

Parameterizing Vertical Turbulent Mixing
Coefficients for The Ocean Surface
Boundary Layer Using Machine Learning

Modeling Vertical Diffusivity for OSBL using Machine Learning

Aakash Sane
(Princeton University / GFDL-Affiliate)

Brandon Reichl, Alistair Adcroft, Laure Zanna



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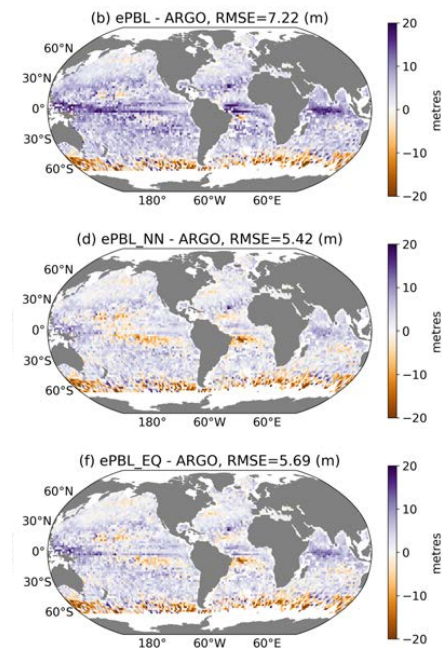
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m2lines.github.io

Key points

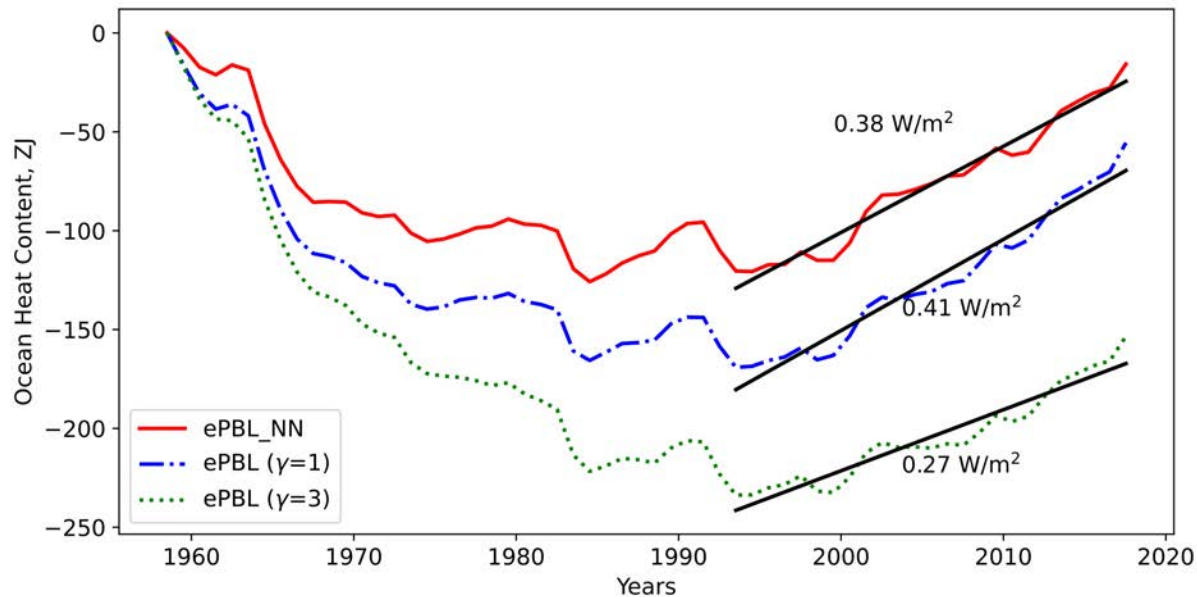
1. Control – baseline mixing scheme
2. Neural Network diffusivity from higher moment scheme
3. With equations that approximate neural networks – similar skill. Enables Interpretation of neural network. Finds deficiency in baseline



