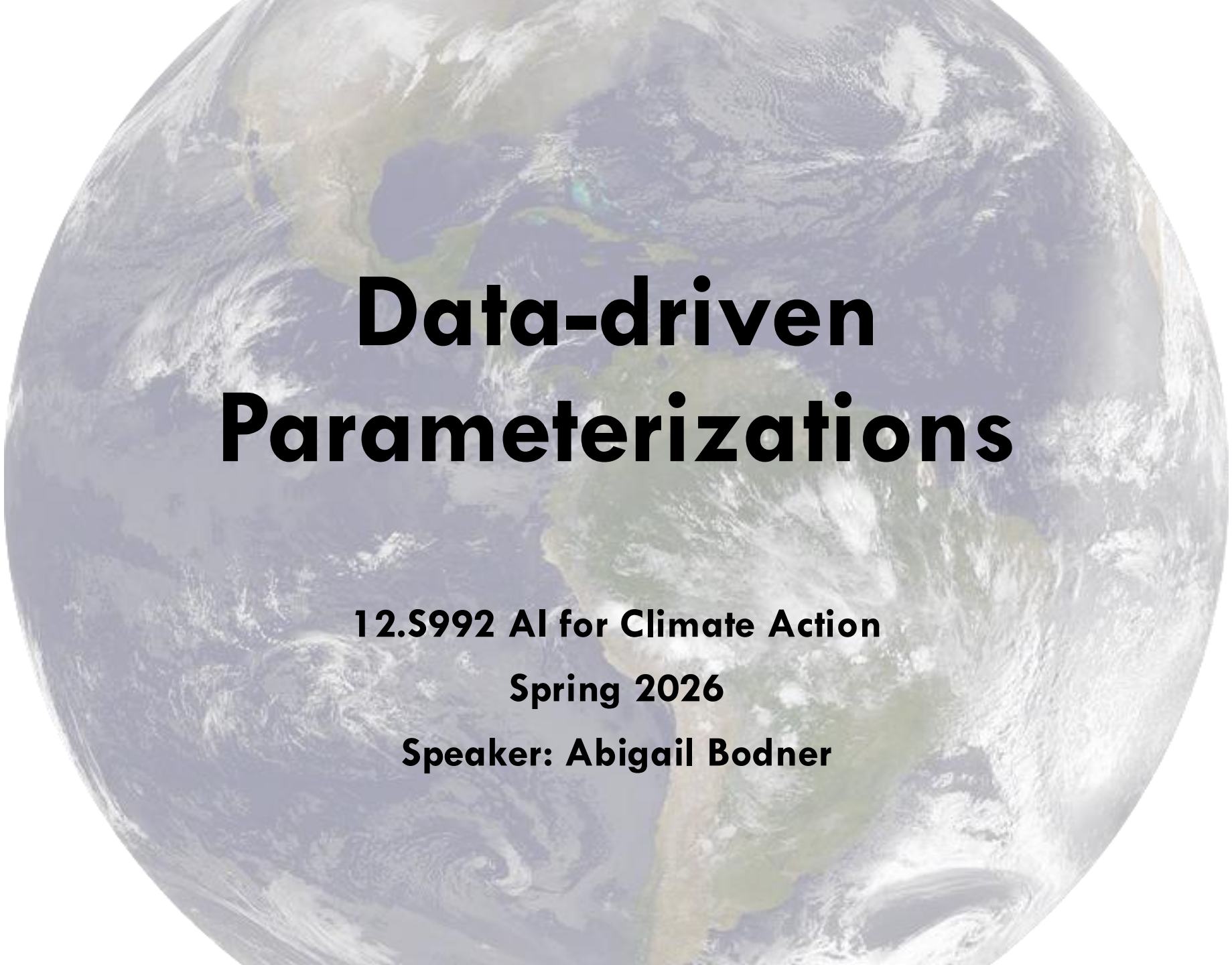
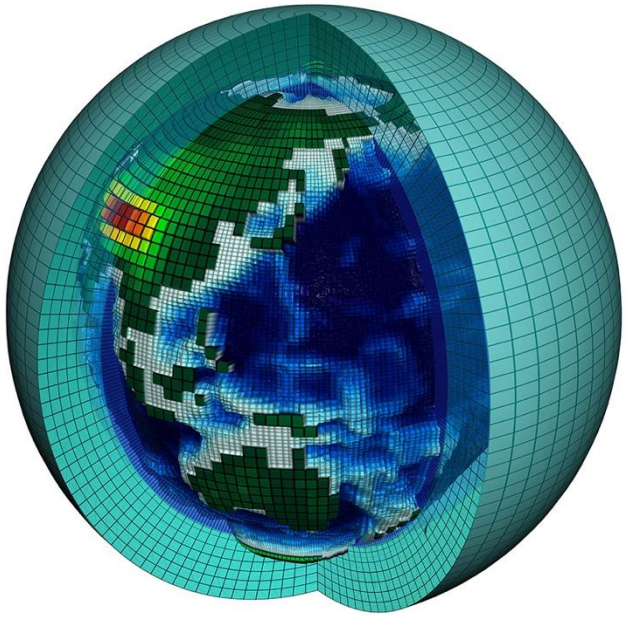


