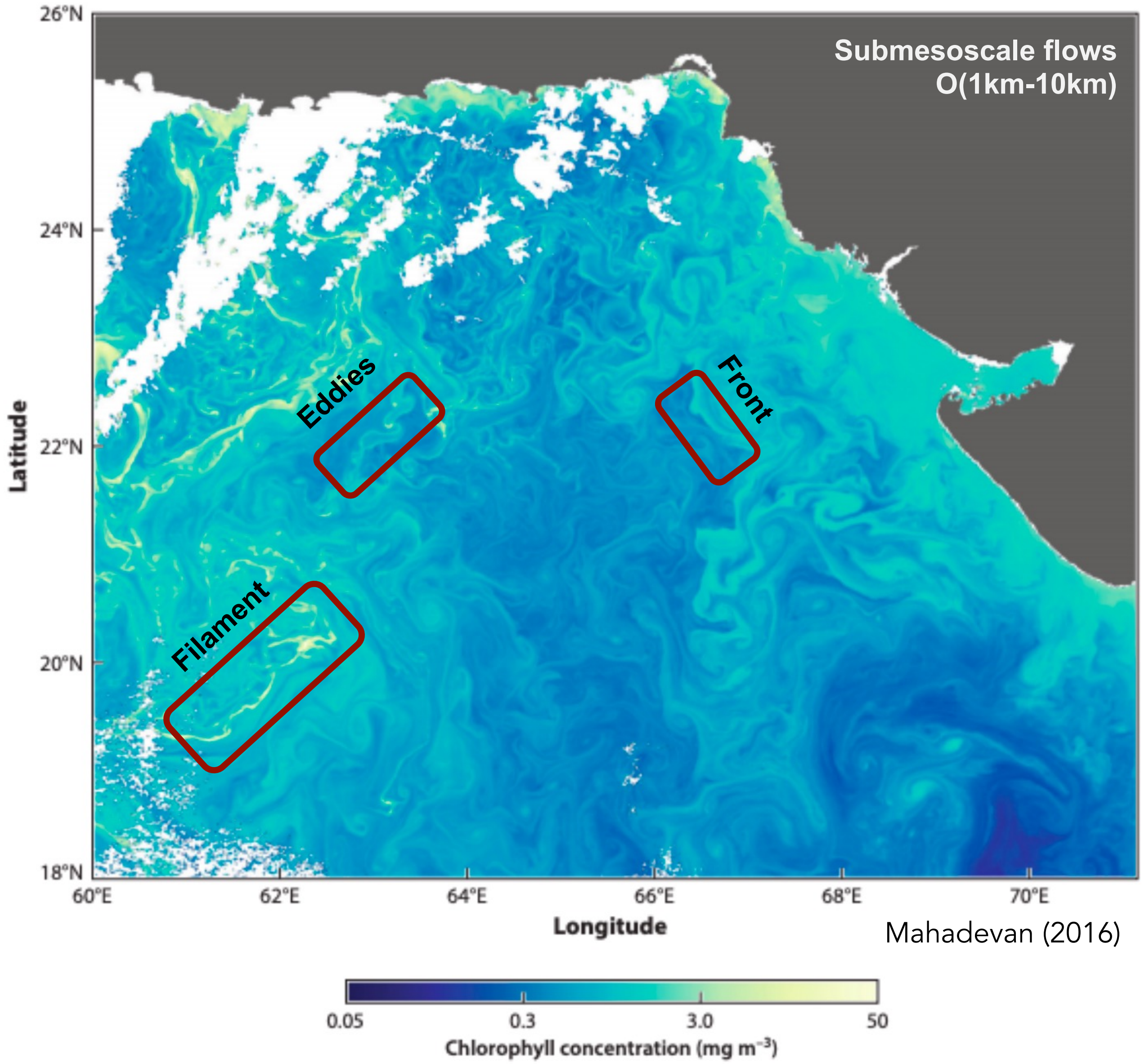
A Data-Driven Approach for the Submesoscale Parameterization

Abigail Bodner
Dhruv Balwada
Laure Zanna



Mahadevan (2016)

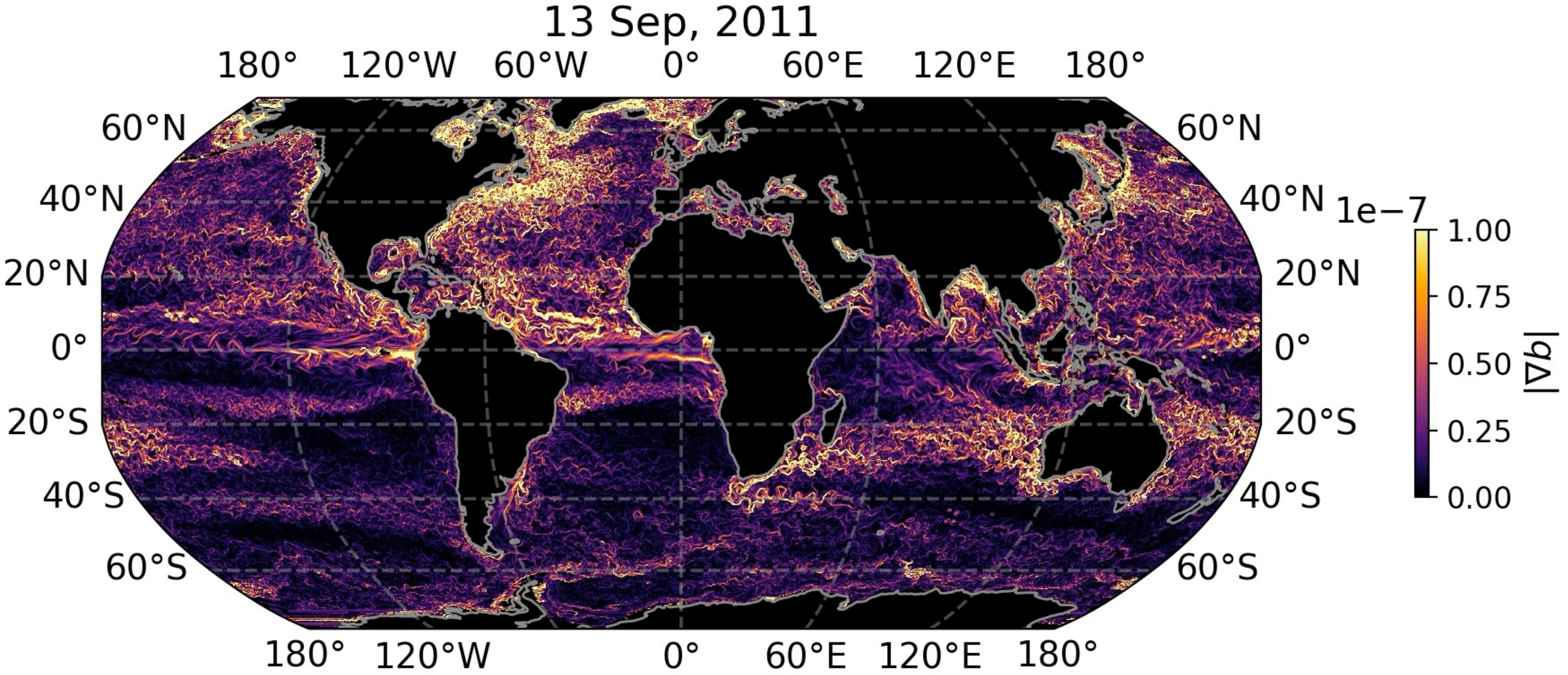
M²LInES

NYU

SIMONS FOUNDATION

Data from submesoscale permitting simulation

MITgcm-llc4320 (horizontal resolution $1/48^o$ ~2km)