Vertical mixing (OSBL) uncertainty

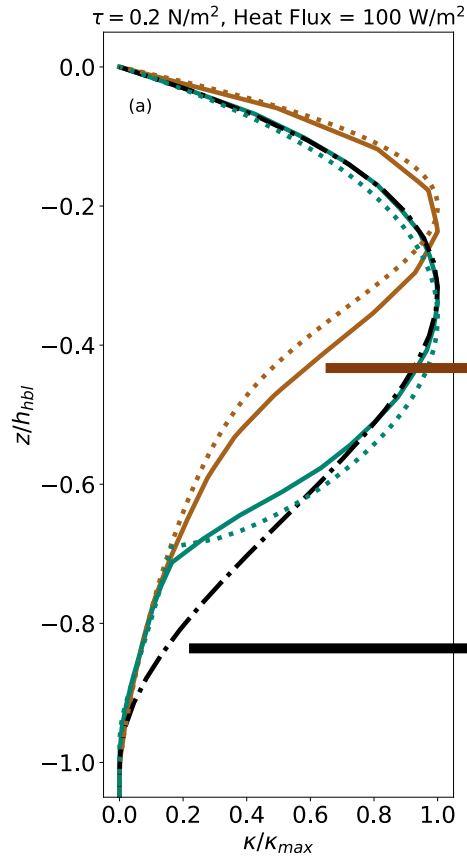
$$\langle w'T' \rangle = -\kappa \frac{\partial \langle T \rangle}{\partial z}$$

$$\kappa \approx L \cdot v$$



Sane et al. (2023), JAMES

Profiles of Diffusivity



What we should use
T.K.E., ϵ , ...

$\Delta t \approx 10 - 60$ seconds

What we are currently using

$\Delta t \approx 20 - 60$ mins

Machine Learning can close
this gap!

Neural network approach:

