

Machine-Learned parameterizations of mesoscale eddies in MOM6 ocean model: convolutional neural network and symbolic regression

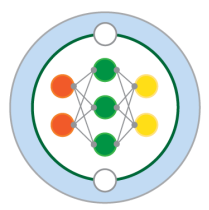
Pavel Perezhogin, Cheng Zhang, Cem Gultekin, Alistair Adcroft, Carlos Fernandez-Granda, Laure Zanna

NYU, Princeton

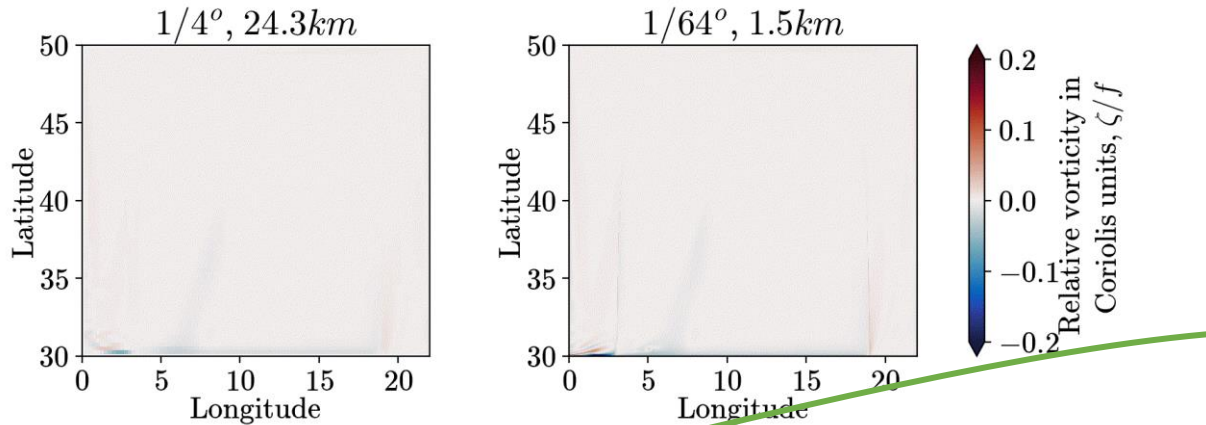
13 Jun 2023 CESM meeting

<https://m2lines.github.io/>





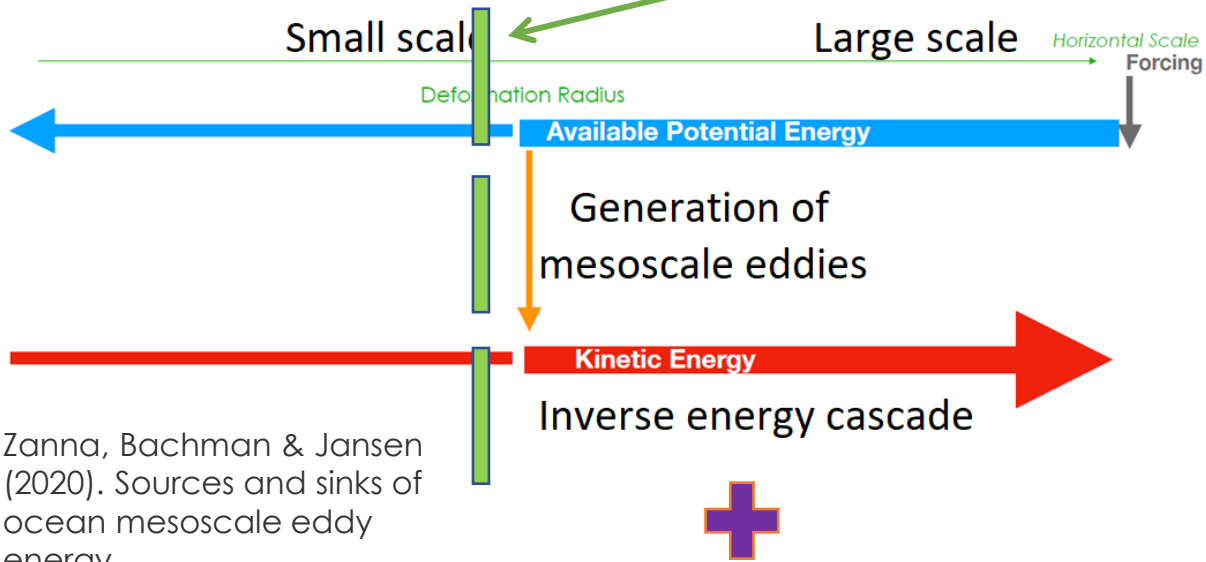
Mesoscale parameterizaion



Mesoscale eddies of size (Rossby deformation radius):

$$R_d = \frac{c}{f} \quad (10-100\text{km})$$

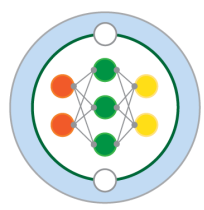
Gray zone:
 $\Delta x \approx R_d$



Zanna, Bachman & Jansen (2020). Sources and sinks of ocean mesoscale eddy energy.