Mixed Layer Eddy Parameterization (Fox-Kemper et al 2008)

$$\overline{w'b'}^z \propto \frac{H_{ML}|\overline{\nabla_H b}|^z}{|f|}$$

Buoyancy rescaling factor

$$\Delta s/L_f$$

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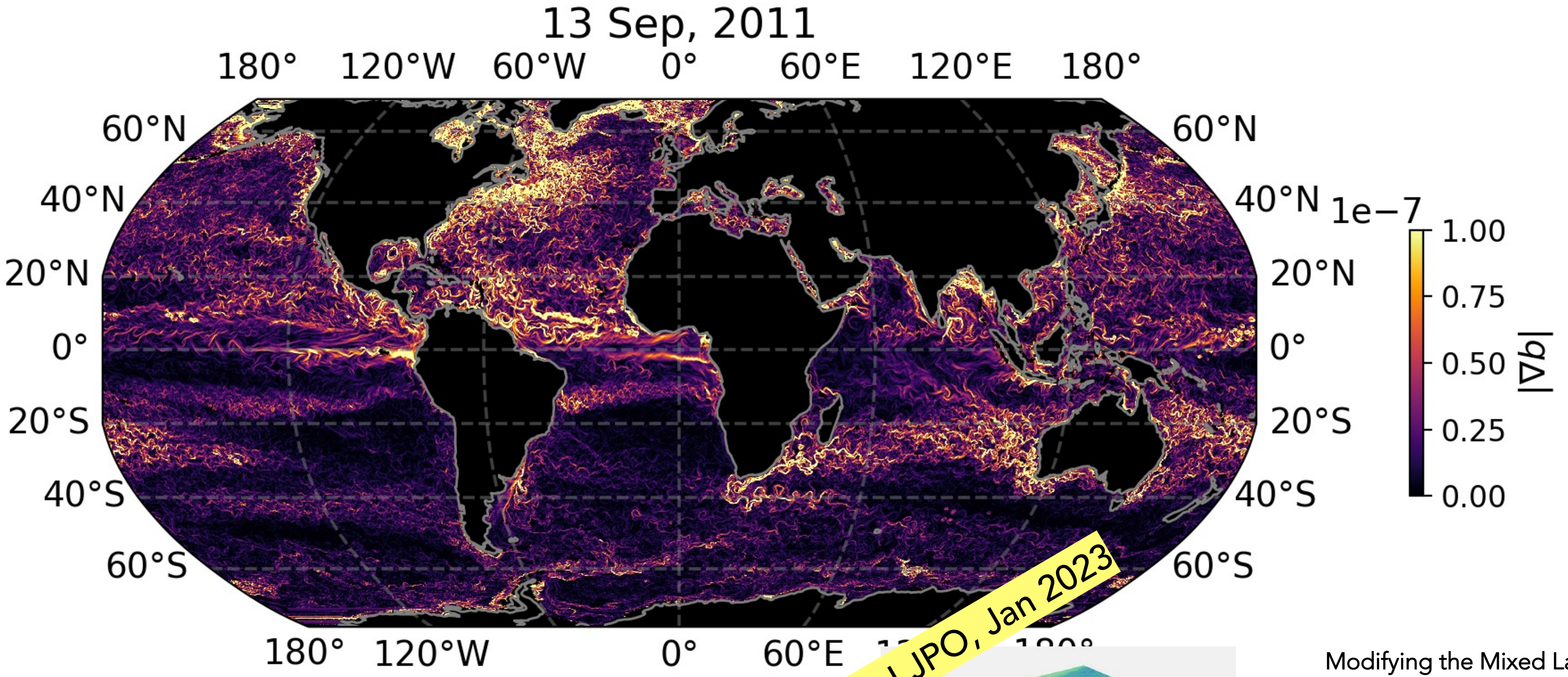
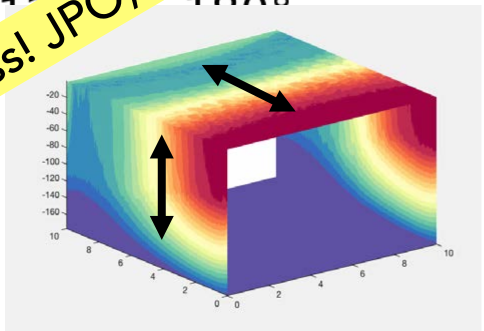


Hot off the press! JPO, Jan 2023



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Modifying the Mixed Layer Eddy Parameterization (Bodner et al 2023)

$$L_f = C_f \cdot \frac{(m_* u_*^3 + n_* w_*^3)^{\frac{2}{3}}}{f^2} \cdot \frac{1}{h}$$