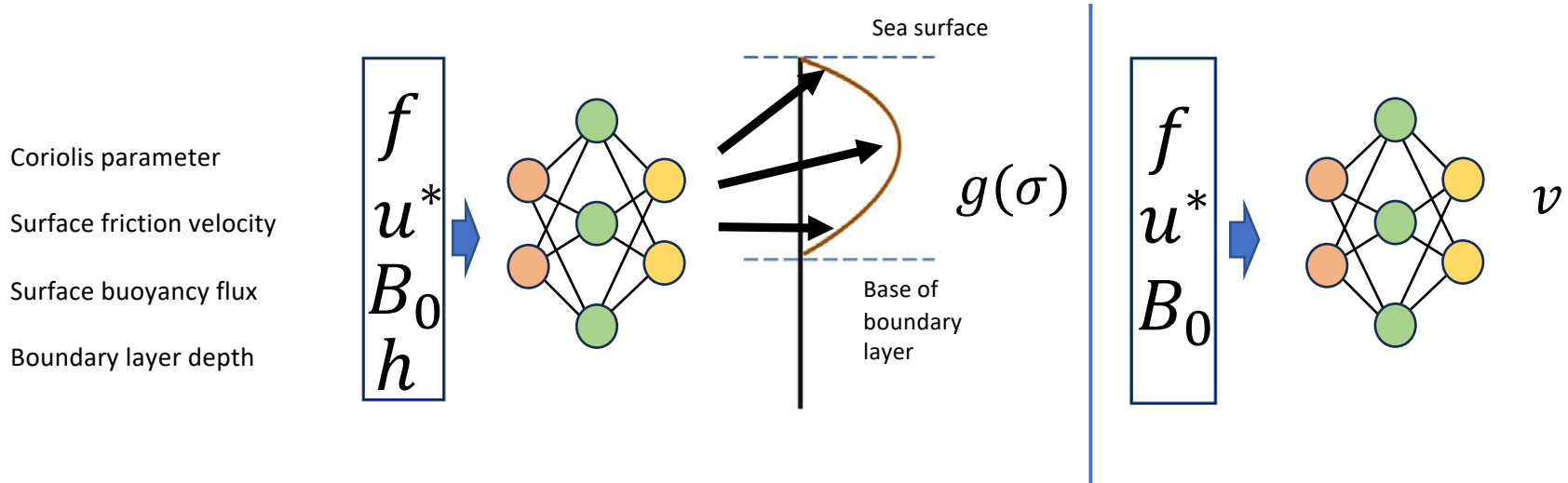
$$\kappa = g(\sigma) \cdot h \cdot v$$

Training data: General Ocean Turbulence Model (1-D turbulence model),
Second moment closure schemes, inexpensive, κ is stored as output.

Neural network approach:

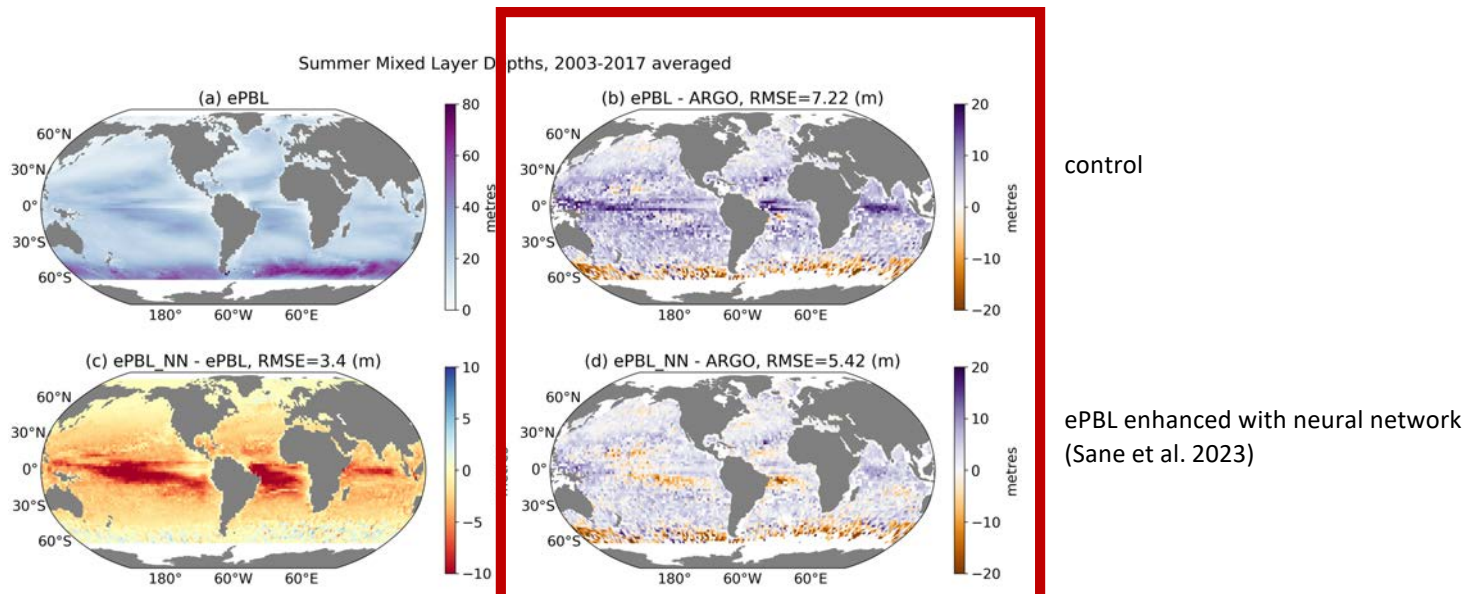
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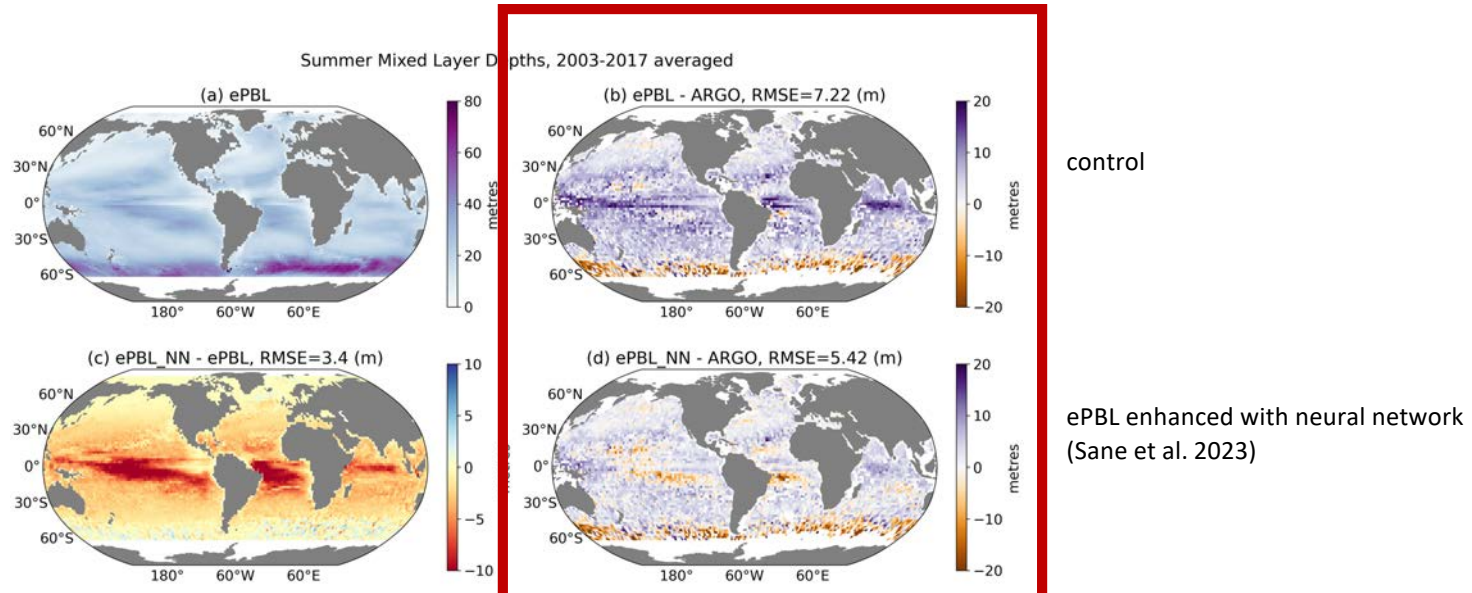