Mesoscale parameterization:

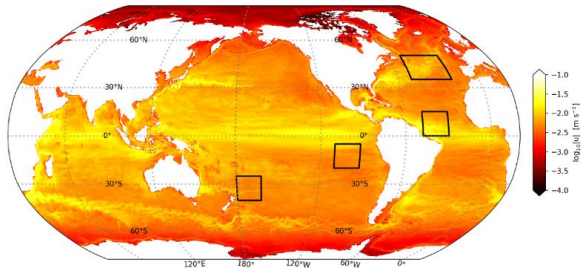
- APE removal (buoyancy forcing)
- KE backscatter (momentum forcing)



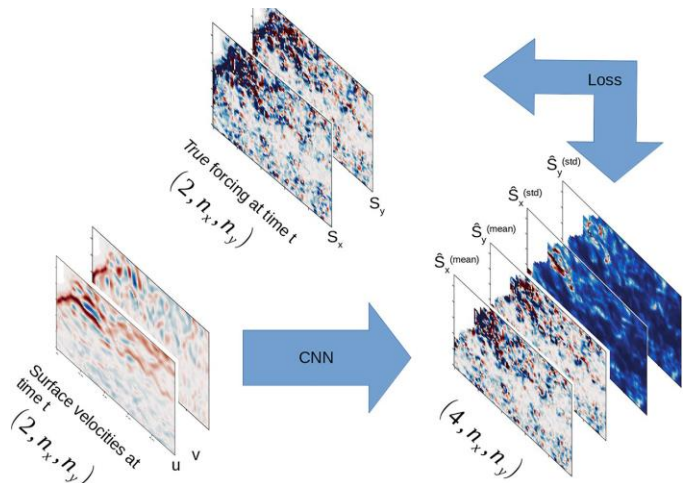
Data-driven mesoscale parameterization

$$\frac{\partial \mathbf{u}_k}{\partial t} + \frac{f + \zeta_k}{h_k} \hat{\mathbf{z}} \times (h_k \mathbf{u}_k) + \nabla K_k + \nabla M_k = \mathbf{F}_k + \mathbf{V}_k + \mathbf{S}_k$$

Guillaumin-Zanna-2021:
CNN model



CM2.6 data

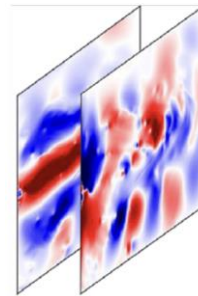


Subgrid momentum forcing

$$\mathbf{S} = (\bar{\mathbf{u}} \cdot \bar{\nabla}) \bar{\mathbf{u}} - \overline{(\mathbf{u} \cdot \nabla) \mathbf{u}}$$