Data from submesoscale permitting simulation

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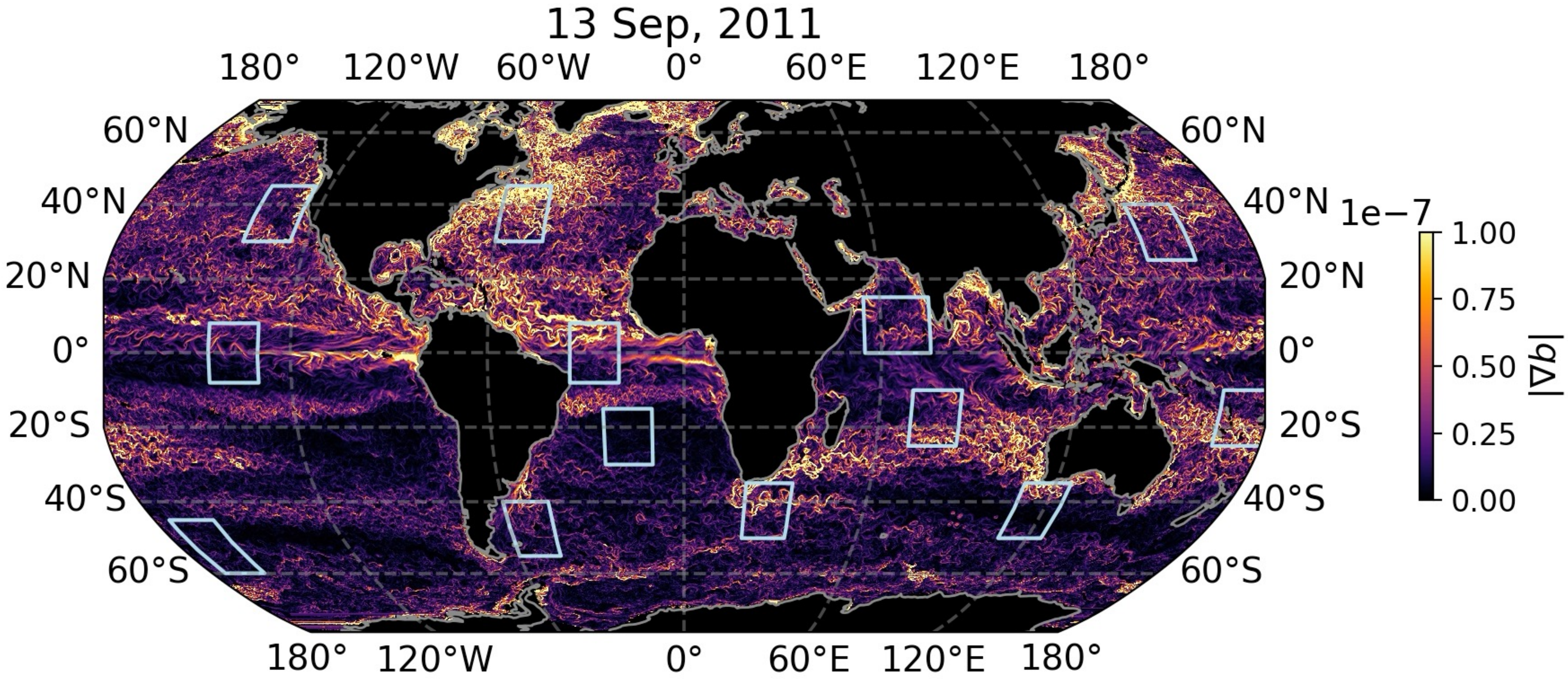

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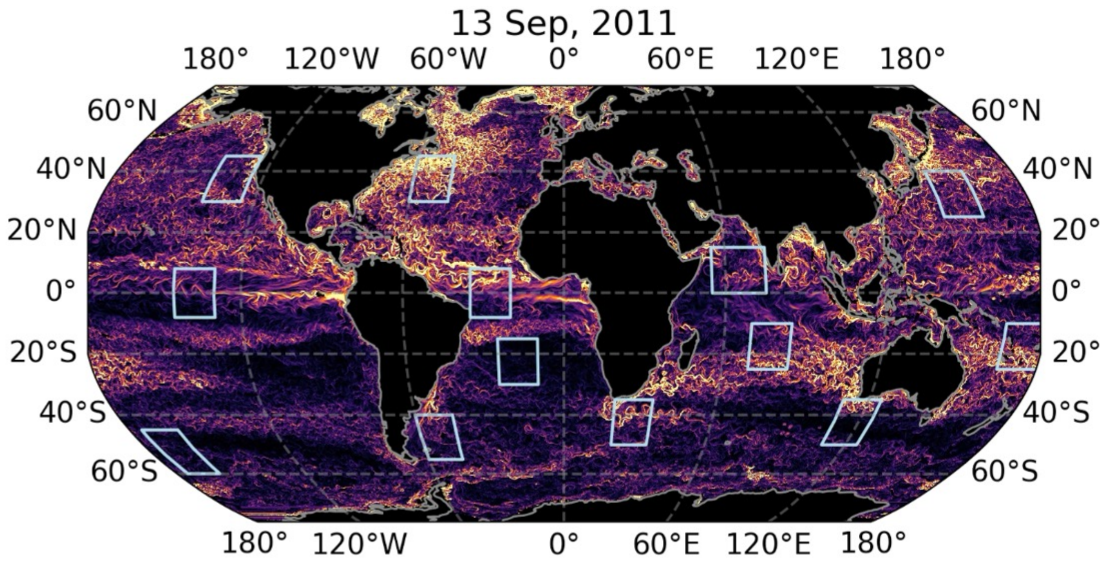

- $1/48^o$ ~2km horizontal resolution
- Select $10^o X 10^o$ domains from global simulation
- Total of 14 months of hourly data, averaged over 12 hours to remove wave signal
- Compute subgrid vertical buoyancy fluxes

Coarse-grain
+ depth average

$$\overline{w'b'}^z = \overline{w}^z \overline{b}^z - \overline{wb}^z$$

$$\Psi = \frac{\boxed{\overline{w'b'}^z}}{\overline{|\nabla b|}^z}$$

Data-Driven

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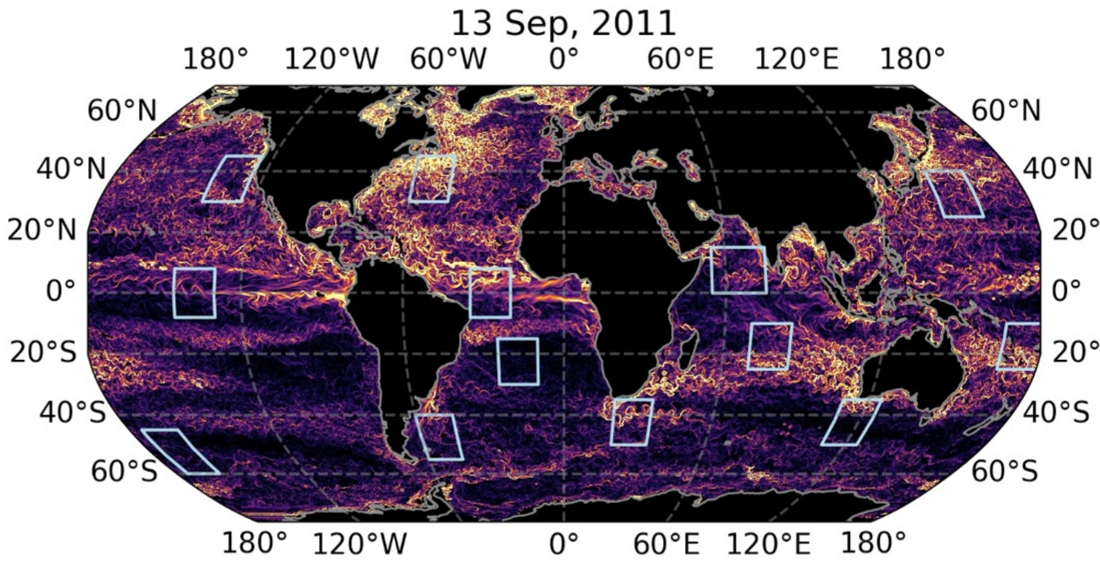