κ - neural network is used in the ePBL mixing scheme (Reichl & Hallberg, 2018)

JRA forced results (MOM6, $\frac{1}{4}^\circ$ grid, OM4): Summer Mixed Layer Depth



JRA forced results (MOM6, $\frac{1}{4}^\circ$ grid, OM4): Summer Mixed Layer Depth

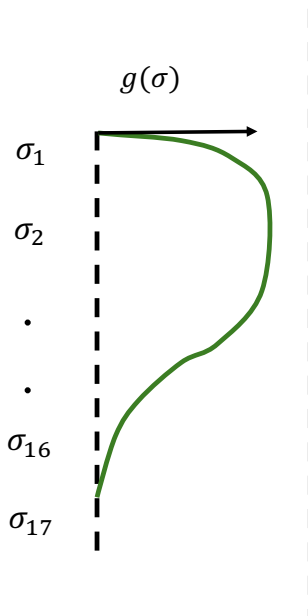
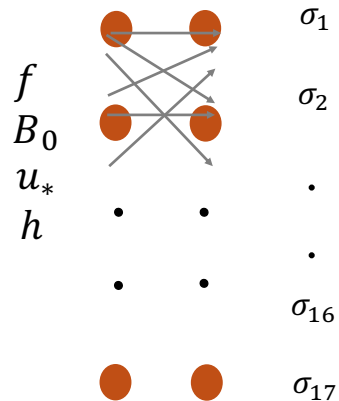