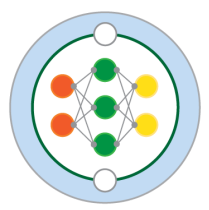
Zanna-Bolton-2020:
Symbolic regression

MITgcm data



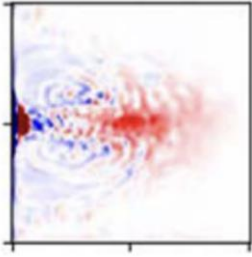
$$\begin{aligned} \zeta &= \partial_x v - \partial_y u, \\ \tilde{D} &= \partial_x u - \partial_y v \\ D &= \partial_y u + \partial_x v \end{aligned}$$

$$\mathbf{T}(\zeta, D, \tilde{D}) = \underbrace{\kappa_{BC} \begin{bmatrix} -\zeta D & \zeta \tilde{D} \\ \zeta \tilde{D} & \zeta D \end{bmatrix}}_{\text{deviatoric stress}} + \underbrace{\frac{\kappa_{BC}}{2} (\zeta^2 + D^2 + \tilde{D}^2)}_{\text{hydrostatic stress}} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

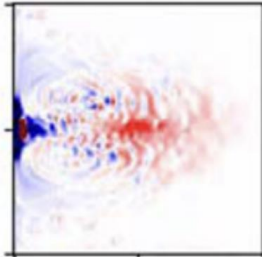


Offline skill of data-driven closures

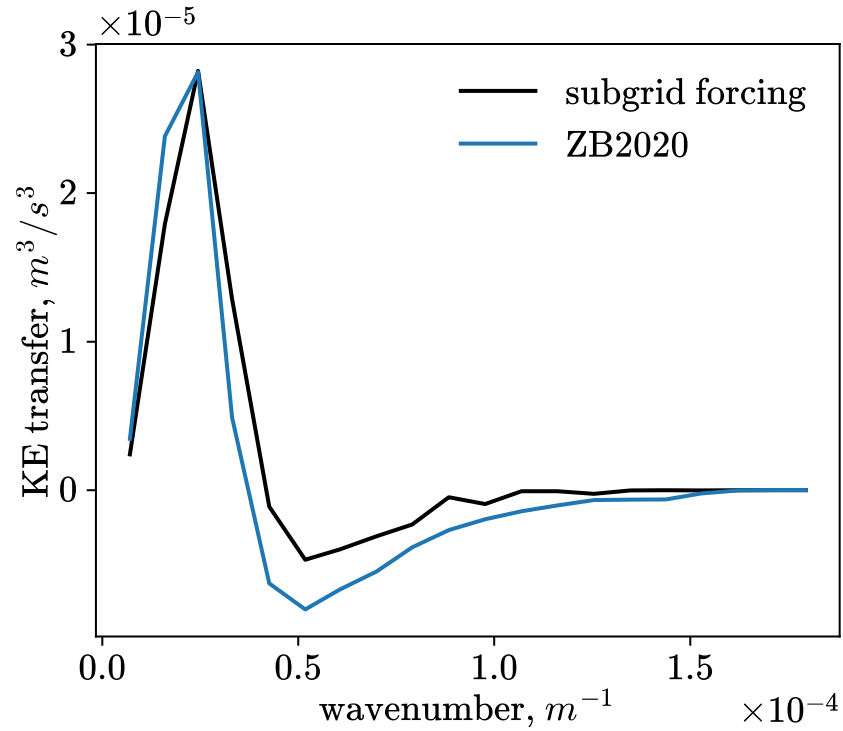
Subgrid forcing



ZB2020



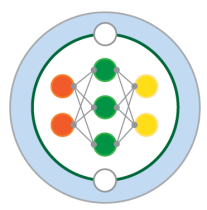
Predicts instantaneous momentum fluxes due to unresolved mesoscale eddies