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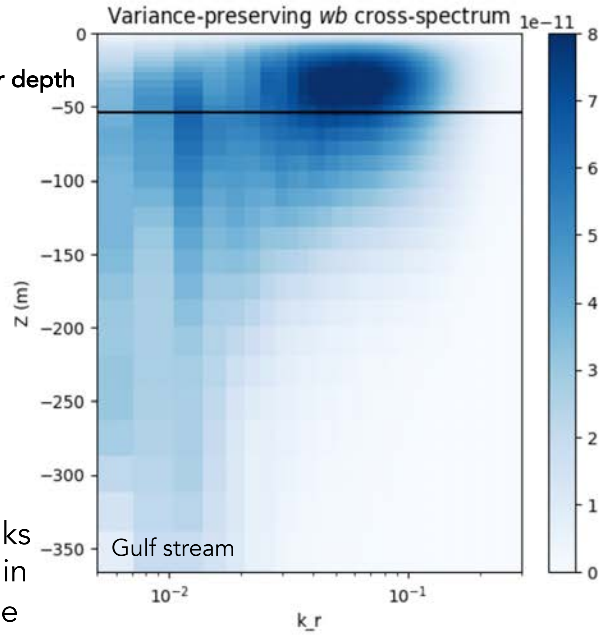
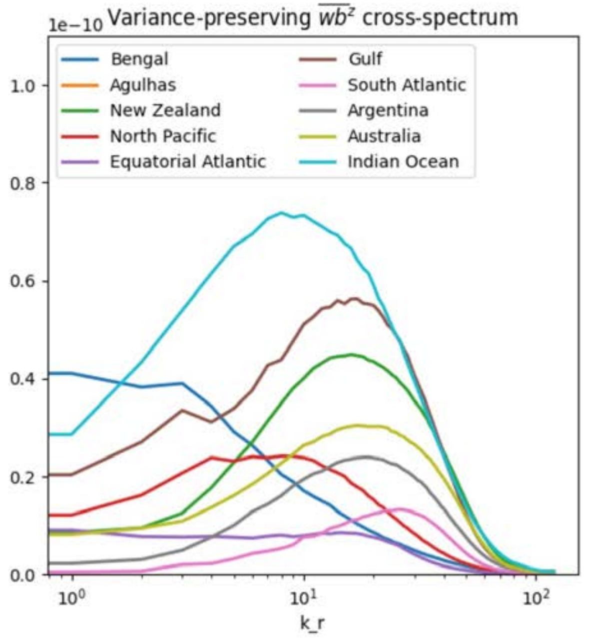


wb cross-spectrum peaks within mixed layer and in the submesoscale range

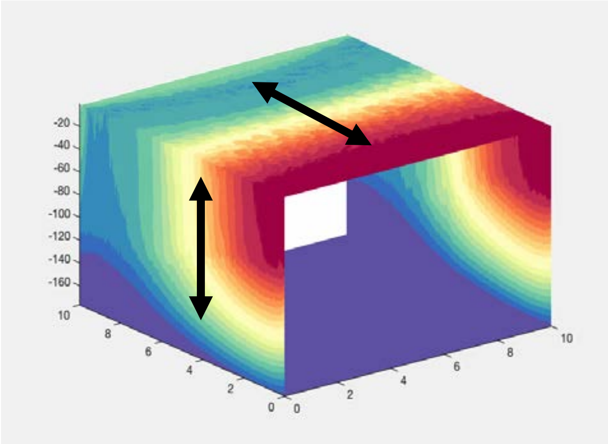


Data from submesoscale permitting simulation

- Inputs ($1/4^o$ resolution):
  Mixed layer depth, boundary layer depth, wind stress, surface heat flux, Coriolis, MLD-averaged buoyancy gradient, MLD-averaged stratification

- Target ($1/4^o$ resolution): :
  MLD-averaged vertical buoyancy flux

MITgcm-llc4320



$$H_{ML},\ h_B,\ \tau,\ Q^*, f \quad \overline{|\nabla b|}^z, N^2$$

Fox-Kemper et al 2008

$$\Psi = C_e \frac{\Delta s}{L_f} \frac{H^2 \nabla \bar{b}^z \times \hat{\mathbf{z}}}{\sqrt{f^2 + \tau^{-2}}} \mu(z)$$

Bodner et al 2023

$$\Psi = \frac{C_e}{C_f} \frac{\Delta s |f| h H^2 \nabla \bar{b}^z \times \hat{\mathbf{z}}}{(m_* u_*^3 + n_* w_*^3)^{\frac{2}{3}}} \mu(z)$$

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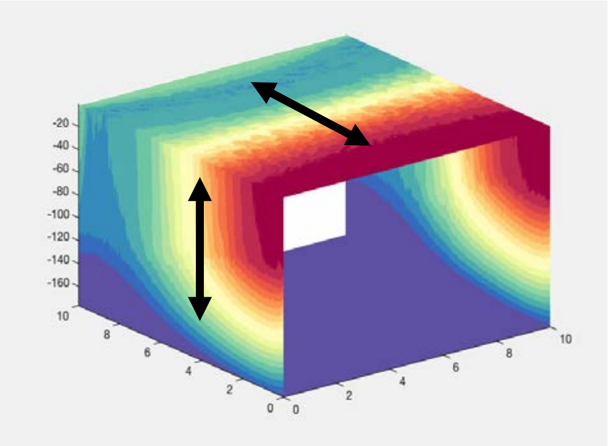

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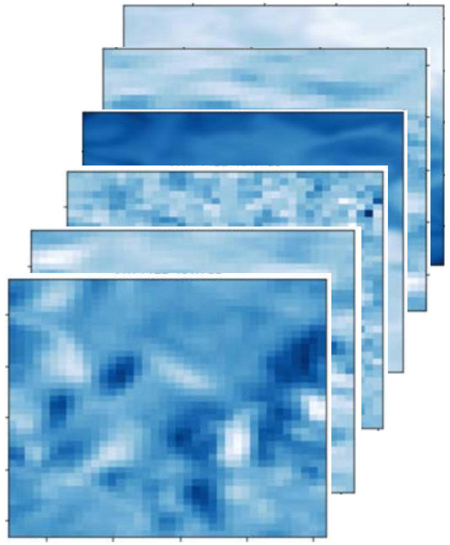
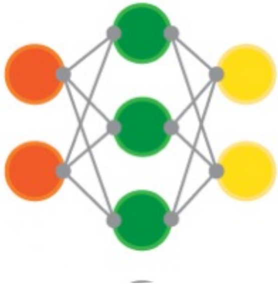
Inputs (resolved by GCM):