1. Neural network enhanced diffusivity improves the physics.
2. Can we interpret what the networks are doing with equations? - YES
3. And replace the networks? - YES

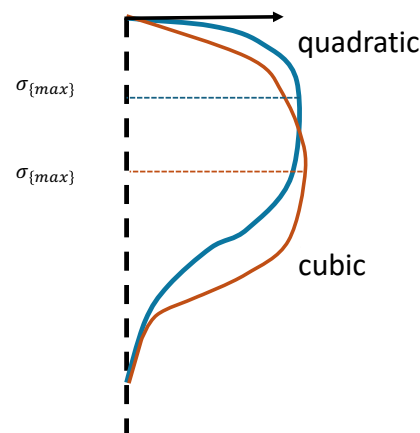
Equation Discovery: Shape Function

$$\kappa = g(\sigma) \cdot h \cdot v$$

(a)



(b)



$$p_1 = \frac{h}{L_{\{EK\}}}, p_2 = \frac{h}{L_{\{MO\}}}$$

Symbolic regression was challenging.
Empirical fitting worked!

$$\sigma_m = \frac{c_0}{1 + \frac{c_1}{F \cdot p_1}}$$

Where,

$$F = \frac{c_2}{1 + \exp(-p_2 - c_3)} + c_4$$

Equation Discovery: Velocity scale using Genetic Programming

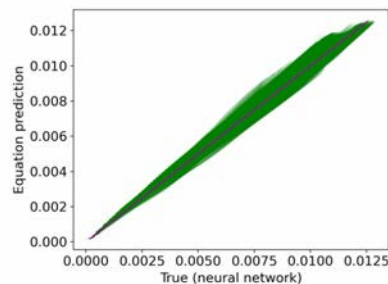
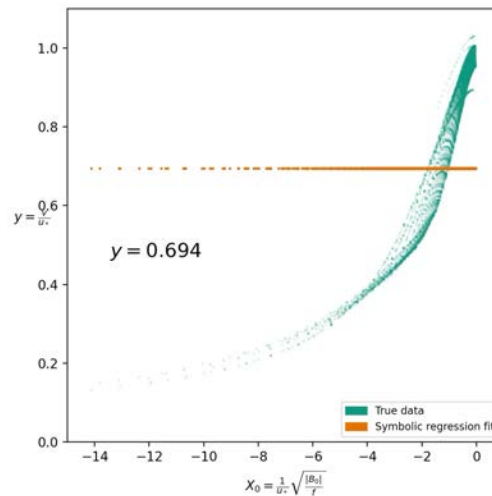
$$x = \left(\frac{1}{u_*}\right) \sqrt{\frac{|B|}{f}}$$

B : Surface buoyancy flux
 u_* : Surface friction velocity
 f : Coriolis parameter