Data-driven Parameterizations

12.S992 AI for Climate Action

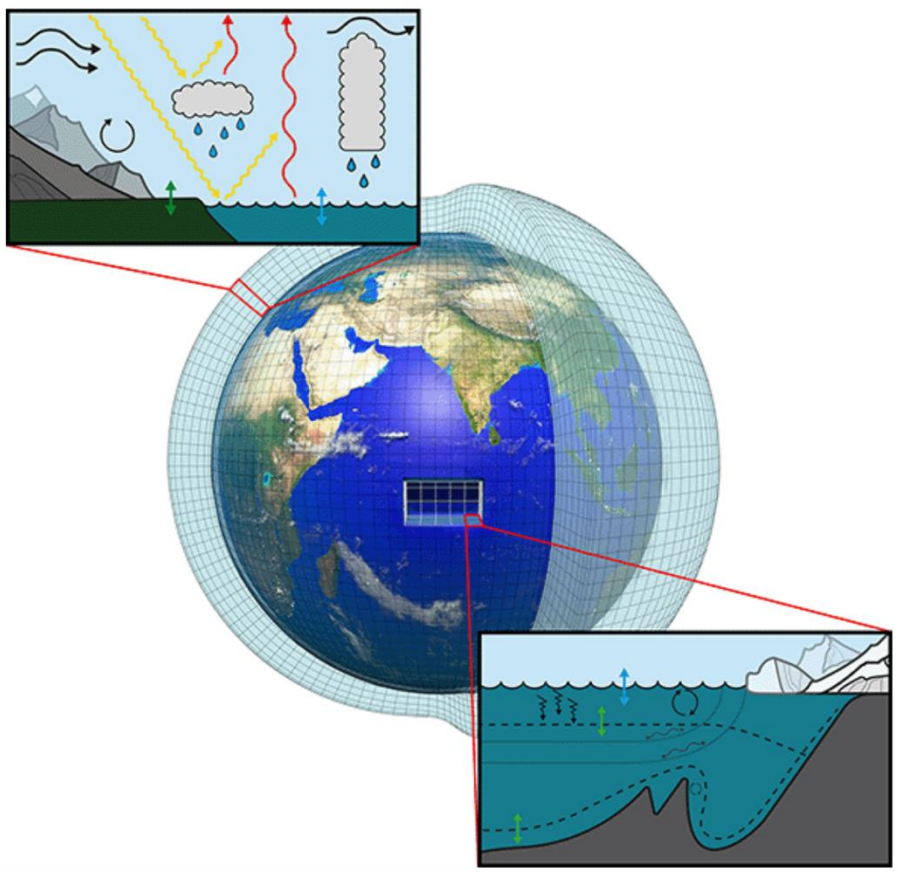
Spring 2026

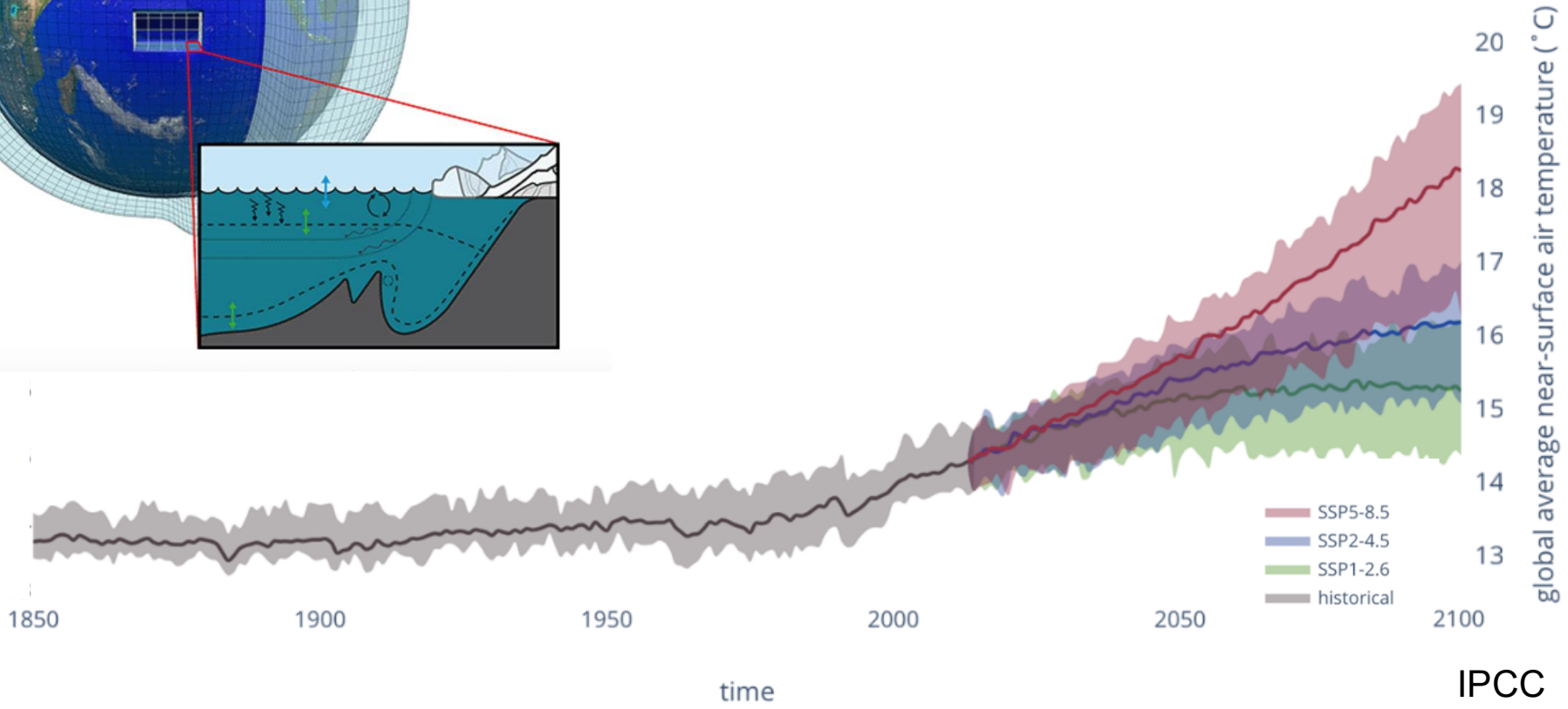
Speaker: Abigail Bodner



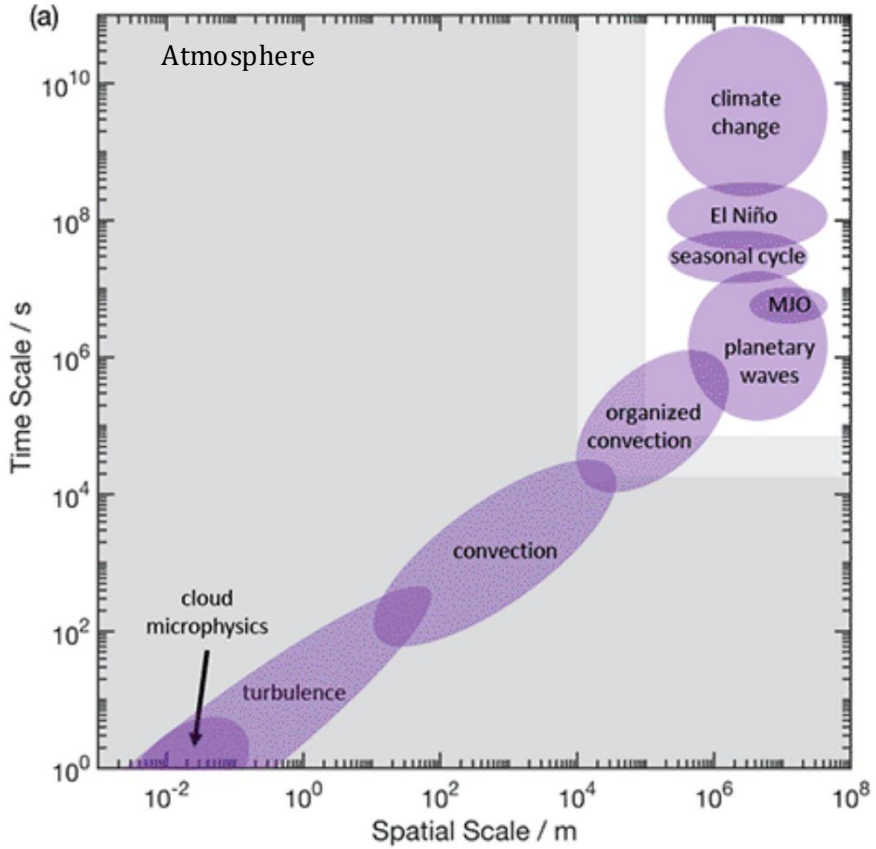
General Circulation Model

Global Climate Change

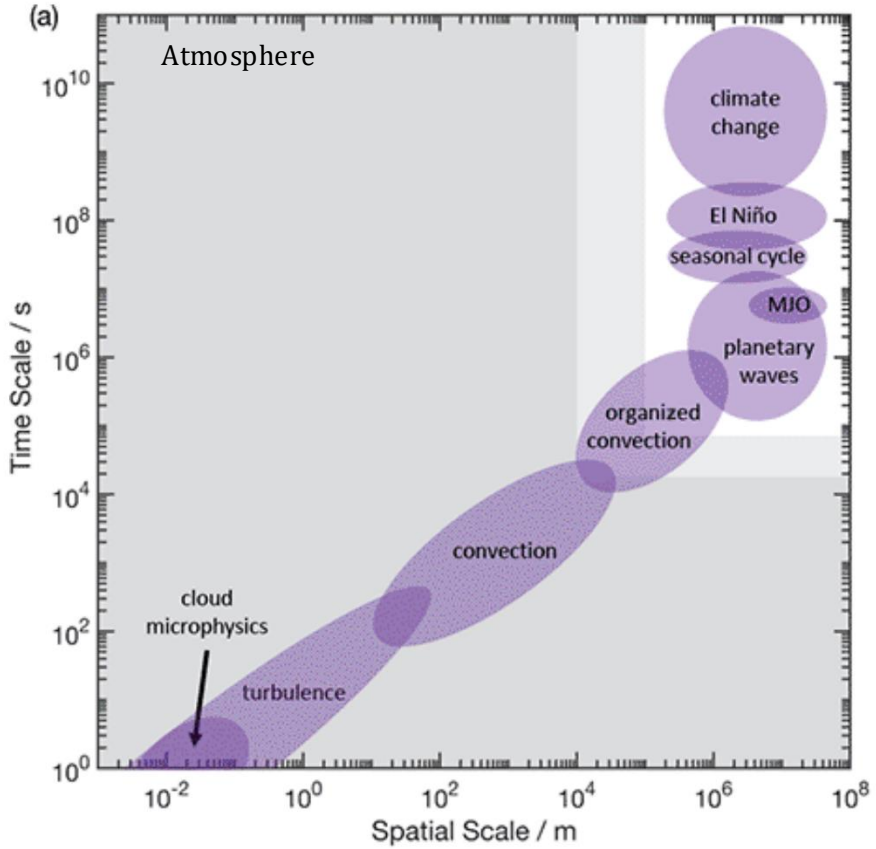