$H_{ML},\ h_B,$

$\tau,\ Q^*, f$

$\overline{|\nabla b|}^z, N^2$

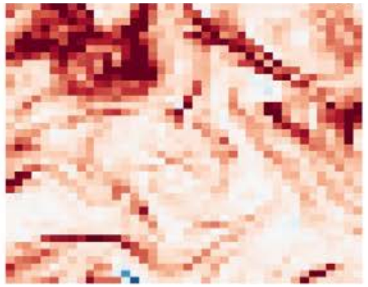




Convolutional Neural Network

Target
Subgrid MLD-averaged vertical buoyancy fluxes

$$\Psi = \frac{\boxed{\overline{w'b'}^z}}{\overline{|\nabla b|}^z}$$



$\overline{w'b'}^z$

Offline Training Results

- Example of Fully Convolutional Neural Network
- ~8000 samples: 90% train, 10% test

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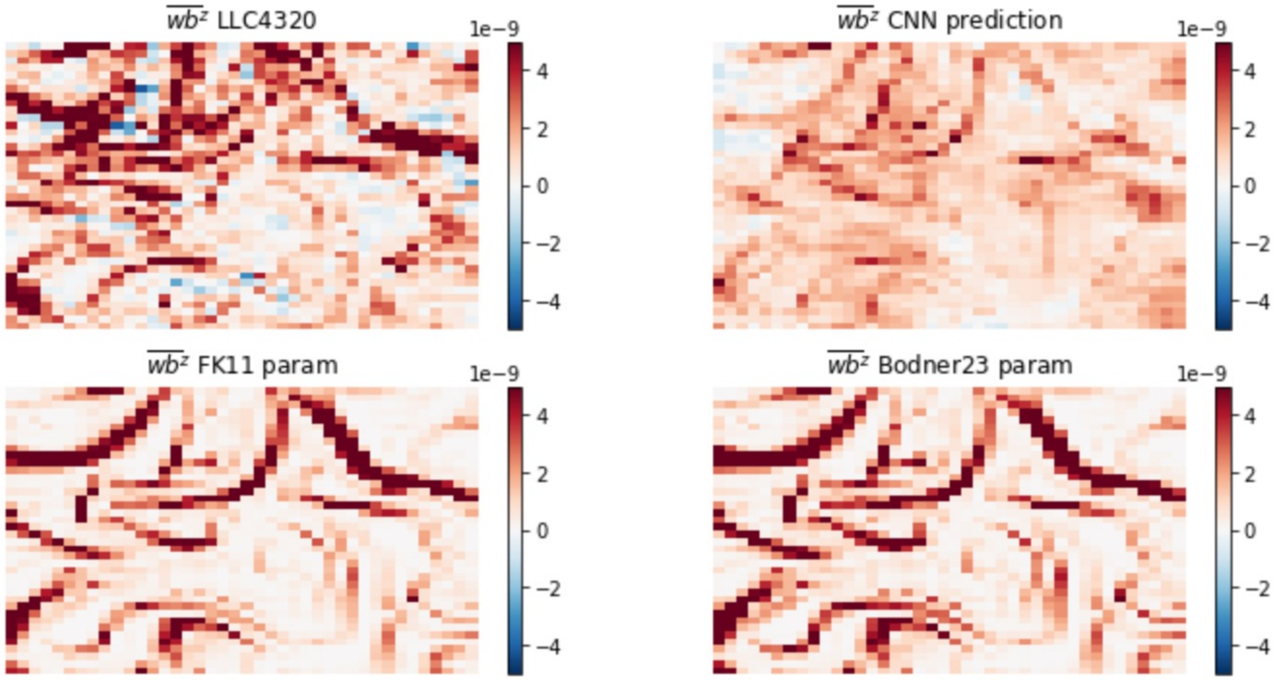

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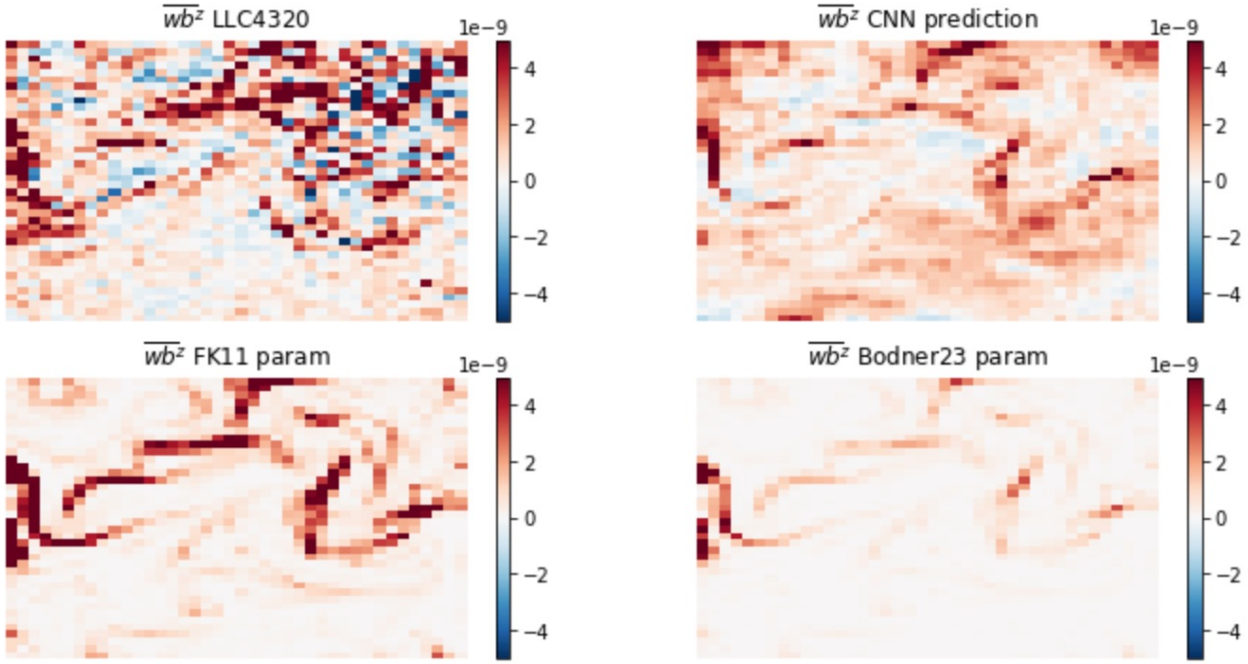