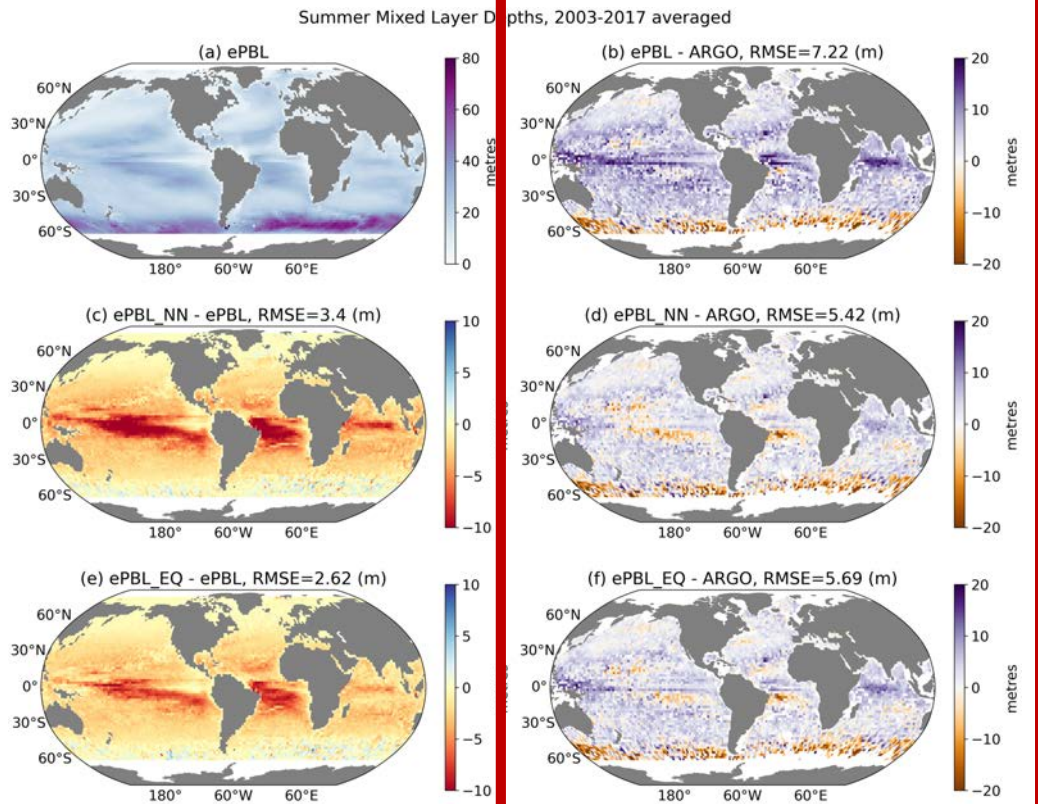
Stable:
$$\frac{v}{u_*} = -\frac{0.1448}{x - 1.12 + \frac{0.476}{x - 0.6}} + c_0$$

Unstable:
$$\frac{v}{u_*} = -\frac{0.1x\sqrt{\frac{f}{\Omega}}}{1 + \frac{(45 e^{-\frac{f}{\Omega}} + 3.29)u^2 f}{B}} + c_1$$

$$\kappa = g(\sigma) \cdot h \cdot v$$



JRA forced results (MOM6, $\frac{1}{4}^\circ$ grid, OM4): Summer Mixed Layer Depth



Baseline control scheme

ePBL enhanced with neural network
(Sane et al. 2023)

ePBL enhanced with discovered equations

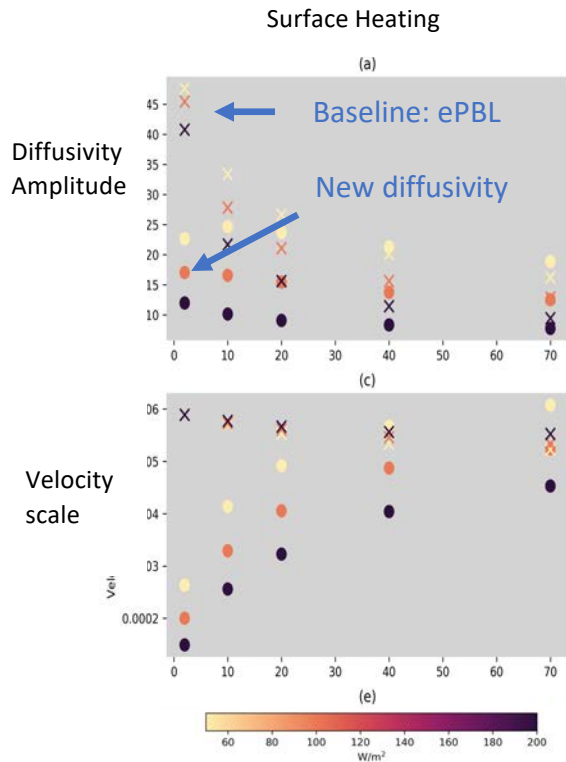
What was deficient in baseline scheme? → cause of MLD bias?