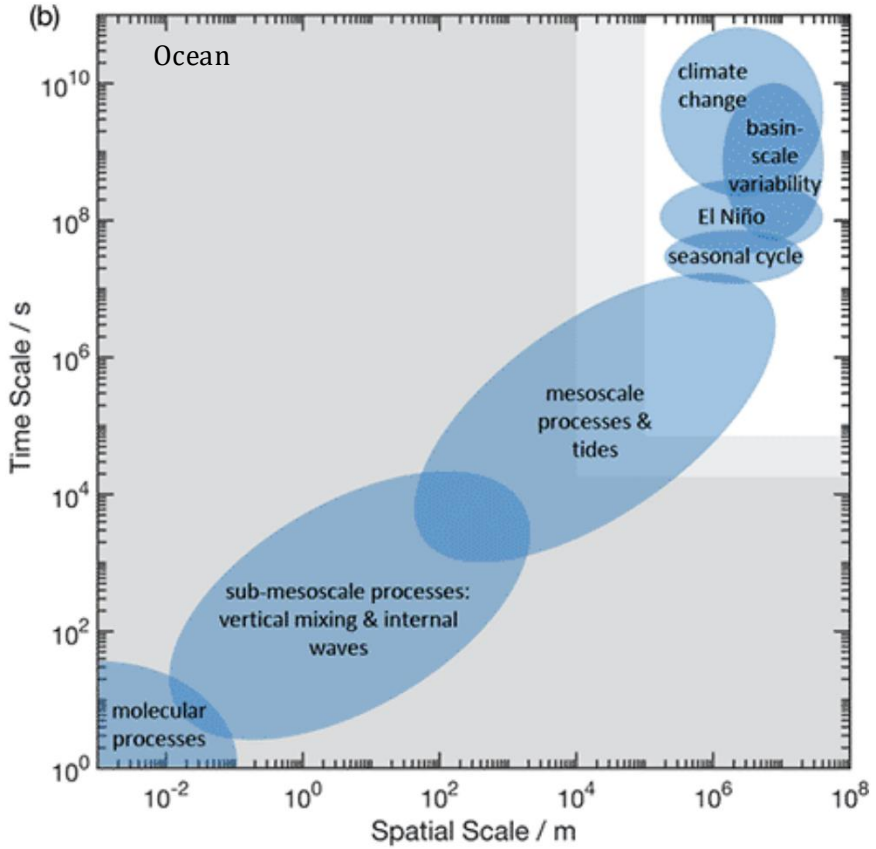


IPCC



Christensen & Zanna (2022)





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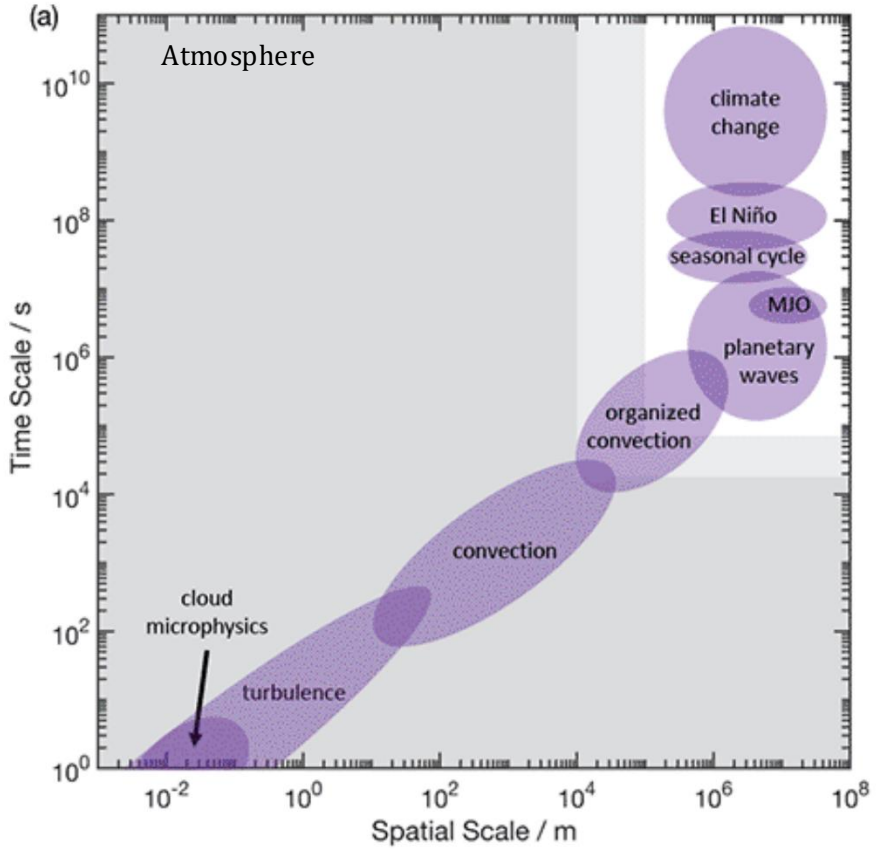
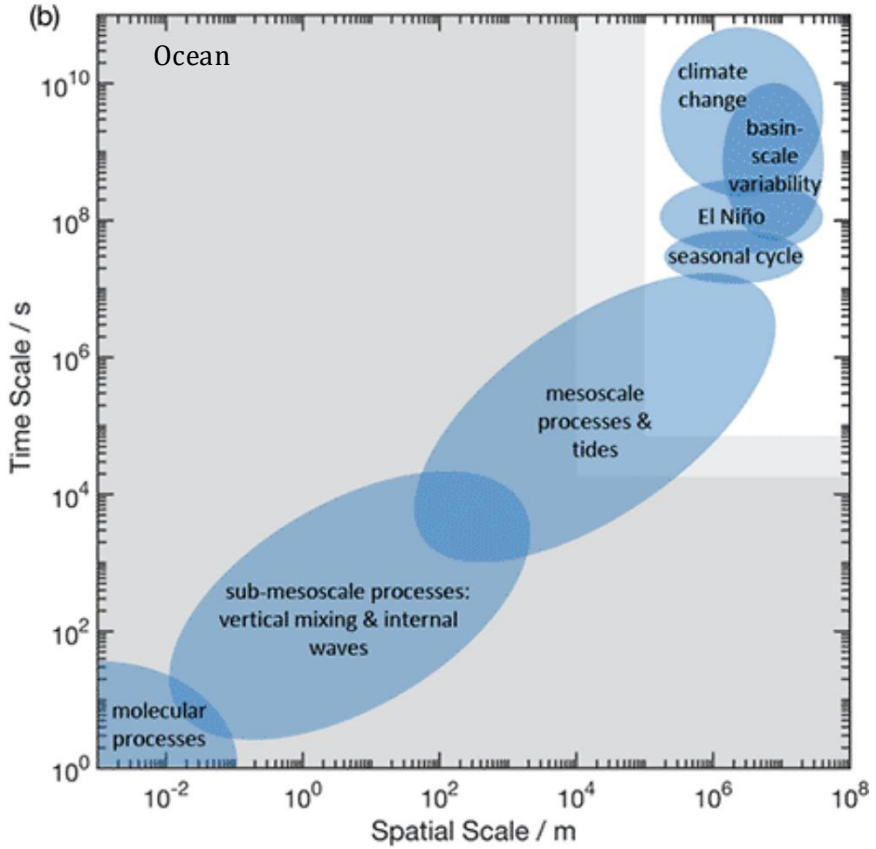
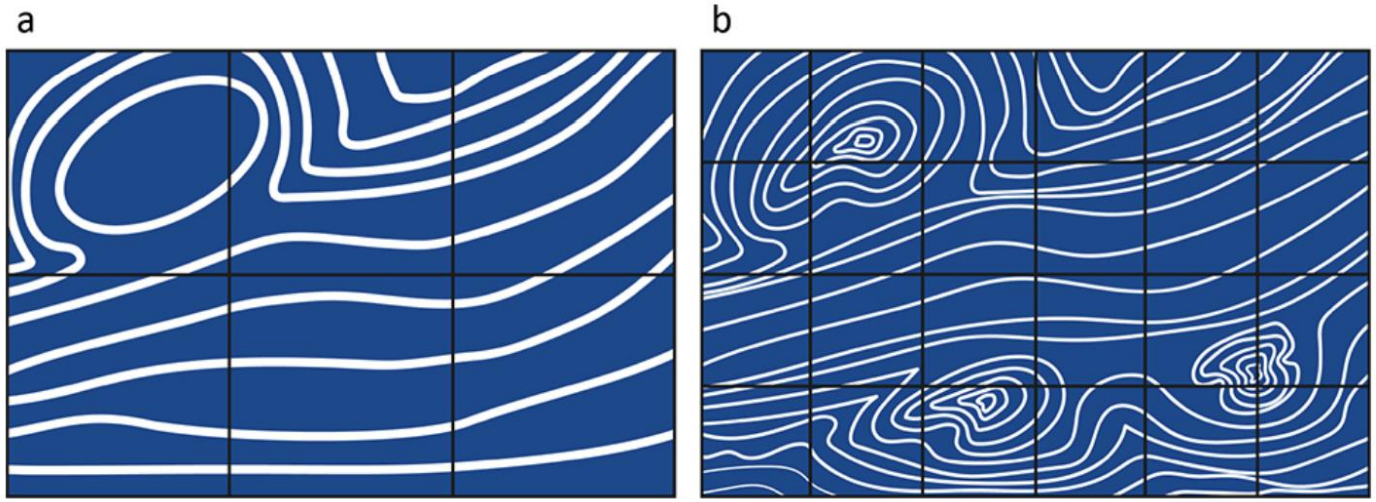
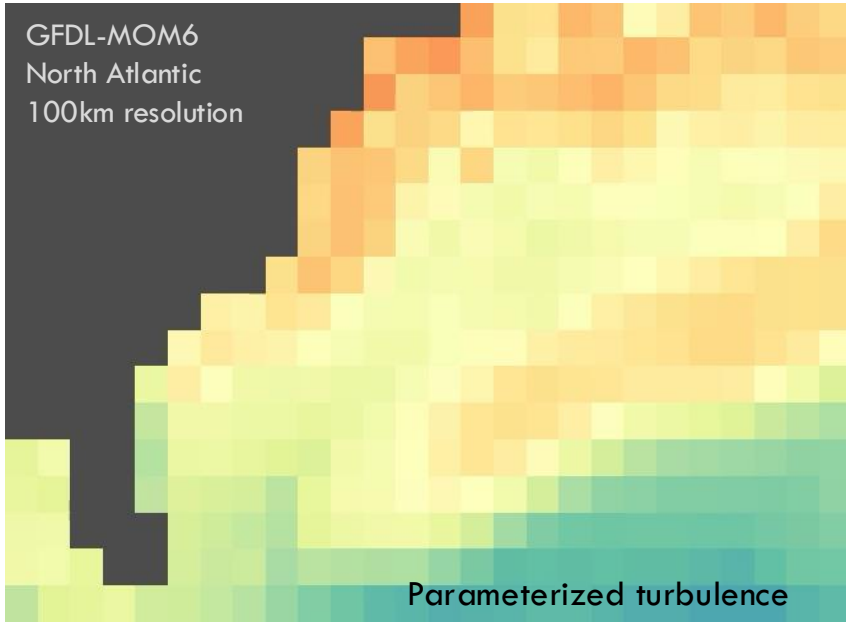