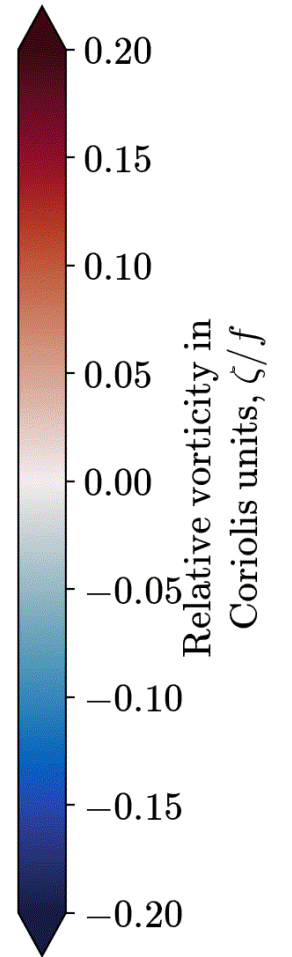
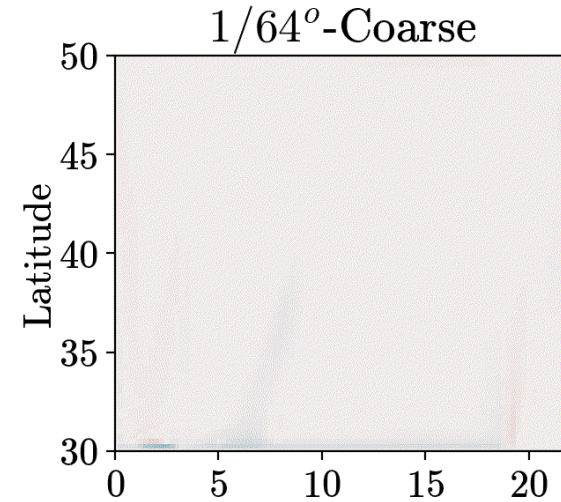
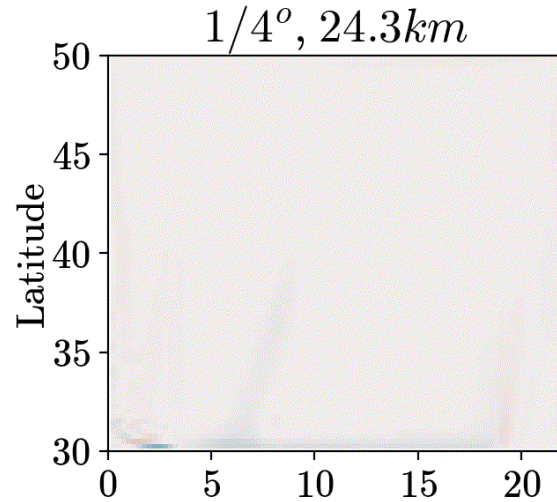
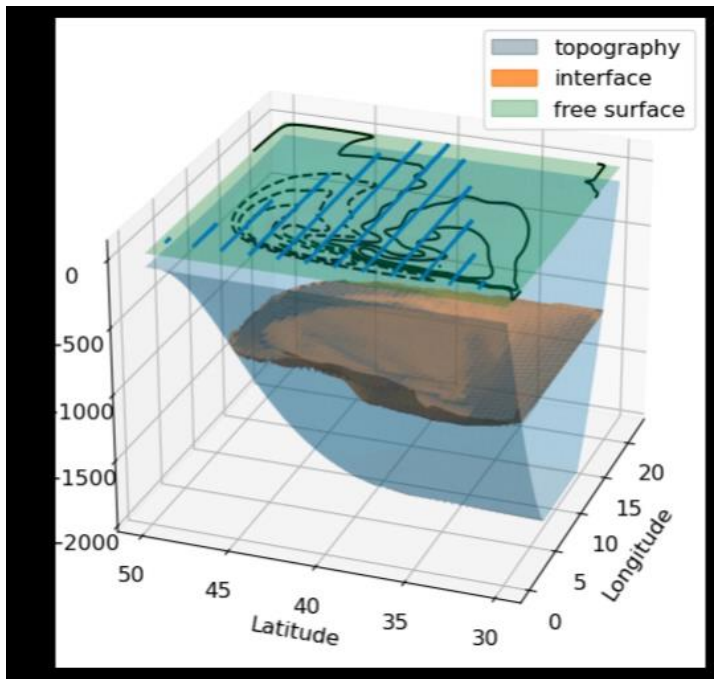
Predicts KE transfer