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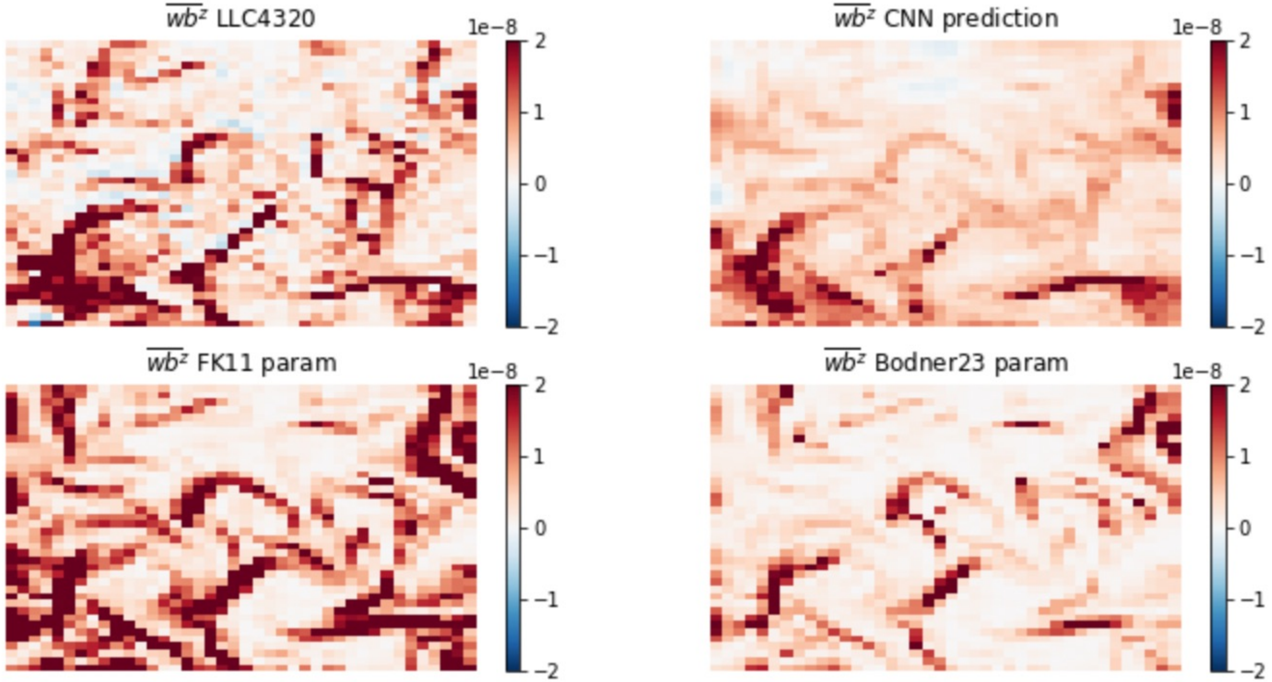

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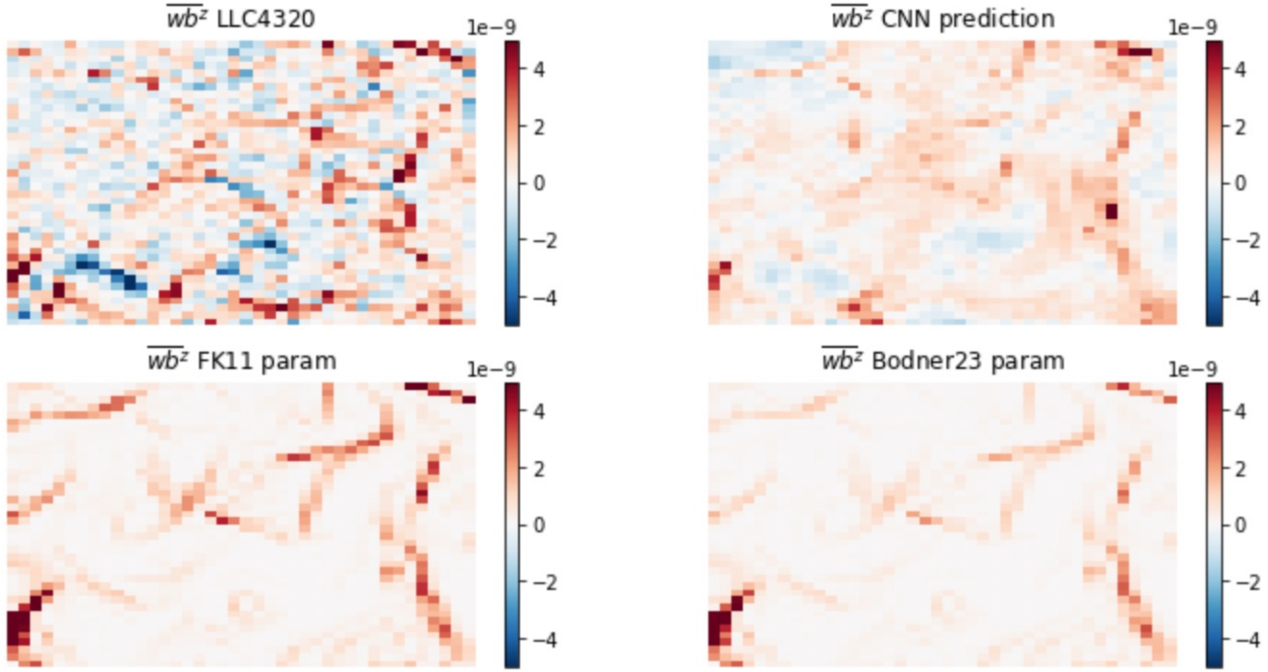

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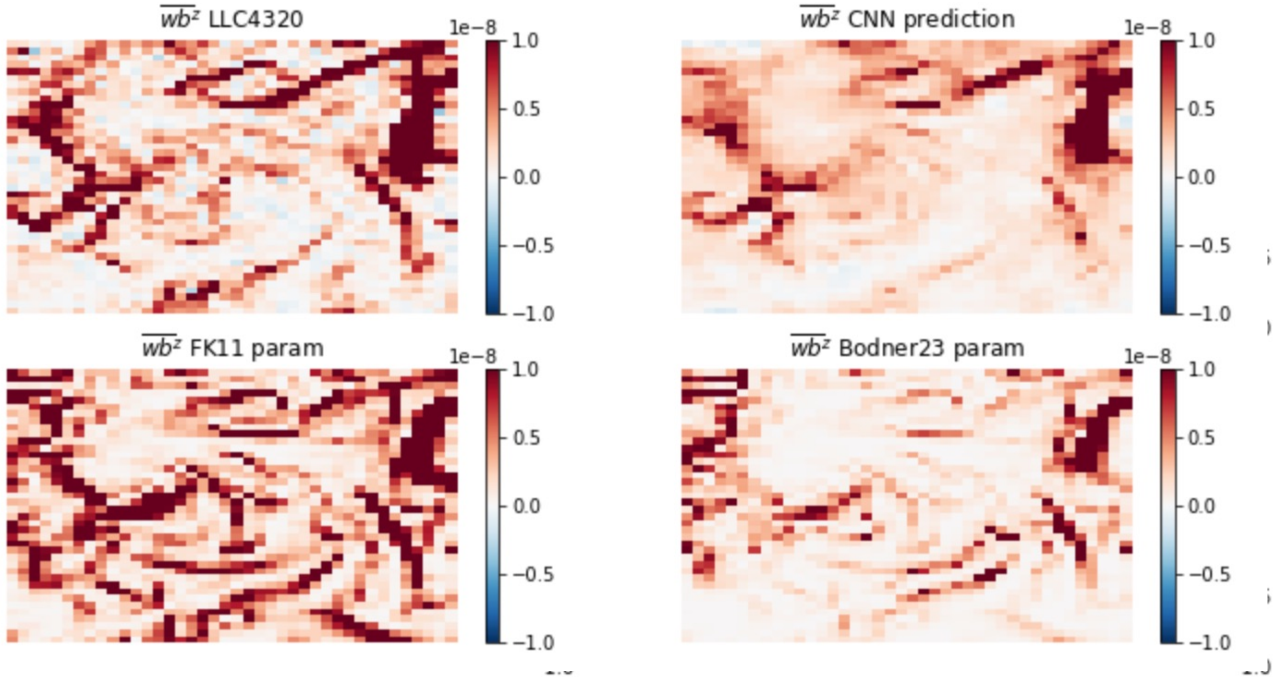