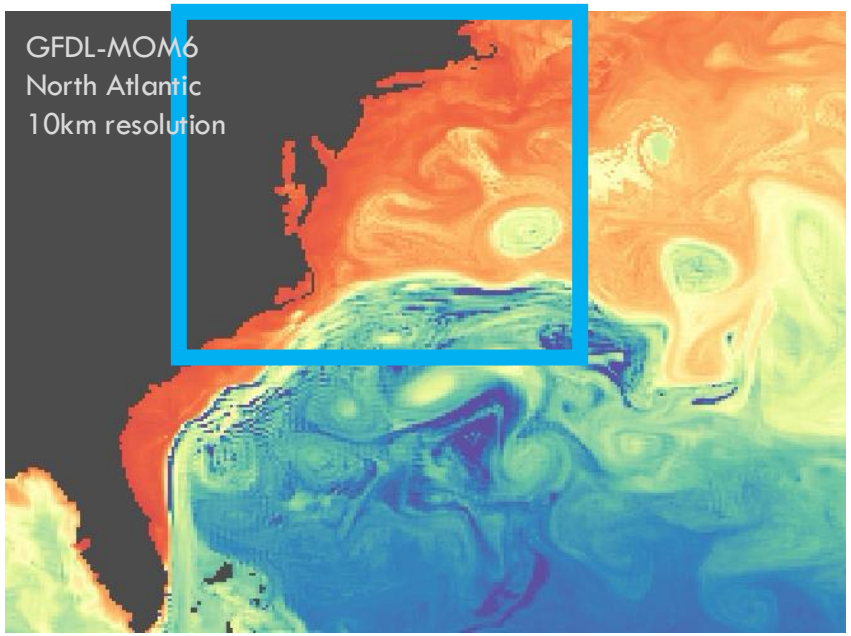




Christensen & Zanna (2022)

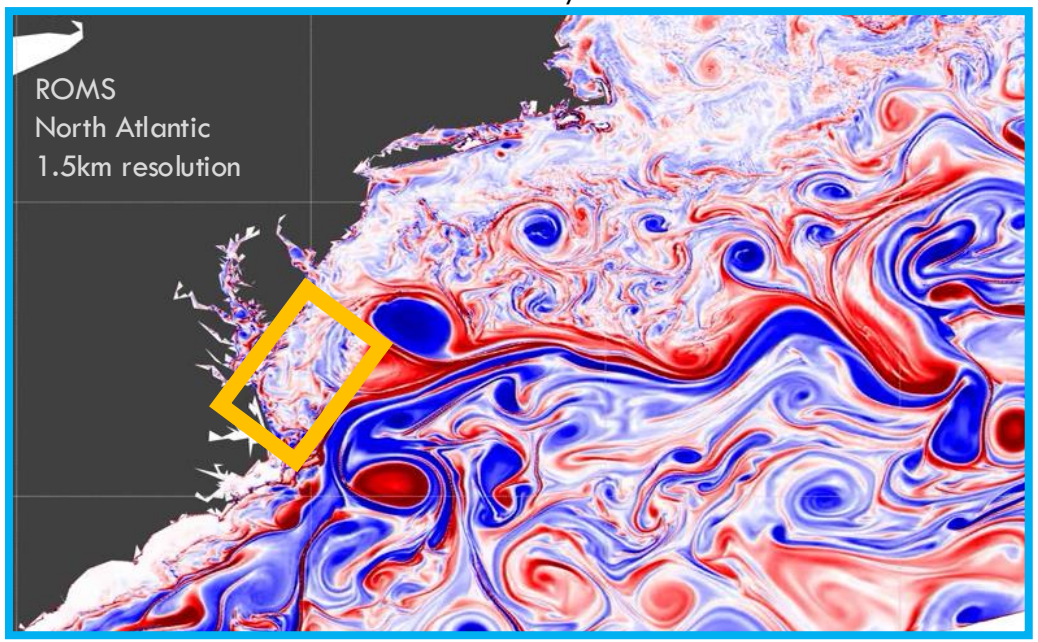
Sea surface Temperature

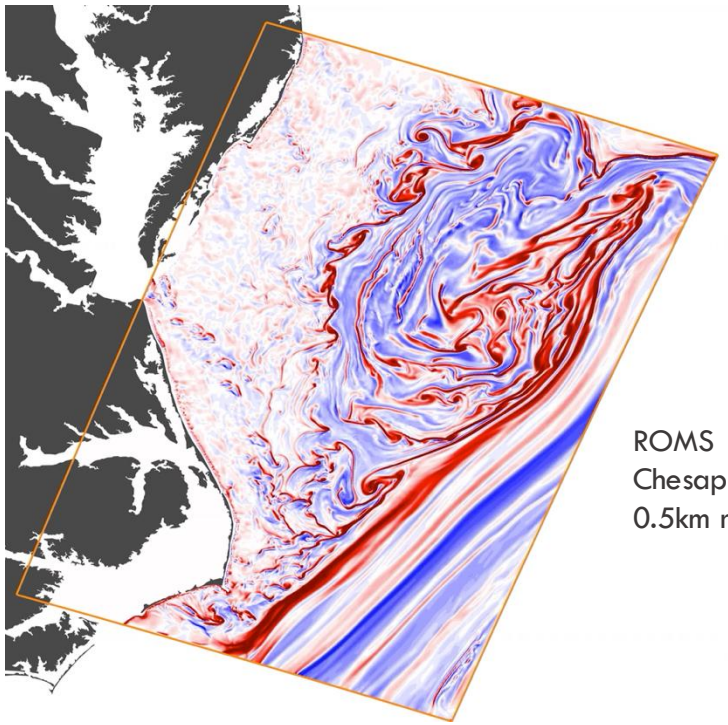




Courtesy of Julius Busecke

Vorticity





Courtesy of Jacob Wenegrat

Reynolds averaging: resolved and unresolved processes

$$\frac{Du}{Dt} = \frac{\partial u}{\partial t} + u\frac{\partial u}{\partial x} + v\frac{\partial u}{\partial y} + w\frac{\partial u}{\partial z} = -\frac{1}{\rho_0}\frac{\partial p}{\partial x} + fv$$

$$\frac{Dv}{Dt} = \frac{\partial v}{\partial t} + u\frac{\partial v}{\partial x} + v\frac{\partial v}{\partial y} + w\frac{\partial v}{\partial z} = -\frac{1}{\rho_0}\frac{\partial p}{\partial y} + fu.$$

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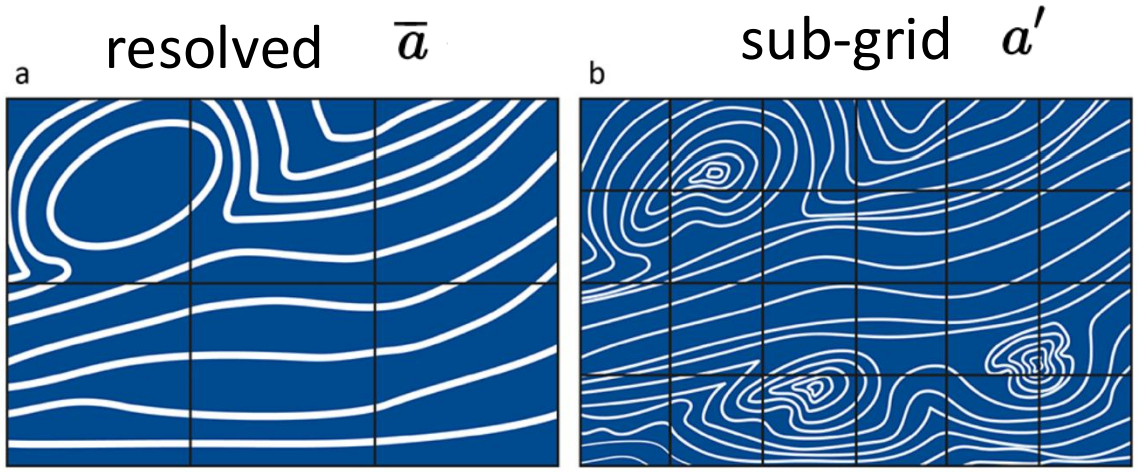
$$a = \overline{a} + a',$$

$$\overline{a'} = 0,$$

$$ab = \overline{ab} + \overline{a'b'}.$$



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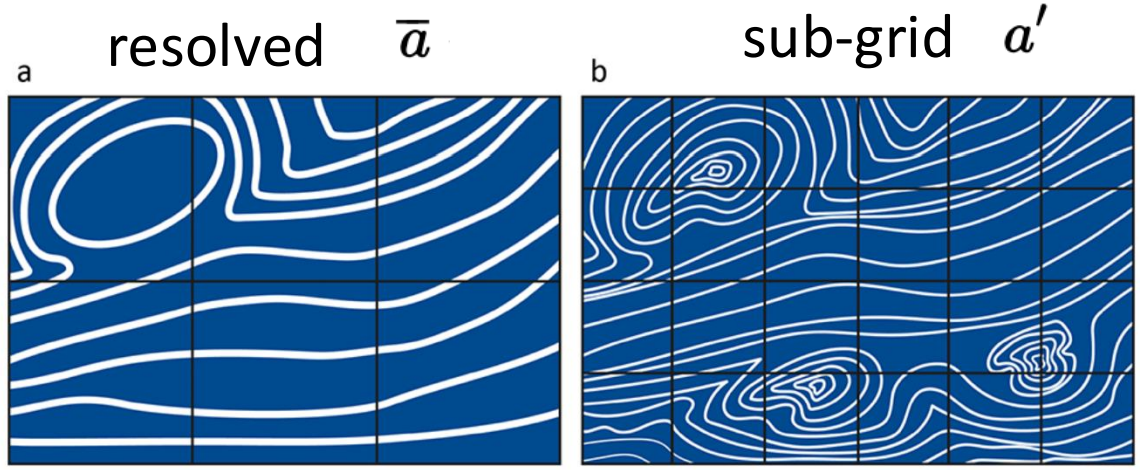