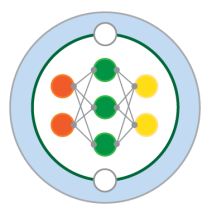


Online skill in realistic ocean models

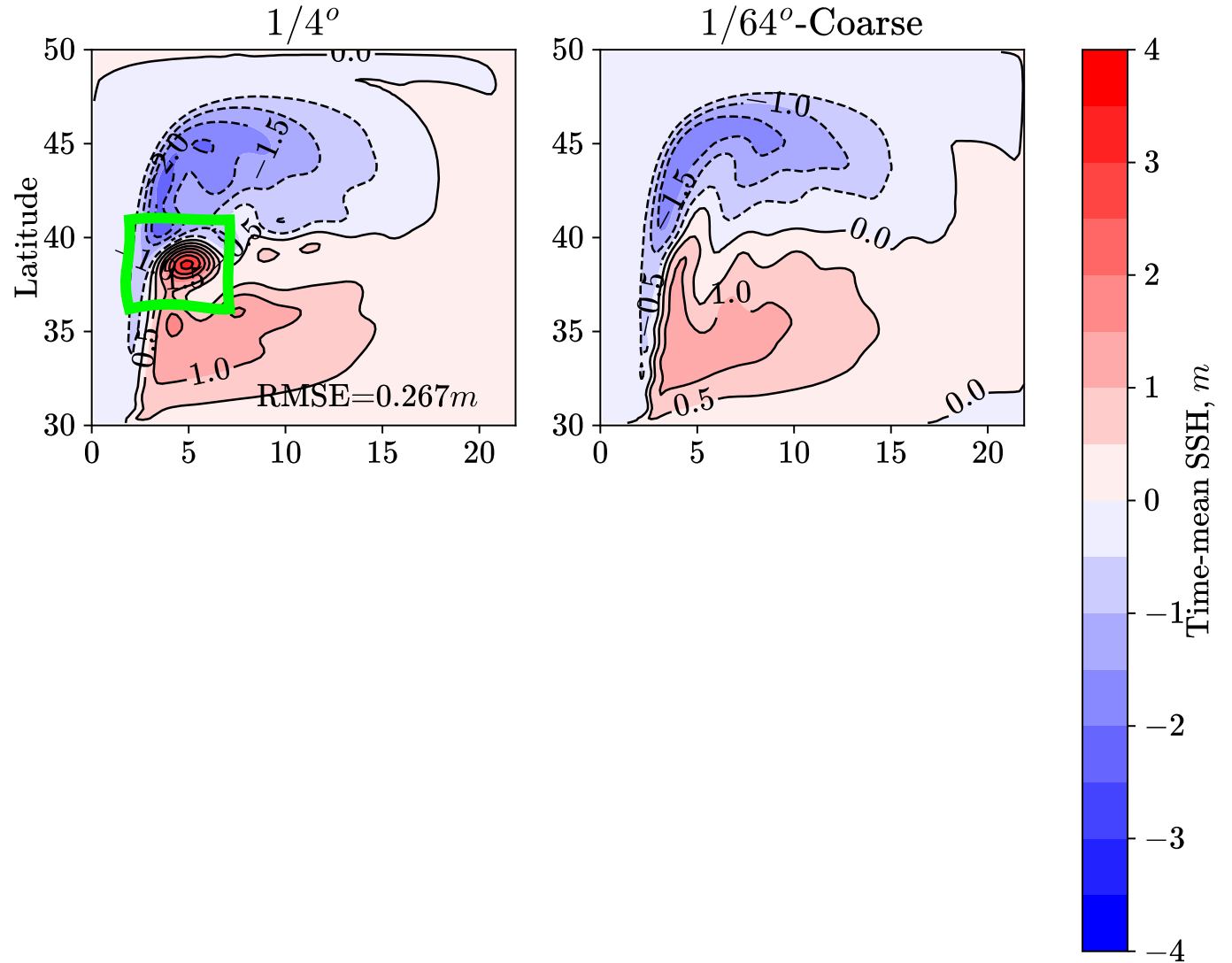


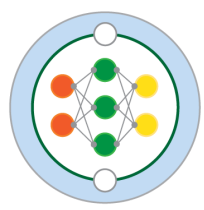
MOM6 ocean model. Double Gyre.