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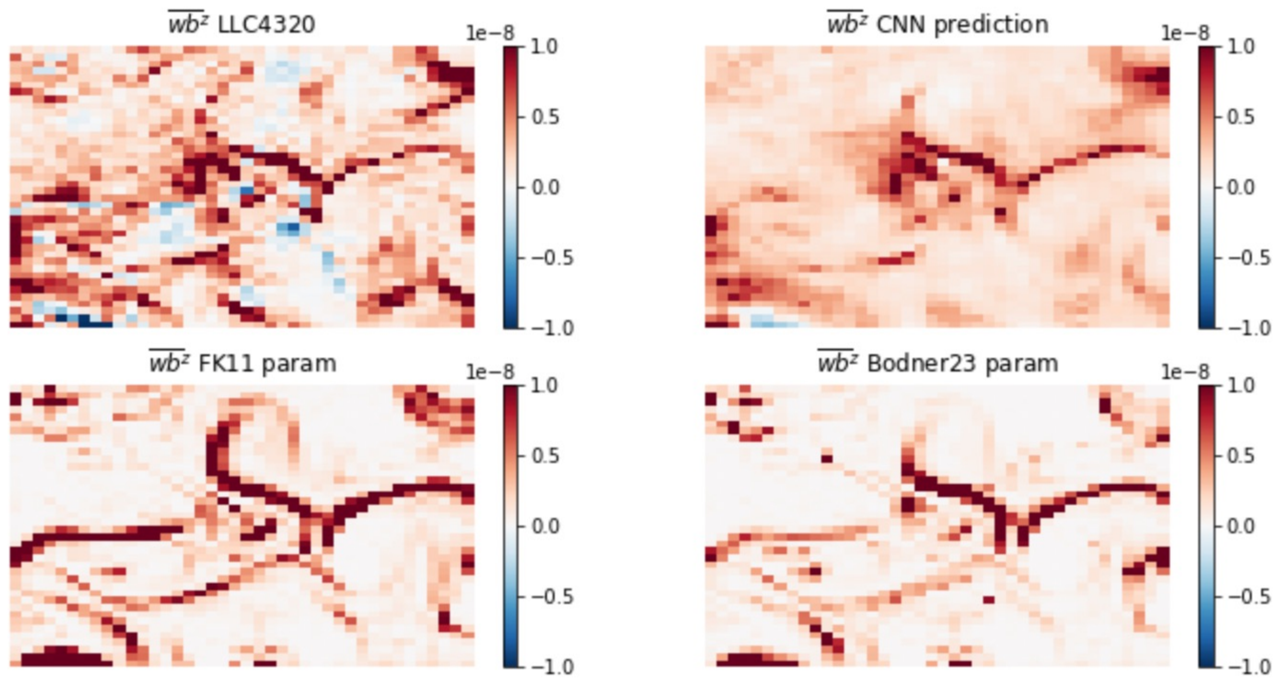

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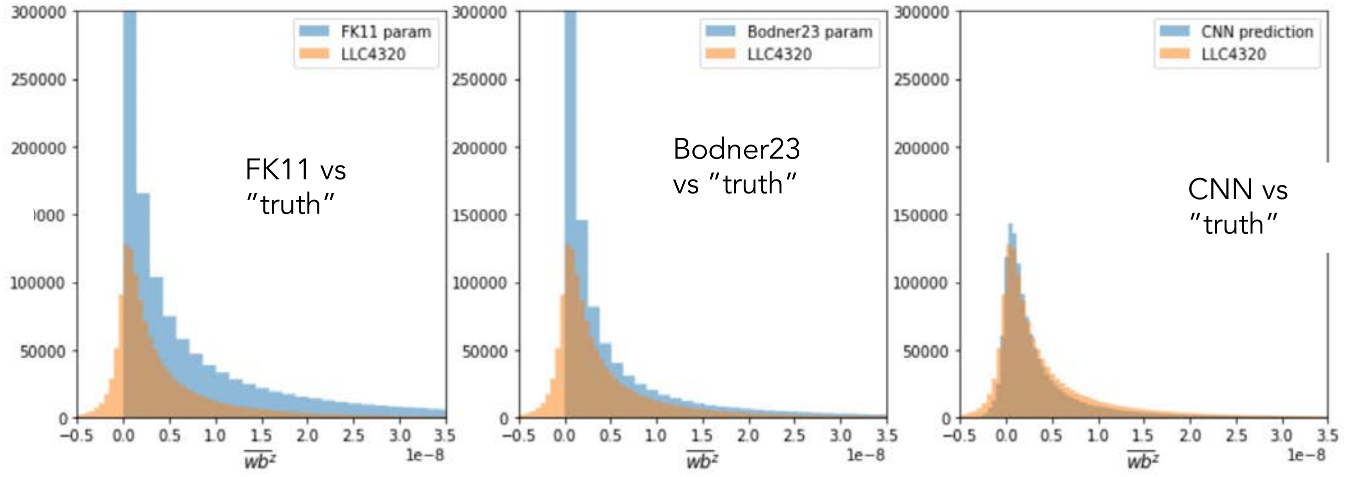
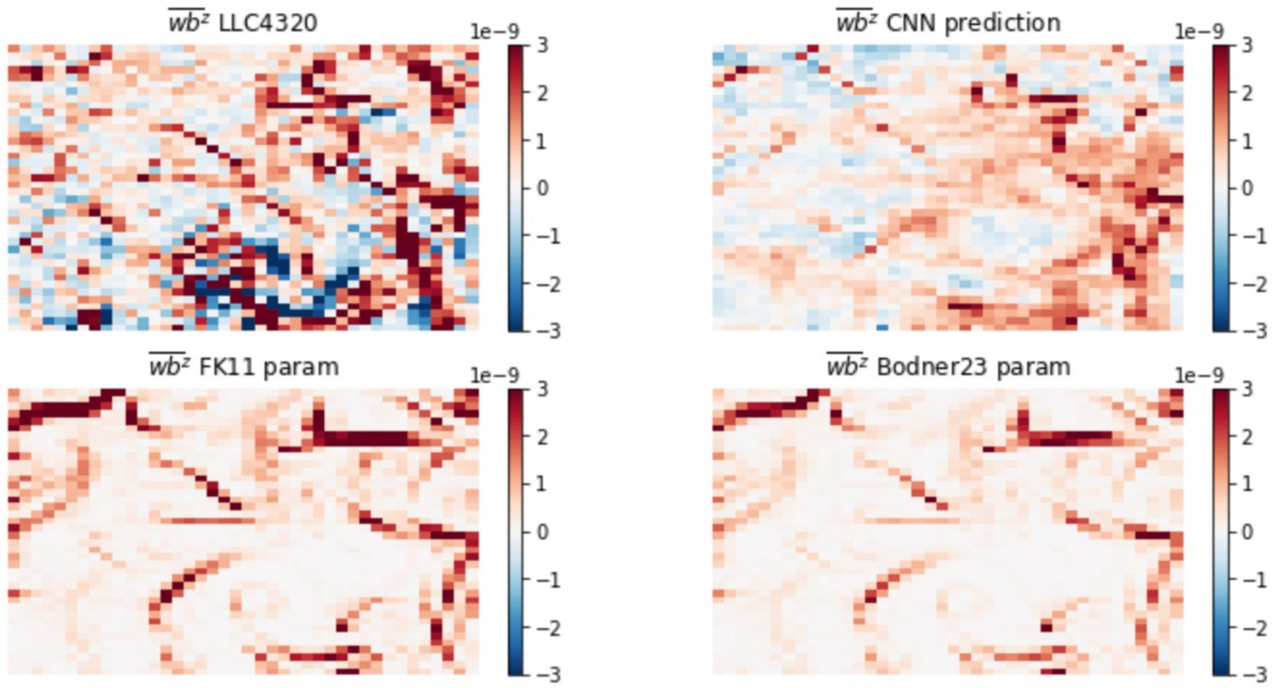
$\overline{w'b'}$ PDFs