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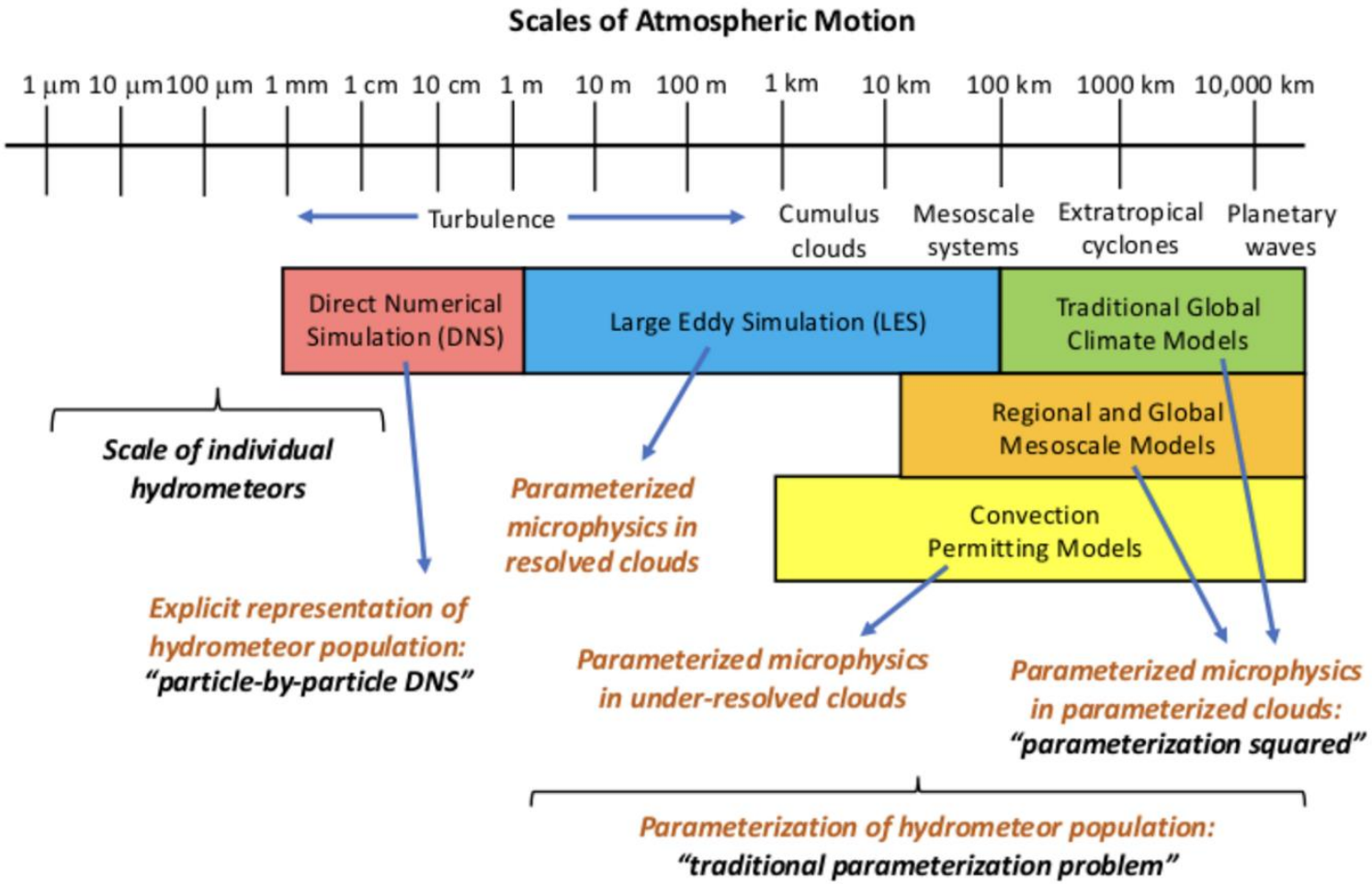
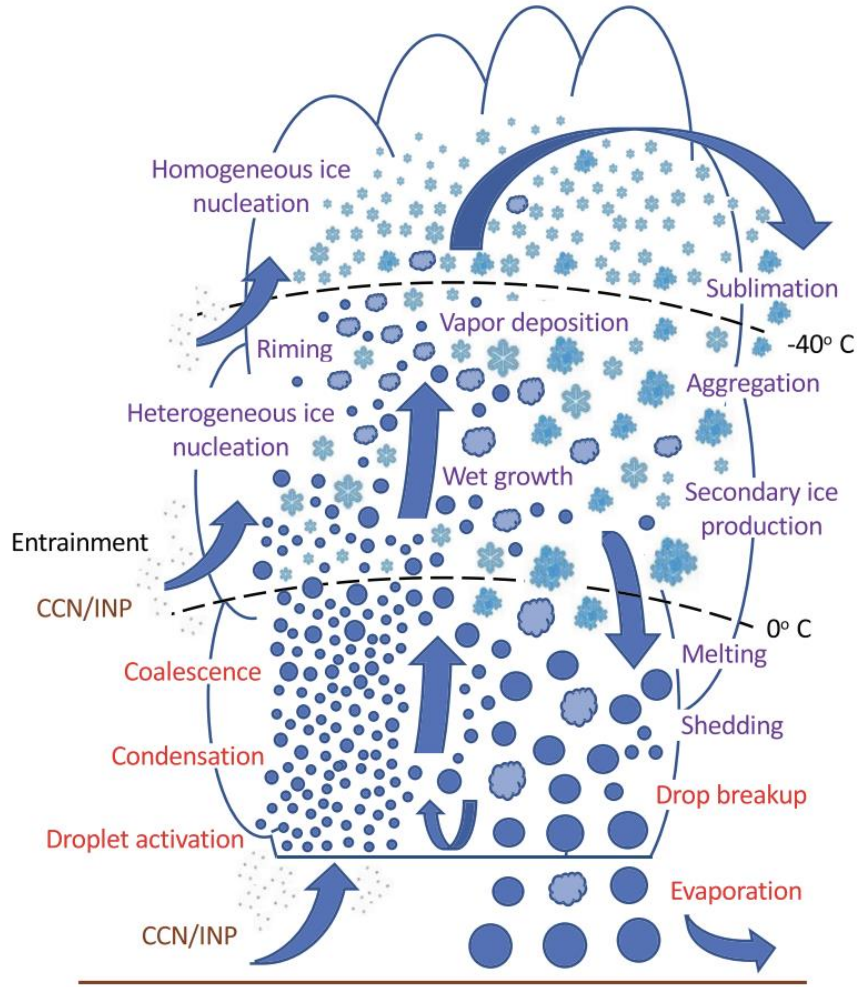
$$\frac{\overline{D}\overline{u}}{Dt} = -\frac{1}{\rho}\frac{\partial \overline{\rho}}{\partial x} + f\overline{v} - \left[\frac{\partial(\overline{u'u'})}{\partial x} + \frac{\partial(\overline{u'v'})}{\partial y} + \frac{\partial(\overline{u'w'})}{\partial z}\right] = -\frac{1}{\rho_0}\frac{\partial \overline{\rho}}{\partial x} + f\overline{v} - S_x$$

