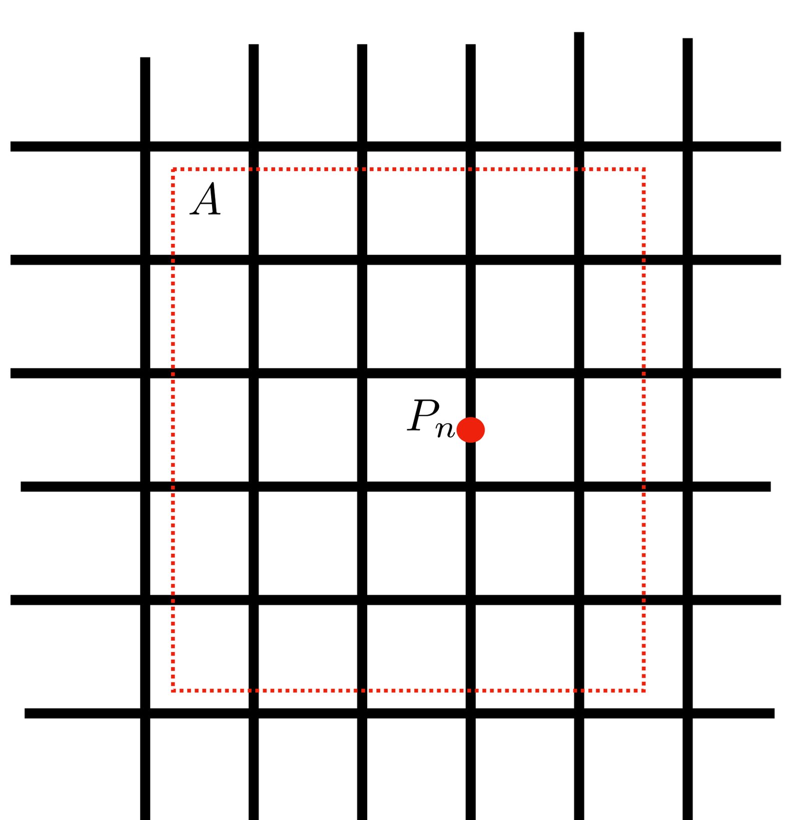
$$\overline{\vec{u}' c'} = \boldsymbol{F_c} = \vec{\vec{\mathcal{K}}} \nabla \bar{c} = \vec{\vec{\mathcal{K}}}_s \nabla \bar{c} + \vec{\vec{\mathcal{K}}}_a \nabla \bar{c}$$

Symmetric part indicates the irreversible diffusion of tracers by mesoscale eddy stirring. The angle of this diffusion is very close to the isopycnal slope due to energetic constraints. So the tracer with no isopycnal gradient (e.g. buoyancy) will not influenced by this diffusion. However the isopycnal mixing plays an important role in the transportation of the biogeochemical in the ocean and ventilation of the ocean.

Asymmetric part indicates the advective part of the mesoscale eddy flux related to the "skew flux" and "bolus velocity". The importance to the climate models has been shown in previous research.

Deep learning method in parameterization

It is noticeable that the parameterization is only influenced by local grid point P_n. With deep learning method, we try to evaluate the influence of the neighbor points to the parameterization of eddy transportation.