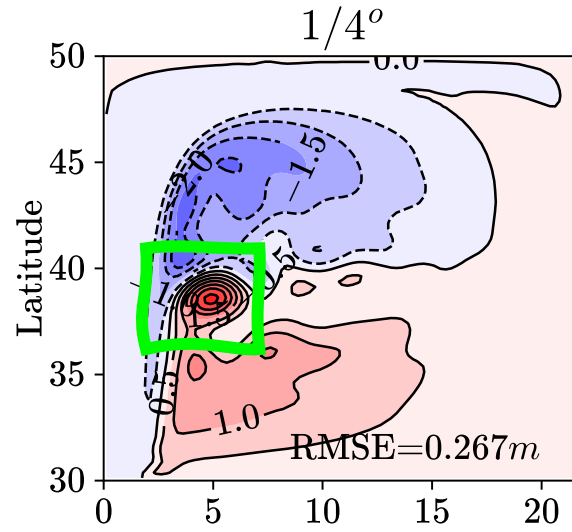
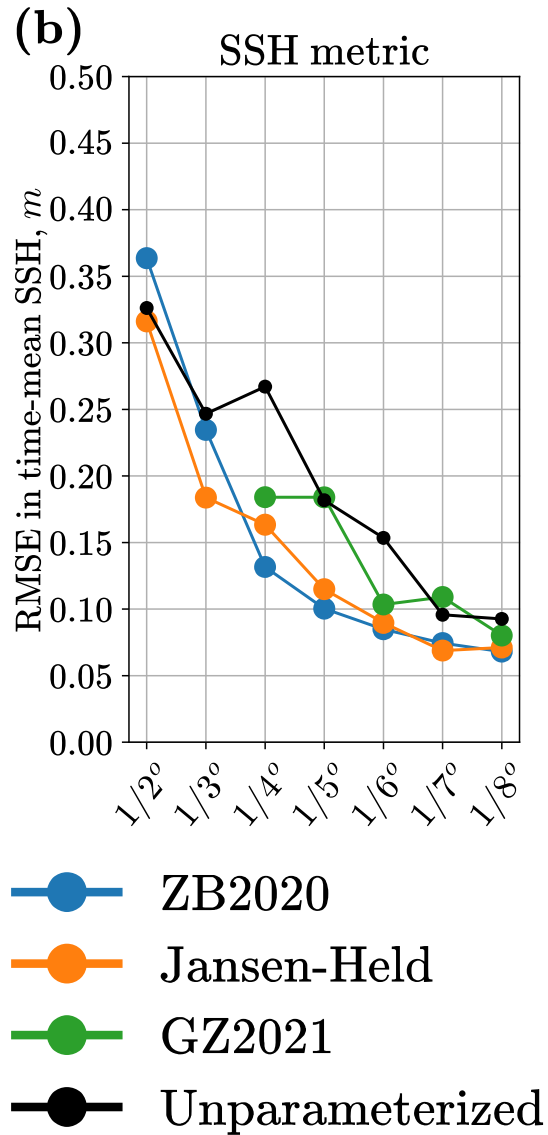