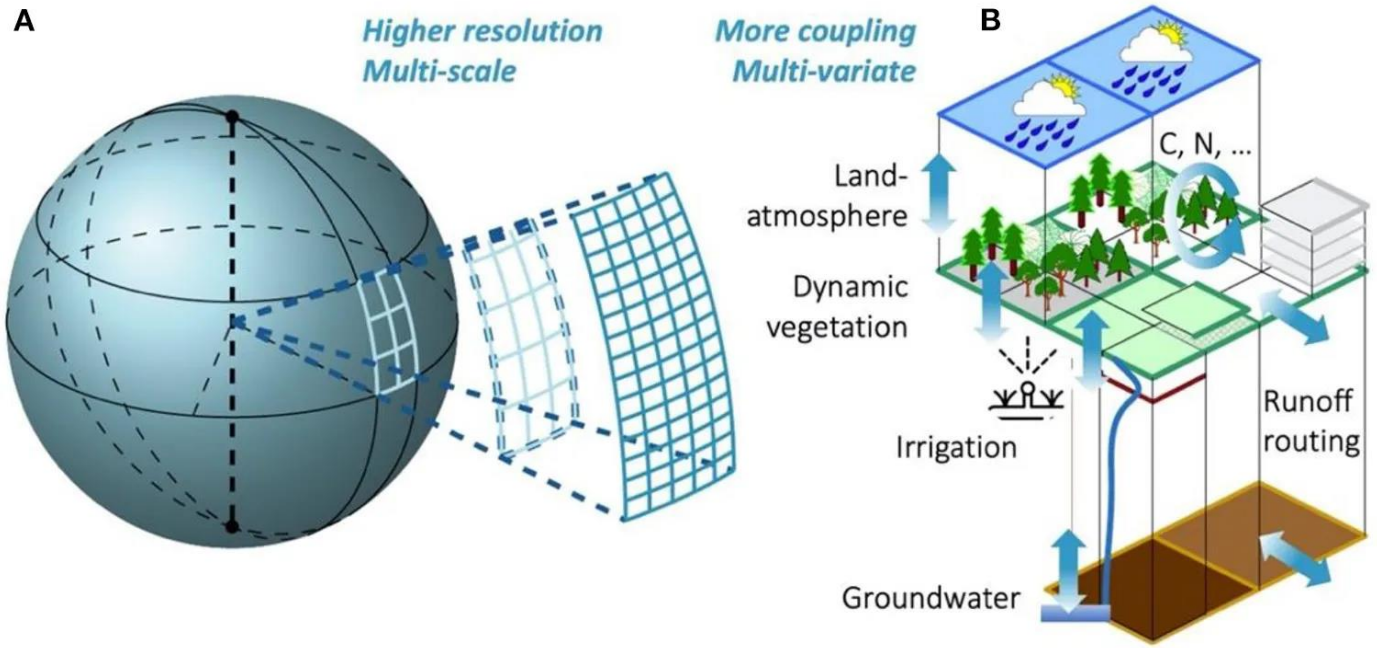
Parameterizations

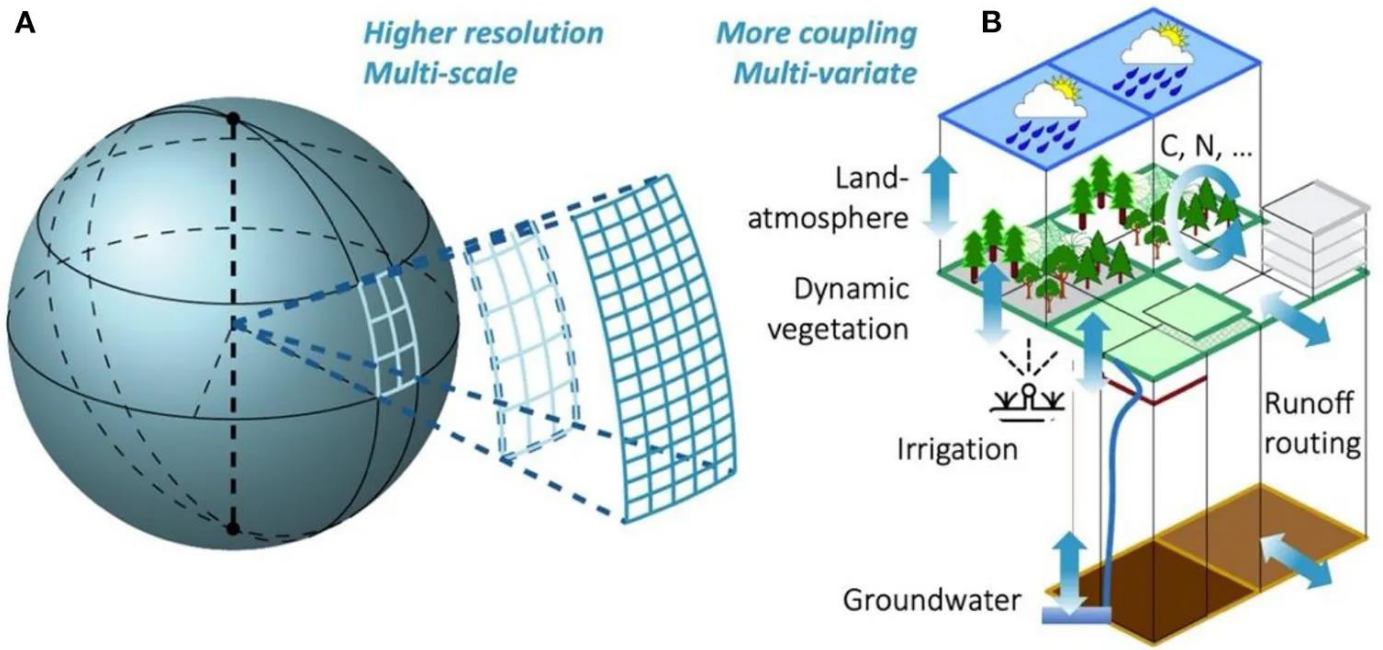
$$\frac{\overline{D}\overline{v}}{Dt} = -\frac{1}{\rho}\frac{\partial \overline{\rho}}{\partial x} + f\overline{u} - \left[\frac{\partial(\overline{u'v'})}{\partial x} + \frac{\partial(\overline{v'v'})}{\partial y} + \frac{\partial(\overline{v'w'})}{\partial z}\right] = -\frac{1}{\rho_0}\frac{\partial \overline{\rho}}{\partial x} + f\overline{u} - S_y,$$





Morrison et al 2020


A
Higher resolution
Multi-scale
More coupling
Multi-variate
B
C, N, ...
Land-
atmosphere
Dynamic
vegetation
Irrigation
Runoff
routing
Groundwater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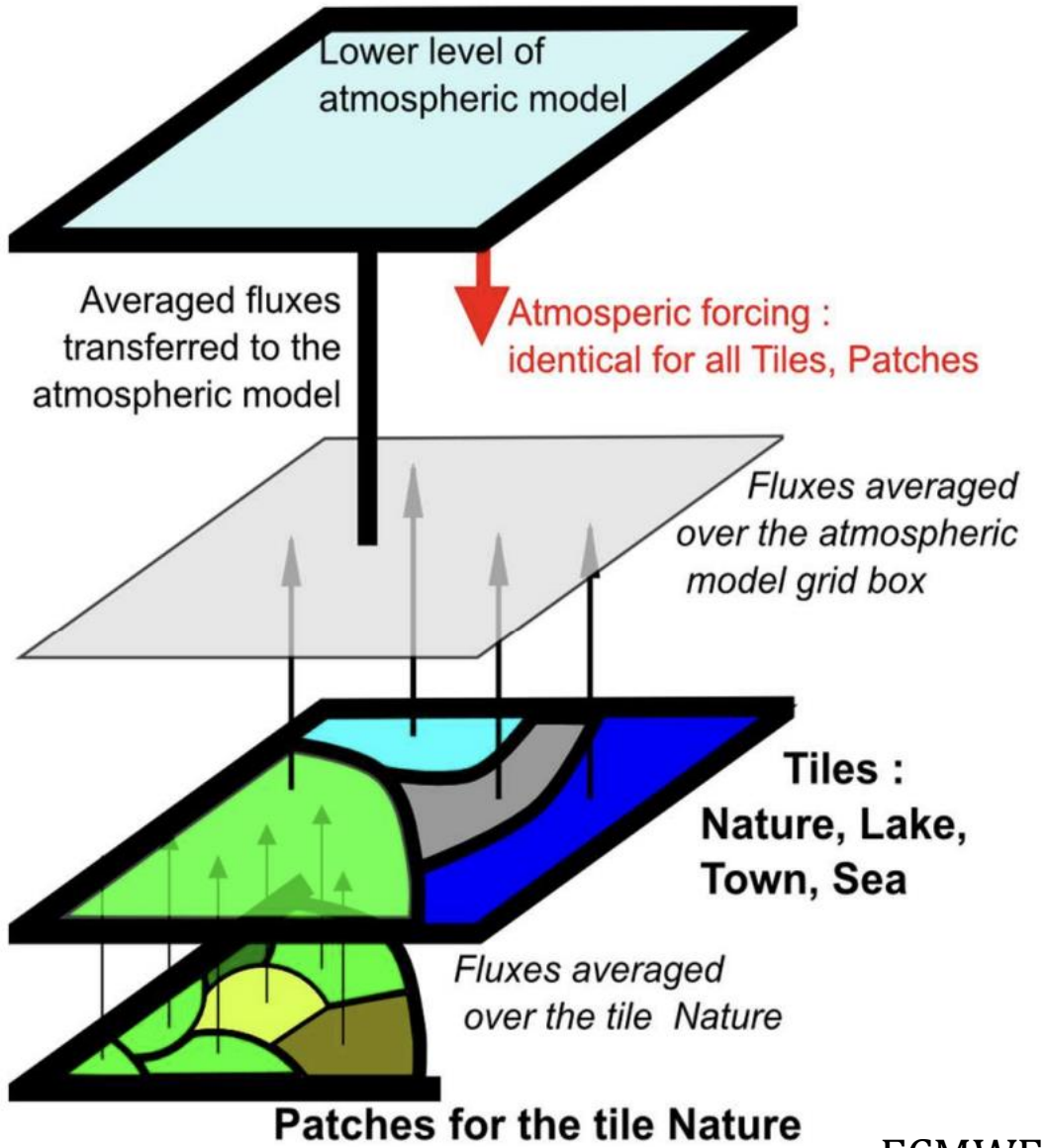
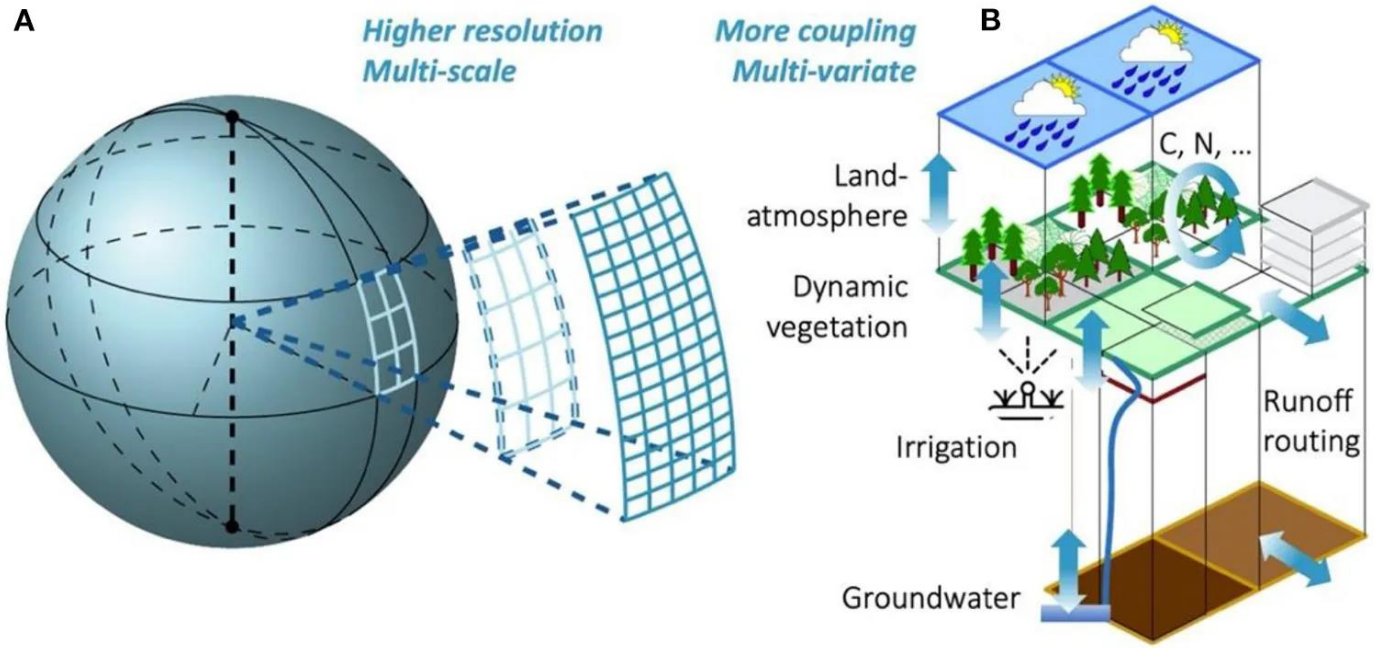
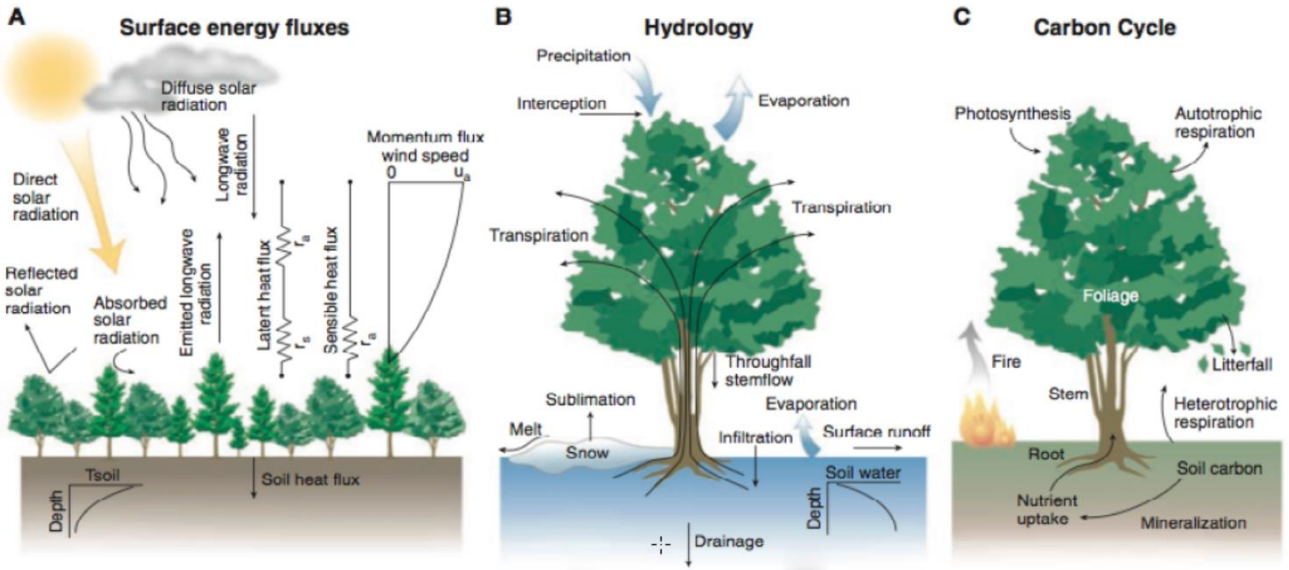
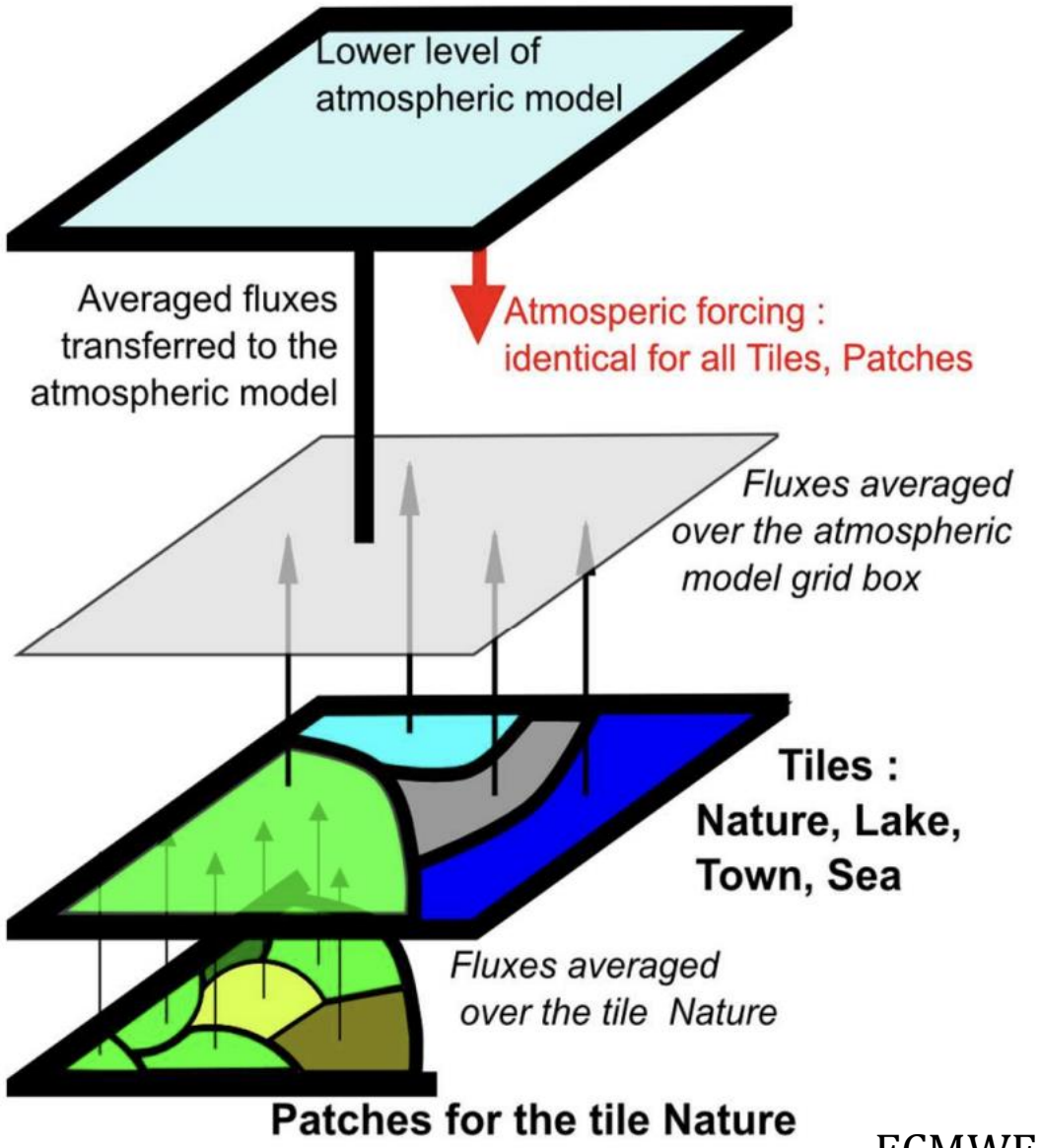