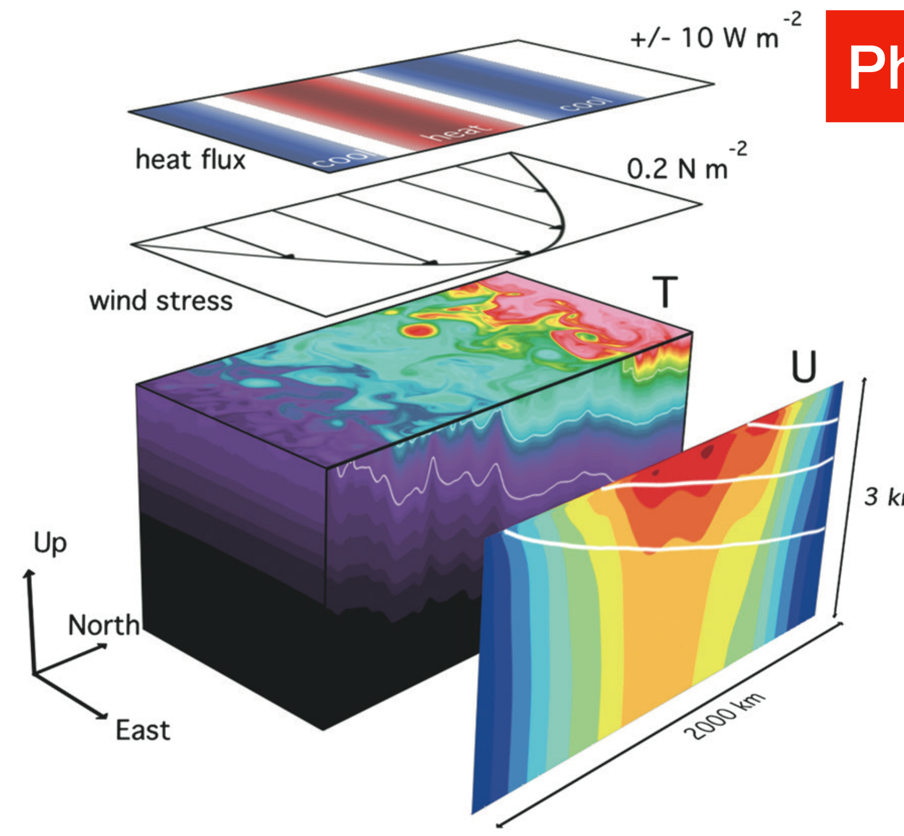


$$F_c|_{P_n} = \overline{\vec{u}' c'} = \frac{1}{A} \iint_A \mathcal{G}(x, y)$$

Evaluated by deep learning

Data Preparation

Before we use the deep learning method in the global climate model, we will test and evaluate the idea on a high resolution, idealized process model which is to quantantively reproduce the Southern Ocean overturning circulation. We run the 5km horizontal resolution which can resolve the eddy transportation to generate the data for our deep learning method. The data from 100km horizontal resolution case is used as the baseline.

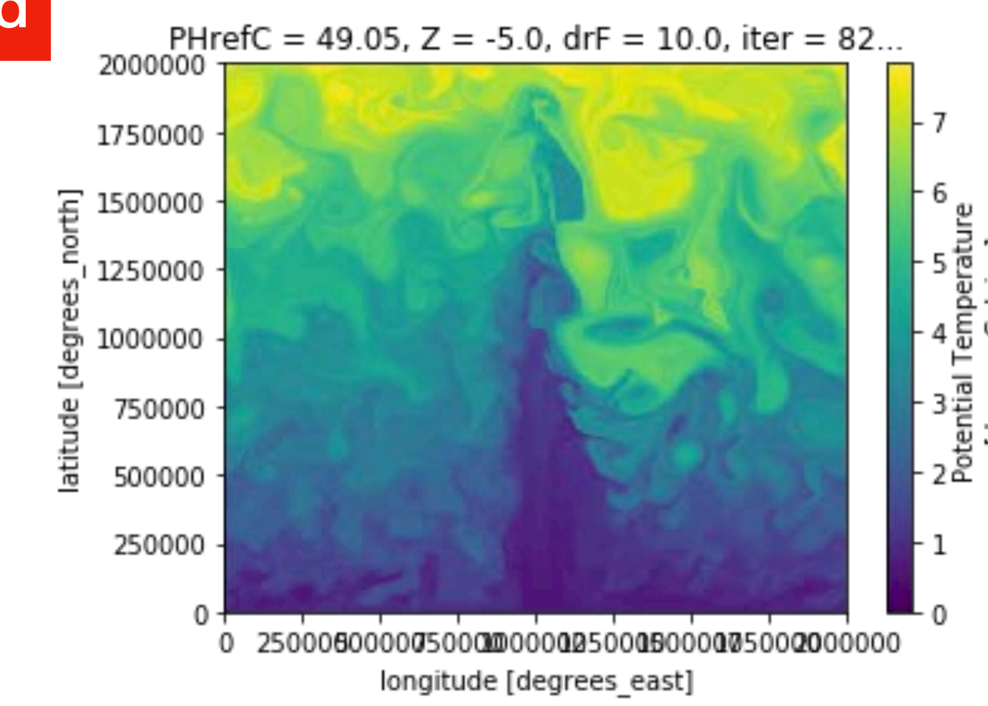


Physical Based Method

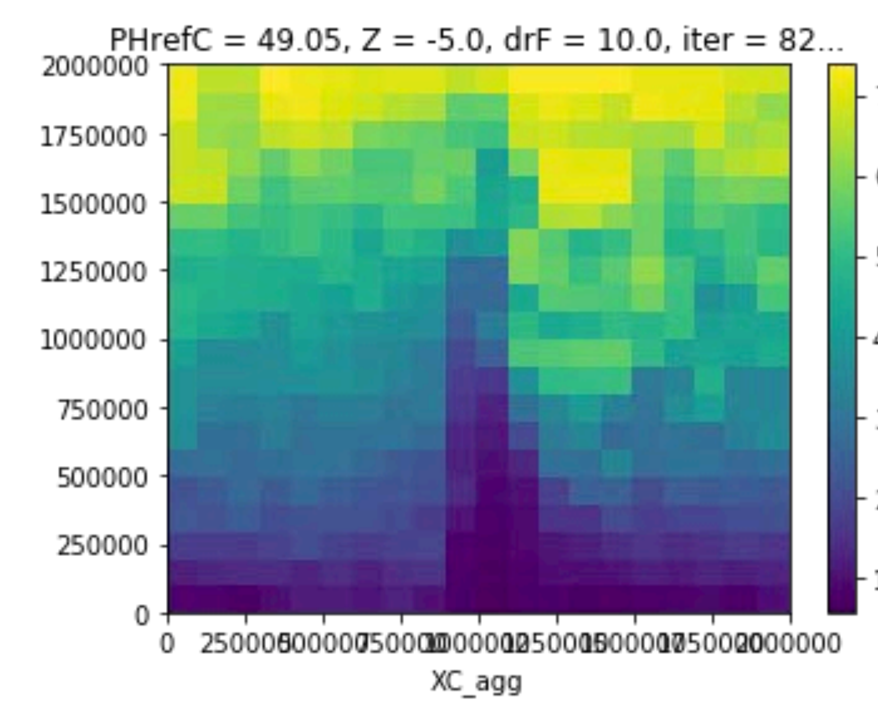
- MITgcm Primitive equation z-direction.
- 5km horizontal resolution.
- 40 vertical levels
- Linear temperature-only equation of state.