Baseline ePBL:

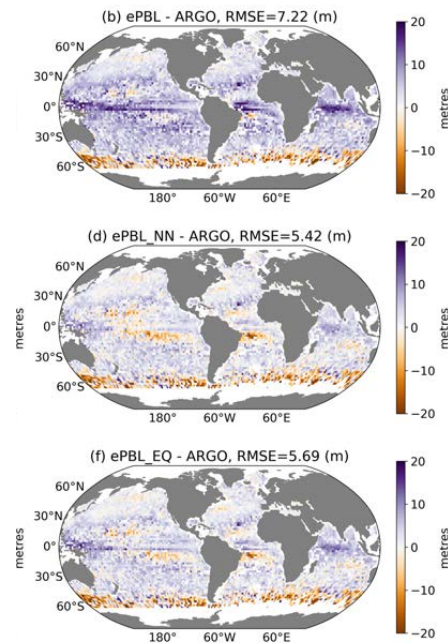
$$v_0 \rightarrow u_*$$

New diffusivity for ePBL:

$$v_0 \rightarrow u_*, B$$



Summer MLD bias



Concluding remarks:

1. Complexity in higher order schemes can be captured and brought into first order closures to assess impacts on longer timescale simulations.
2. NN reduces some biases in ocean only experiments.
3. Equations that replace NNs and approximate second moment closures reduce biases at a much lower cost.
4. Conservation laws satisfied due to predicting fluxes.
5. Enhanced diffusivity (from GLS) has lower amplitude for surface heating conditions – most likely cause of summer MLD improvements.

Thank You

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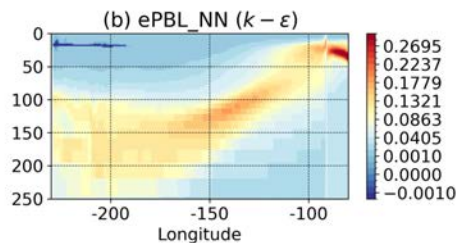
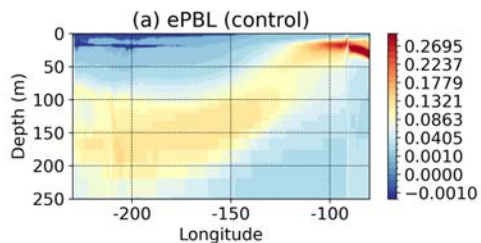
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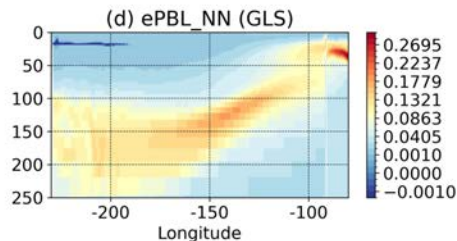
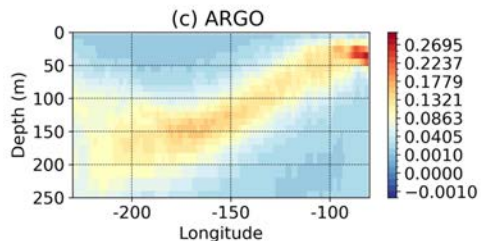
JRA forced results (MOM6, $\frac{1}{4}^\circ$ grid, OM4): Pacific Equator Vertical Transect

$\partial T / \partial z$ ($^\circ\text{C}/\text{m}$) at Equator, 2003-2017 averaged