Lower level of
atmospheric model
Averaged fluxes
transferred to the
atmospheric model
Atmosperic forcing :
identical for all Tiles, Patches
Fluxes averaged
over the atmospheric
model grid box
Tiles :
Nature, Lake,
Town, Sea
Fluxes averaged
over the tile Nature
Patches for the tile Nature

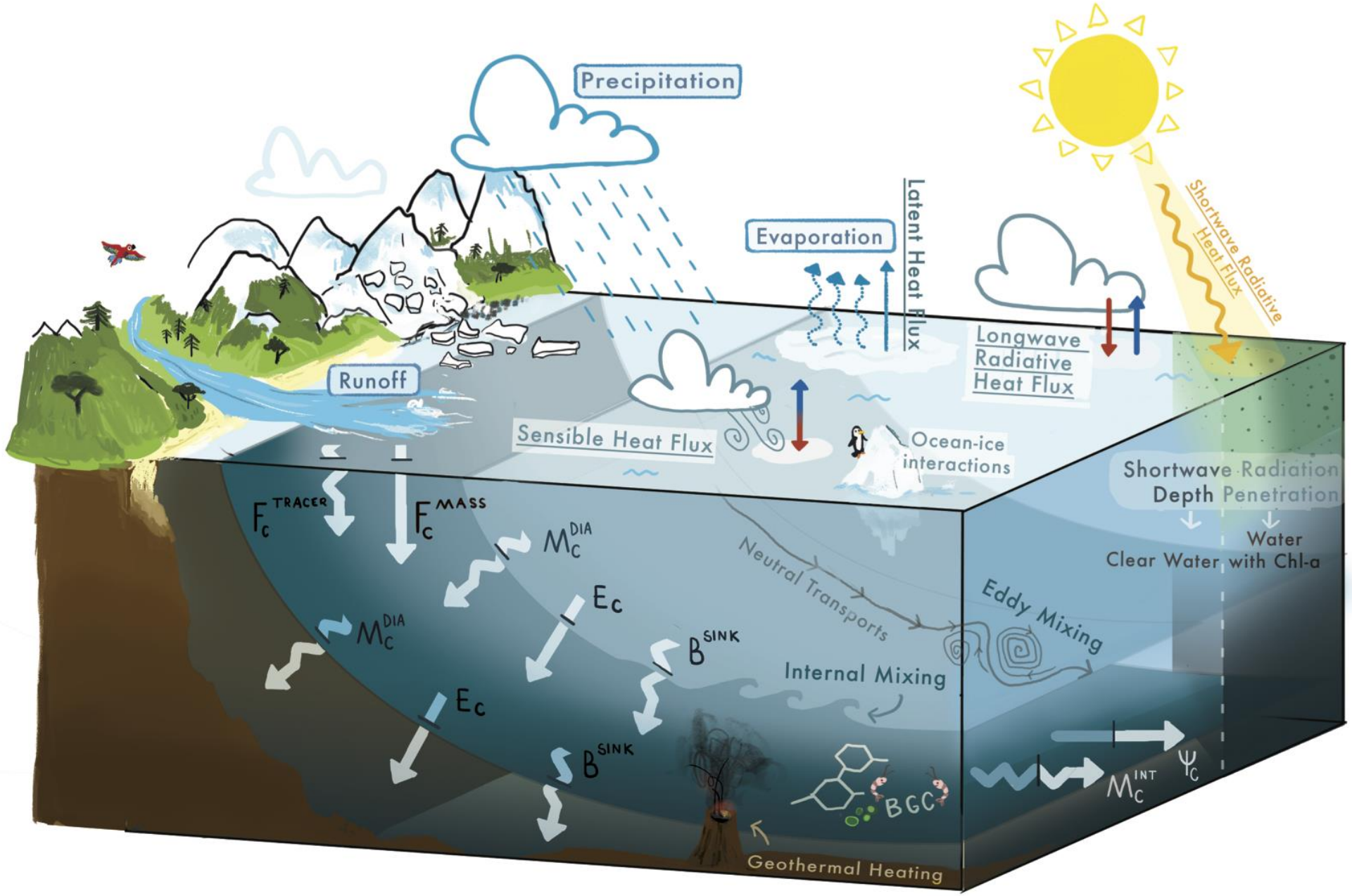
ECMWF



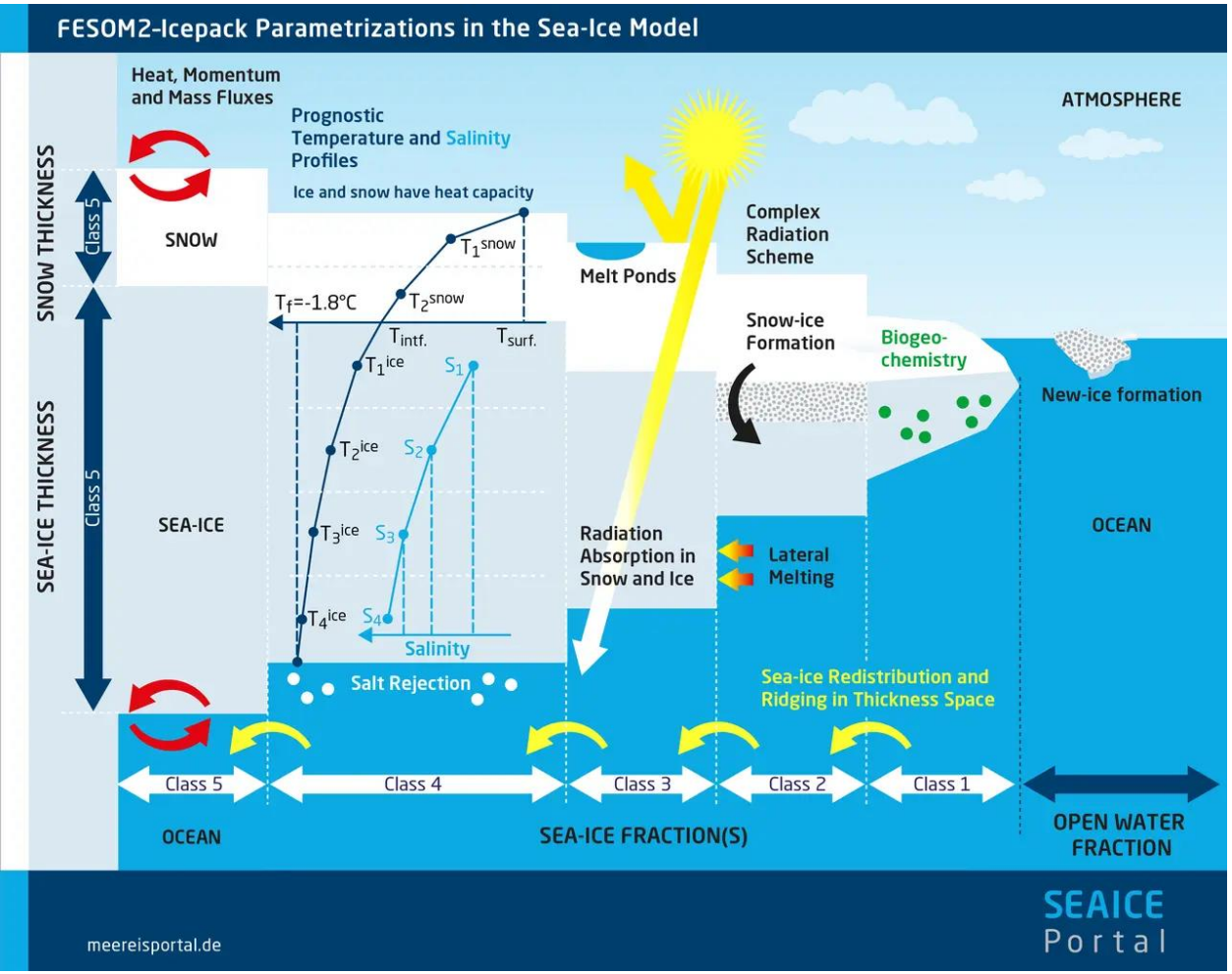


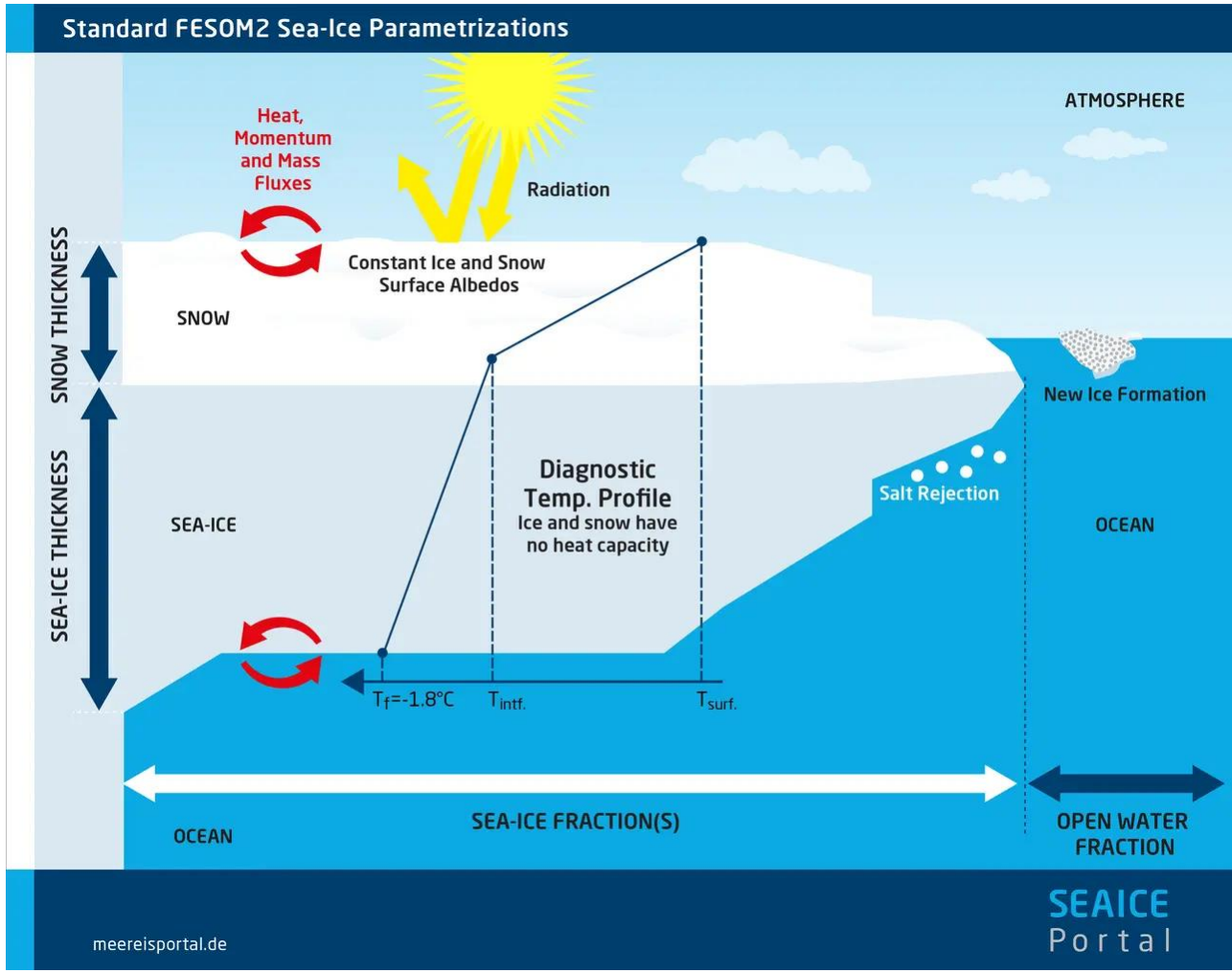
Taken from Bonan (2008) : Fundamental mechanisms of interactions between terrestrial vegetation and climate.





Groeskamp et al (2019) vis Stephen Griffies personal webpage


FESOM2-Icepack Parametrizations in the Sea-Ice Model
Heat, Momentum and Mass Fluxes
Prognostic Temperature and Salinity Profiles
Ice and snow have heat capacity
ATMOSPHERE
SNOW THICKNESS
Class 5
SNOW
SEA-ICE THICKNESS
Class 5
SEA-ICE
T_1^{snow}
T_f=-1.8°C
T_2^{snow}
$T_{intf.}$
$T_{surf.}$
T_1^{ice}
S_1
T_2^{ice}
S_2
T_3^{ice}
S_3
T_4^{ice}
S_4
Salinity
Salt Rejection
Melt Ponds
Complex Radiation Scheme
Snow-ice Formation
Biogeo-chemistry
New-ice formation
OCEAN
Radiation Absorption in Snow and Ice
Lateral Melting
Sea-ice Redistribution and Ridging in Thickness Space
Class 5
Class 4
Class 3
Class 2
Class 1
OCEAN
SEA-ICE FRACTION(S)
OPEN WATER FRACTION
meereisportal.de
SEAICE Portal


Standard FESOM2 Sea-Ice Parametrizations
Heat, Momentum and Mass Fluxes
Radiation
ATMOSPHERE
Constant Ice and Snow Surface Albedos
SNOW THICKNESS
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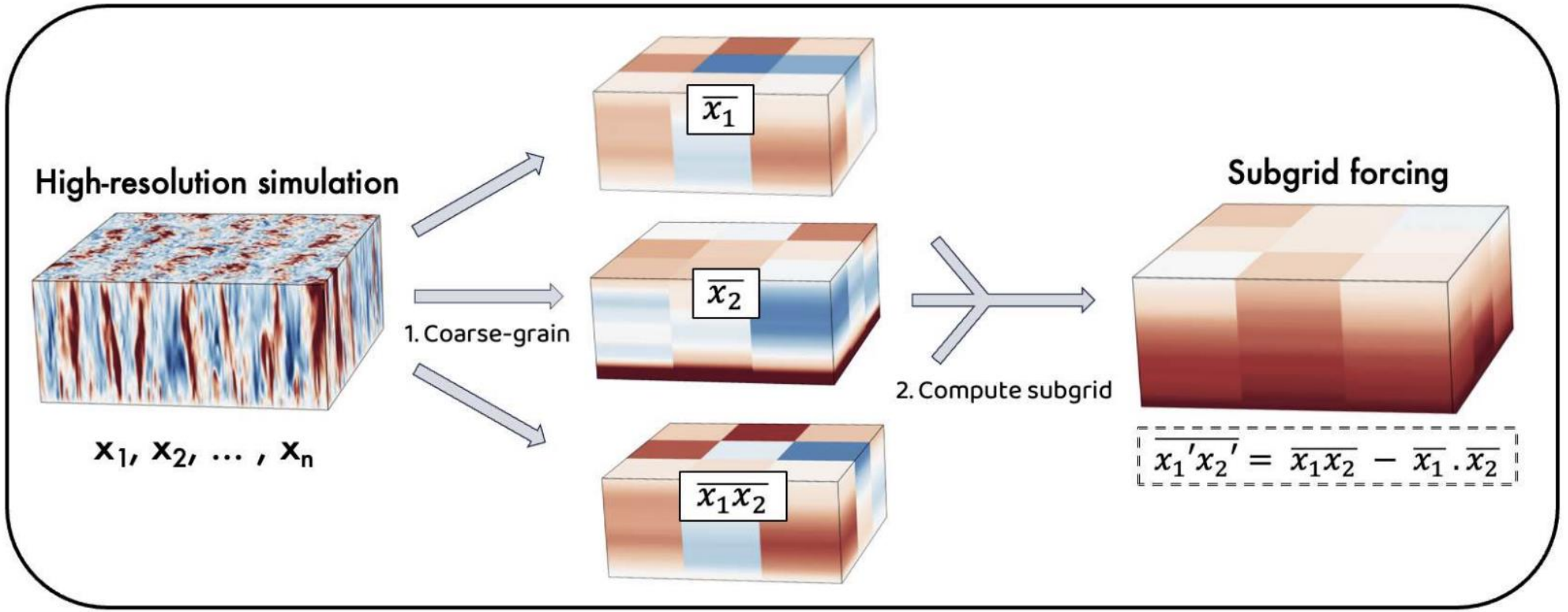
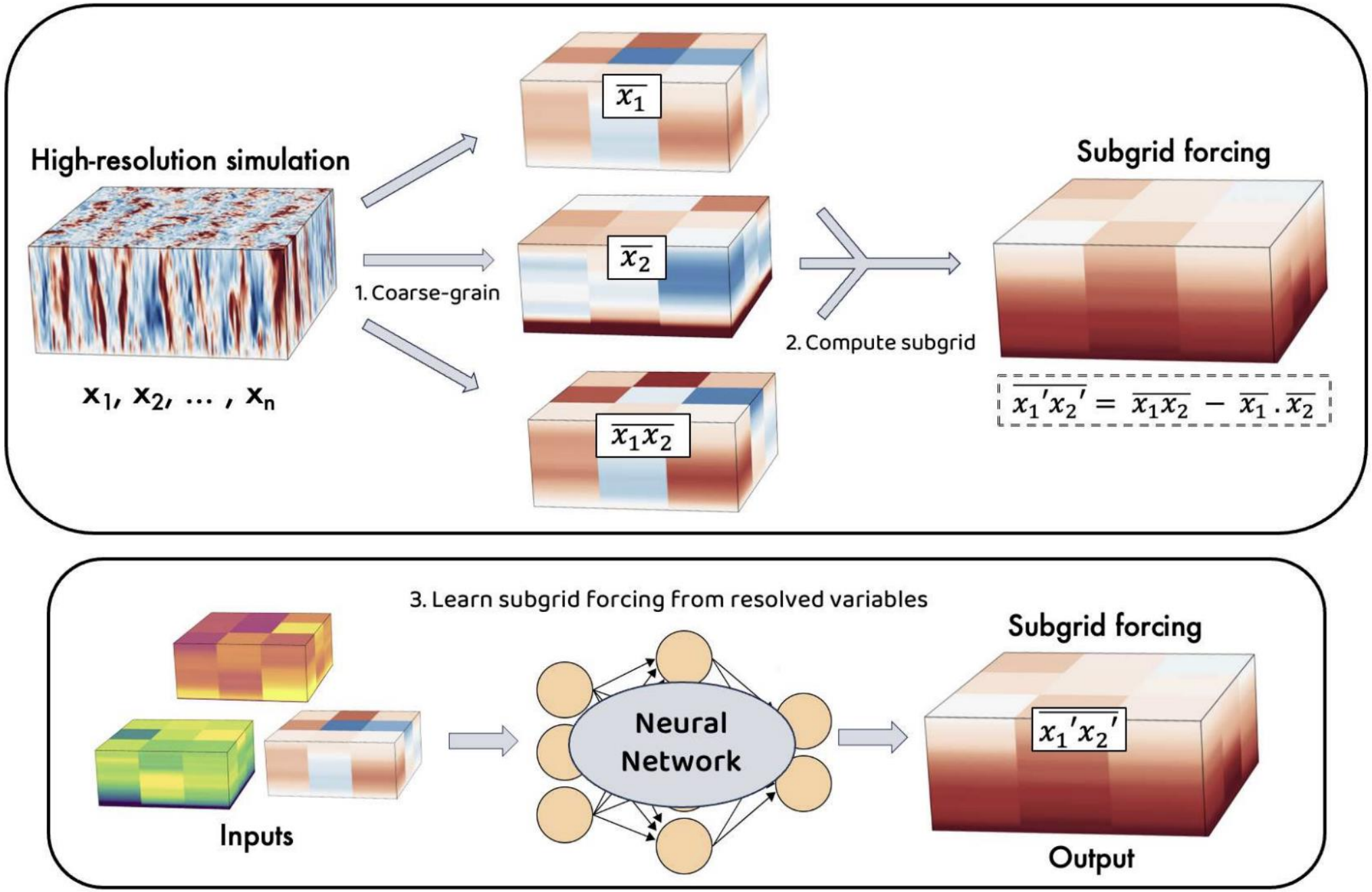