Time-averaged SSH

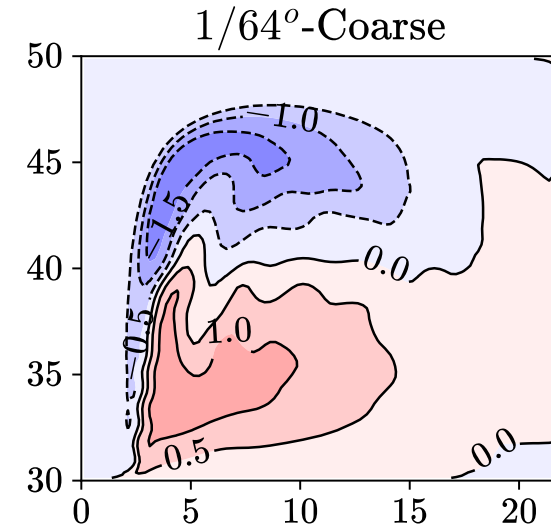
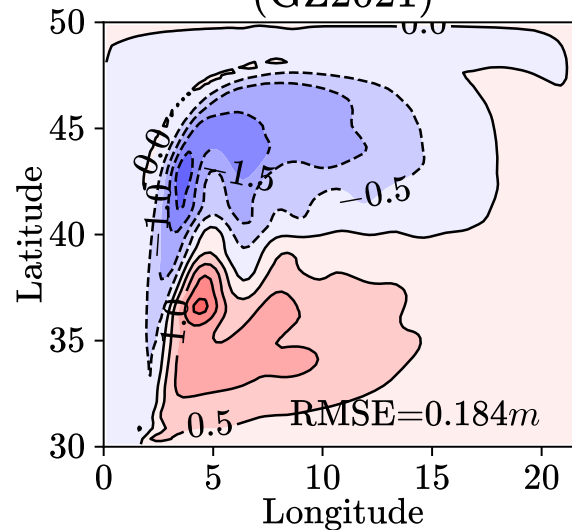




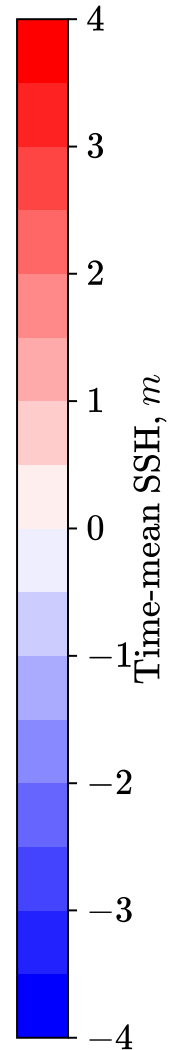
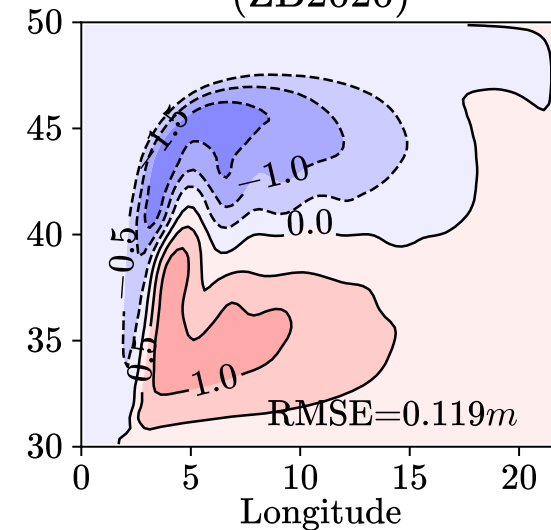
Time-averaged SSH