- All parameterizations resemble in large-scale statistics
- Bodner 2023 rescaling improves predicted fluxes compared with Fox-Kemper 2011
- NN predicts large scale fluxes that closely resemble true data-- including negative fluxes

Climatematch Academy

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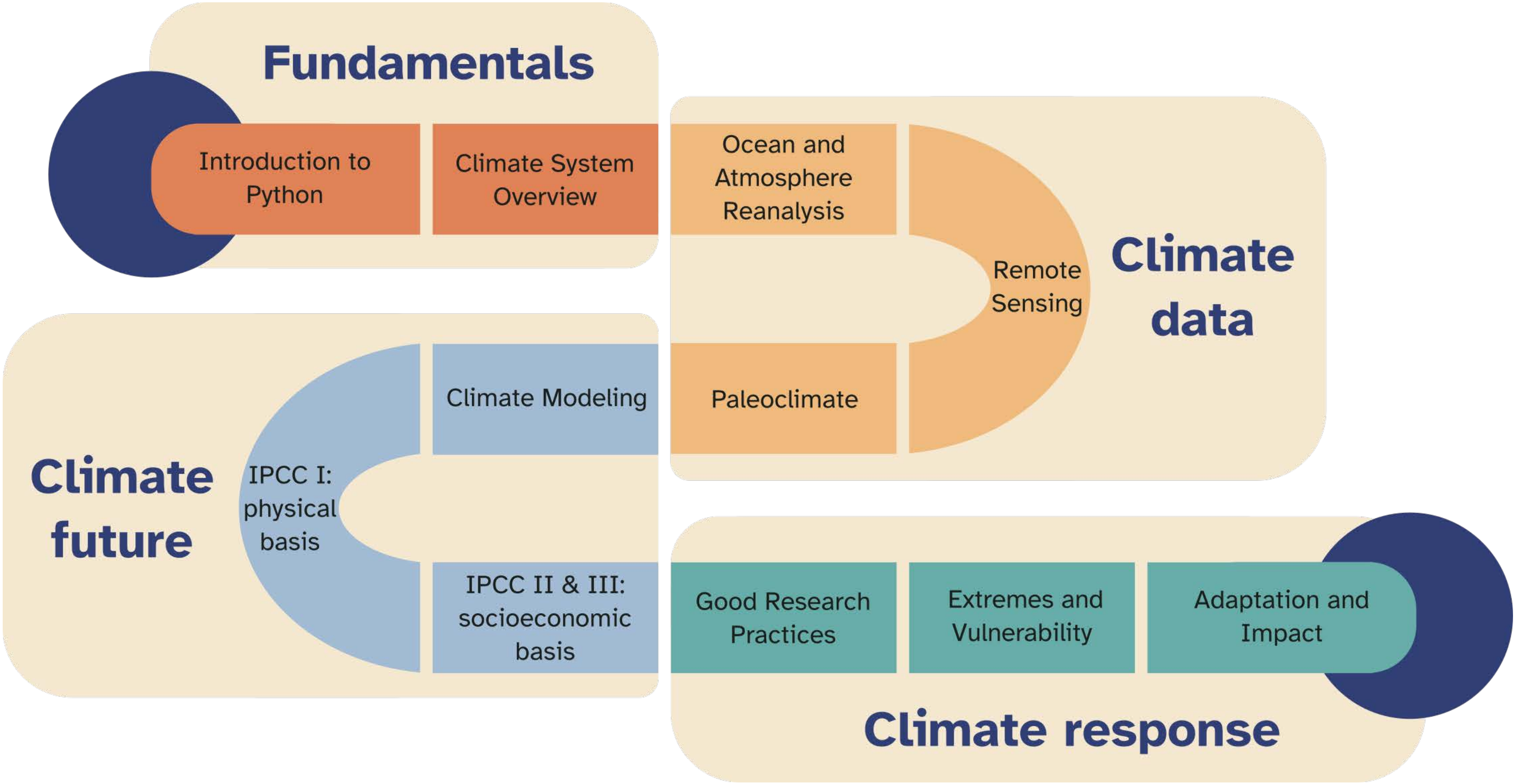
JULY 17-28, 2023



Summary and future work

$$\Psi = \frac{\boxed{\overline{w'b'}^z}}{\overline{|\nabla b|}^z}$$

Data-Driven

- Data-driven approach for parameterizing vertical submesoscale buoyancy fluxes given by the ultra-high resolution MITgcm-llc4230

- All parameterizations resemble in large-scale statistics: Bodner 2023 rescaling improves predicted fluxes compared with Fox-Kemper 2011

- NN predicts large scale fluxes that closely resemble true data-- including negative fluxes

- Testing sensitivity to input variables
  - Do we need all?
  - Any others relevant? e.g. strain, divergence

- Developing different approaches for GCM implementation which correspond to relevant ocean parameterizations