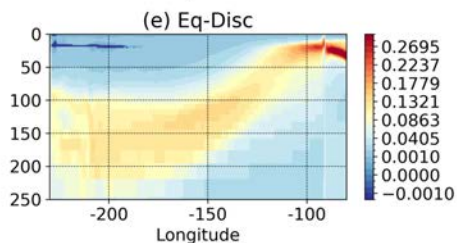
control



ARGO

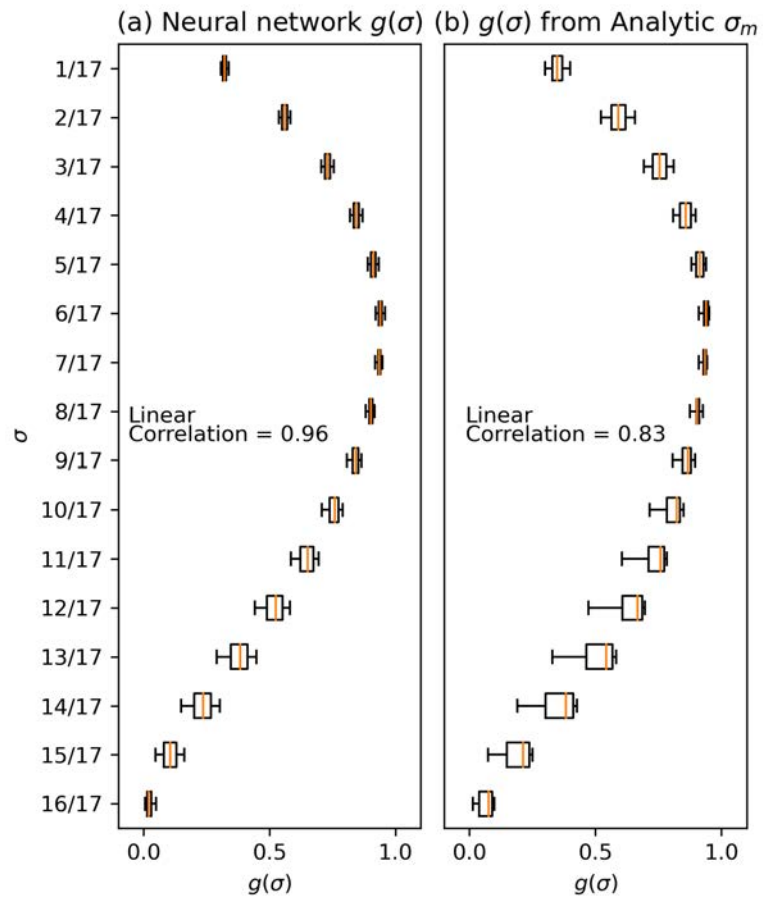


ePBL + Neural networks (Sane et al. 2023)

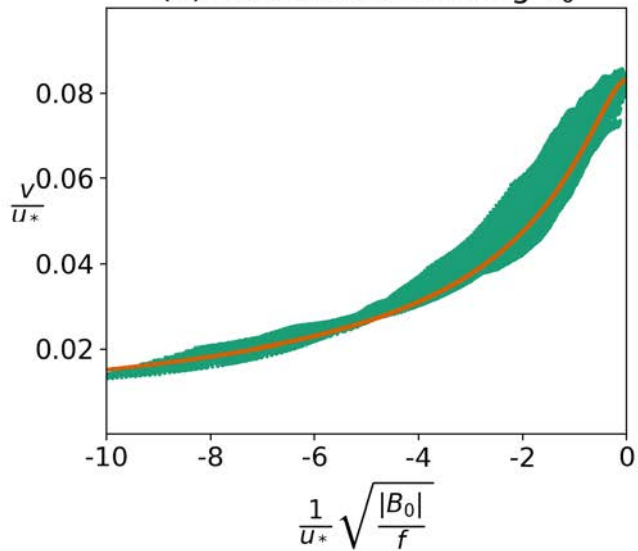


ePBL + discovered equations
(work in progress)

Shape function accuracy:



(a) Surface stabilizing v_0



(b) Surface destabilizing v_0