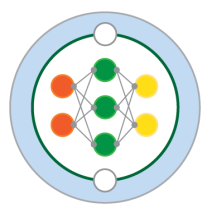


**CNN
(GZ2021)**

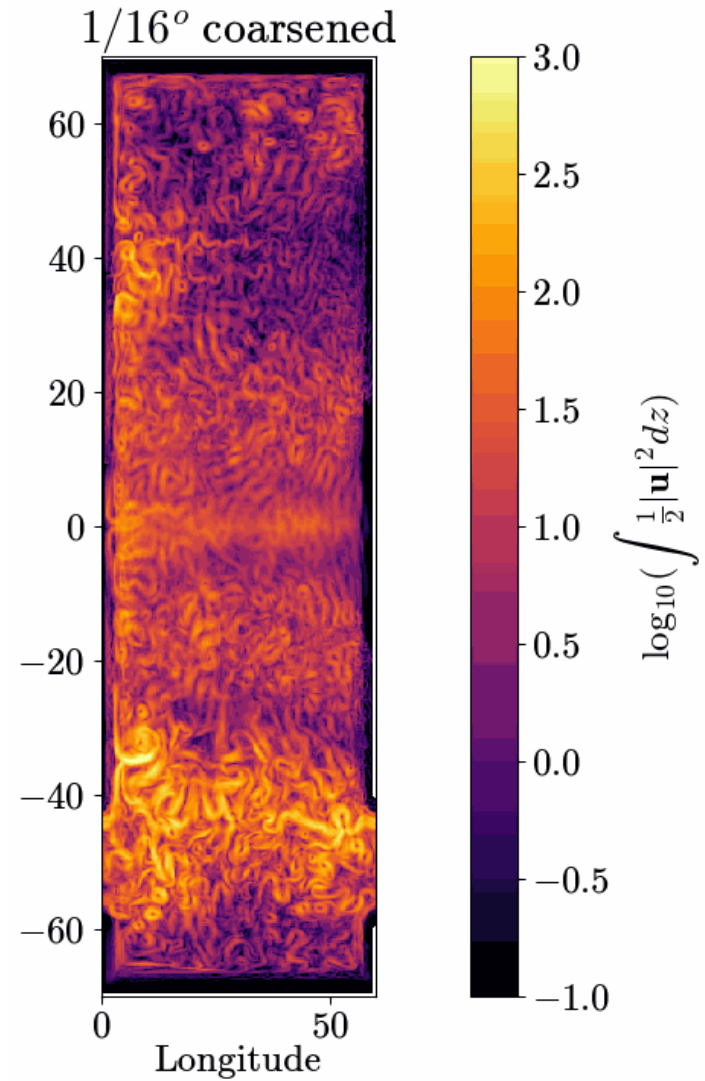


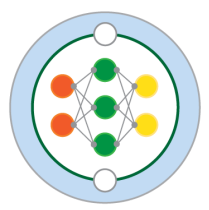
**Symbolic regression
(ZB2020)**





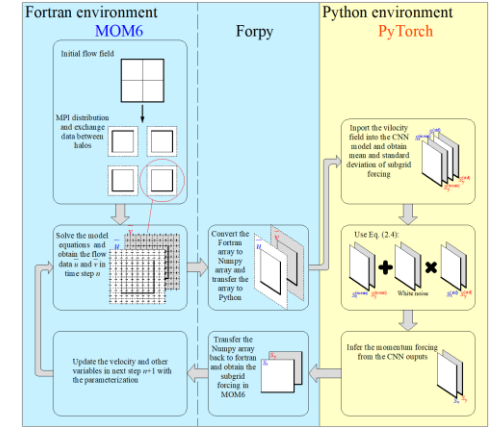
Ongoing research: NewerWorld2 configuration

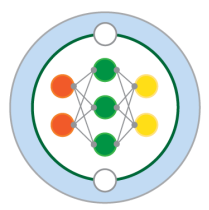




Challenges

- Implementation:
 - **CNN**: Fortran-Python barrier
- A posteriori tuning:
 - **CNN**: vertical profile
 - **Symbolic regression**: additional filters
- Computational cost:
 - **CNN**: requires GPU for affordable runtime
 - **Symbolic regression**: Additional filters increase runtime





Conclusions

- Two **data-driven** mesoscale parameterizations are implemented and evaluated in **MOM6** ocean model
- In some cases they simulate **backscattering** (and improve resolved eddies)
- Both models improve the mean flow (mean SSH)
- Improvement in more realistic configuration (NW2) is more evident by eye
- **Papers:**
 - **CNN:** Zhang2023 submitted
 - **Symbolic regression:** Perezhogin2023 in prep.