Training Data

For the supervised machine learning method, one of the most important things is to find the correct supervisory data. In our problem, we build a coarse-grained model to convert the data from high resolution grid to low-resolution grid.



Coarse-grained model to convert the data from high resolution grid to low-resolution grid.

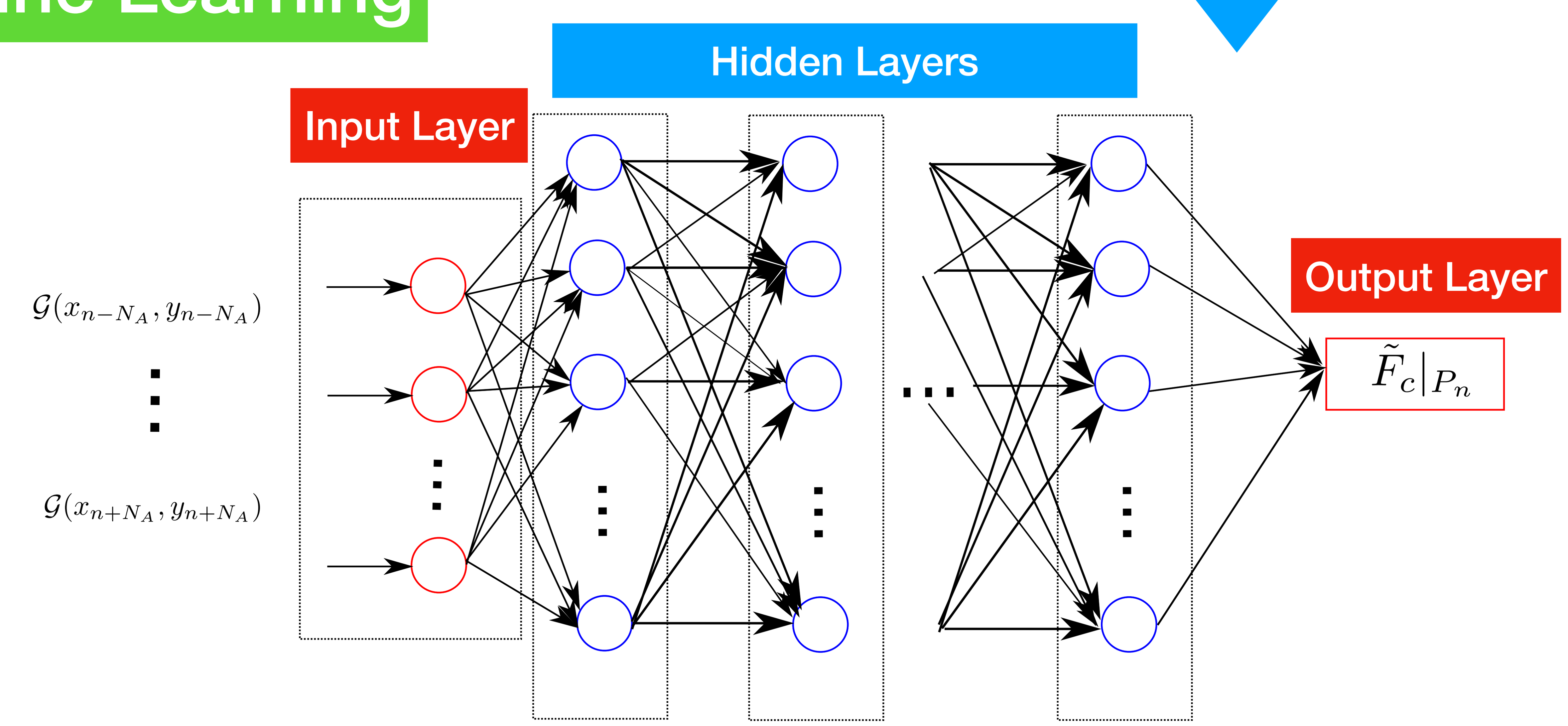


Data-Driven method

Data for machine learning

Offline Mitgcm to extract the eddy flux of tracers only from data.

Machine Learning



A is the area around P_n . With deep learning method, we will take larger and larger area into consideration until the accuracy doesn't increase anymore. With this cutoff A, we can define a "Correlation Area" for eddy flux and improve the accuracy of the parameterization of eddy flux in mesoscale turbulence.