Zanna et al (2025)



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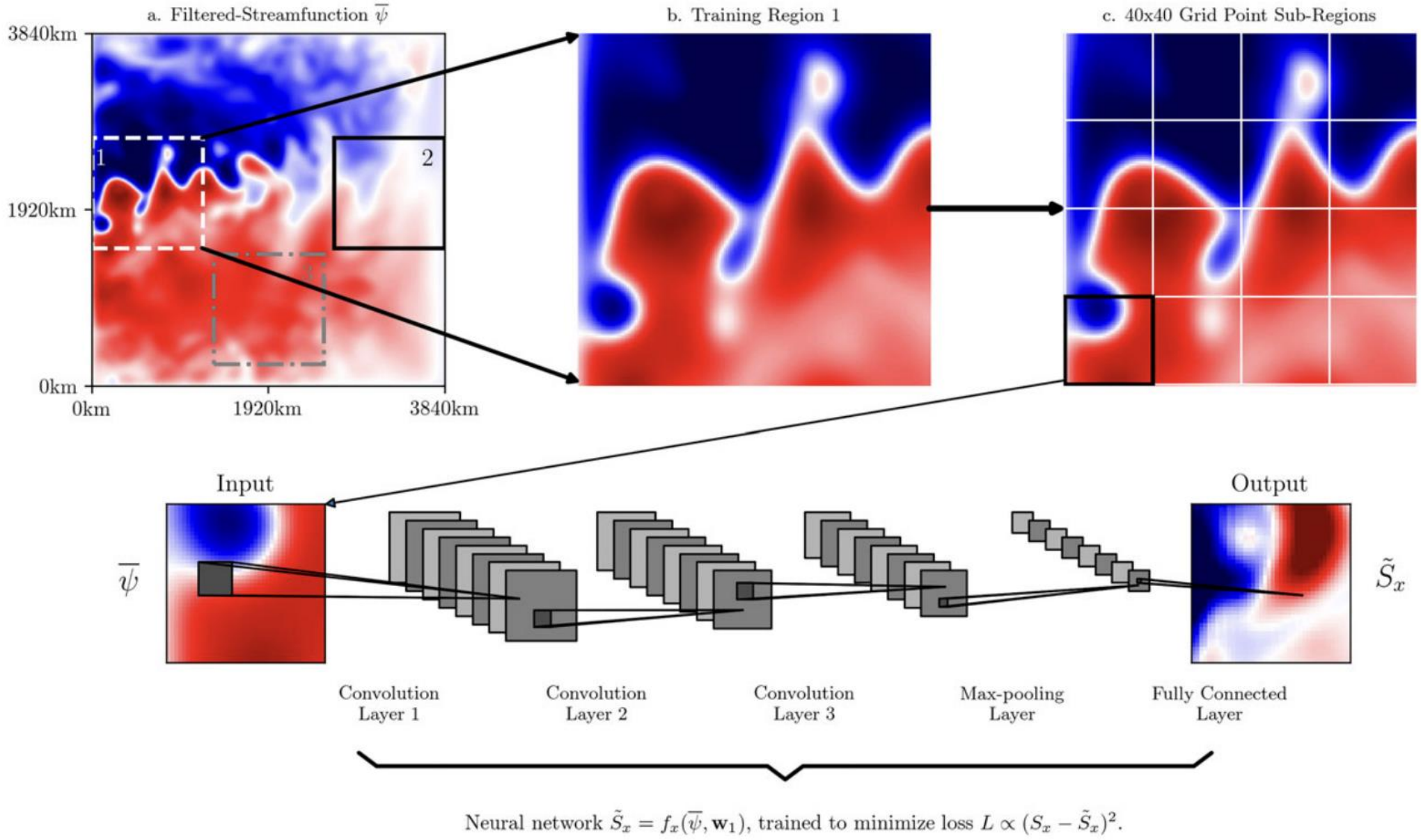
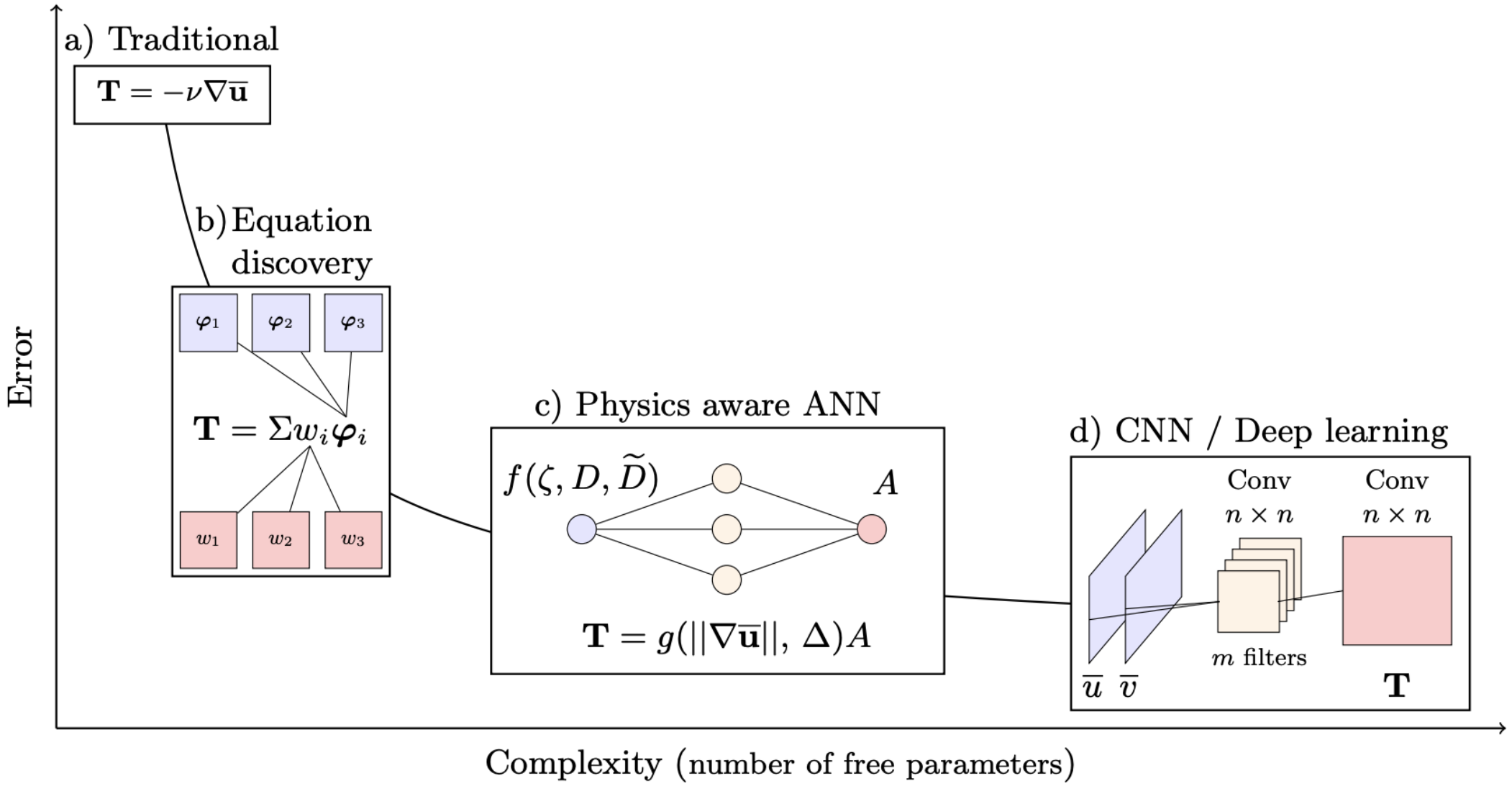
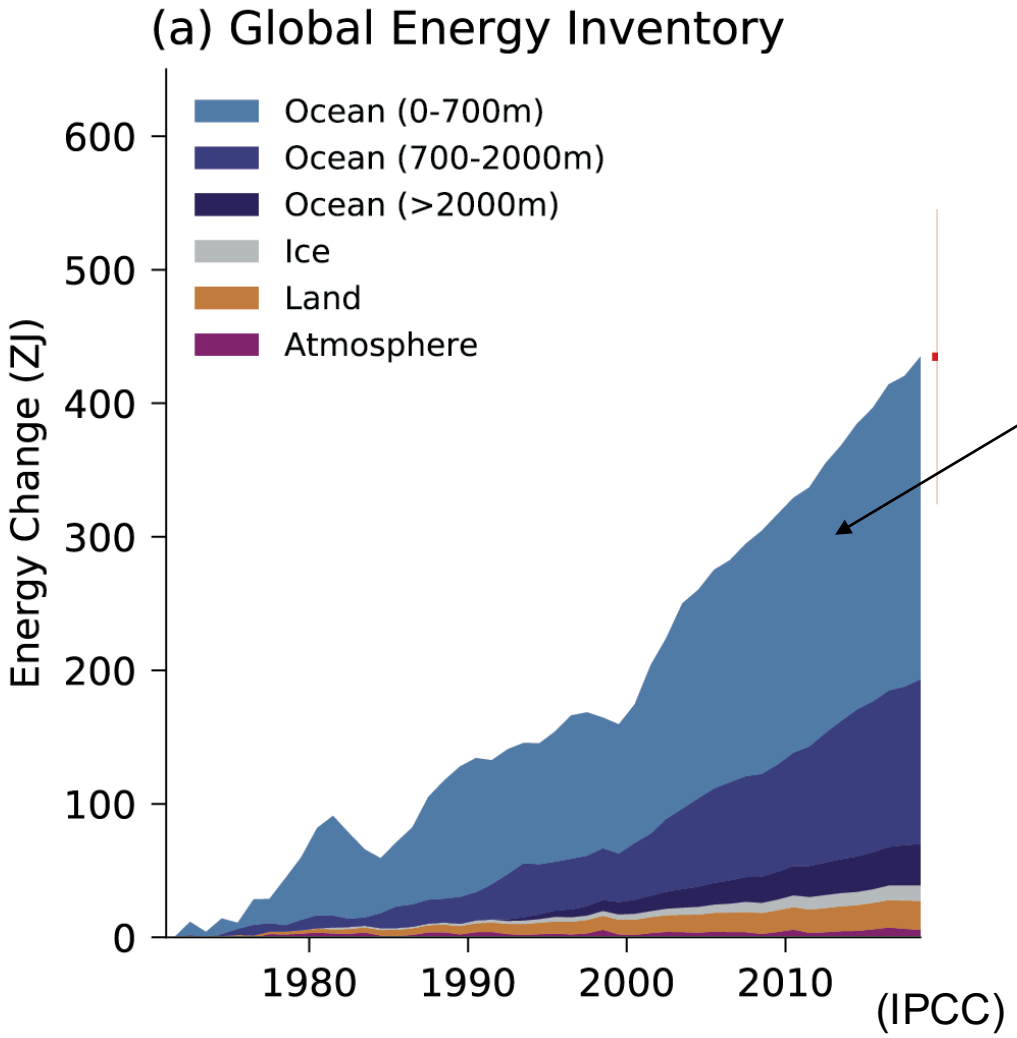


Bolton & Zanna (2019)



Zanna et al (2025)

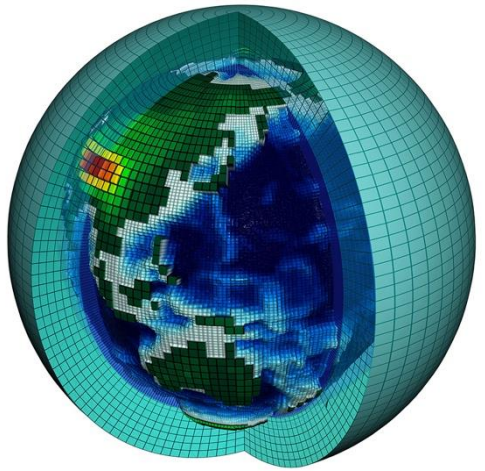
What is the impact of upper ocean turbulence on climate?

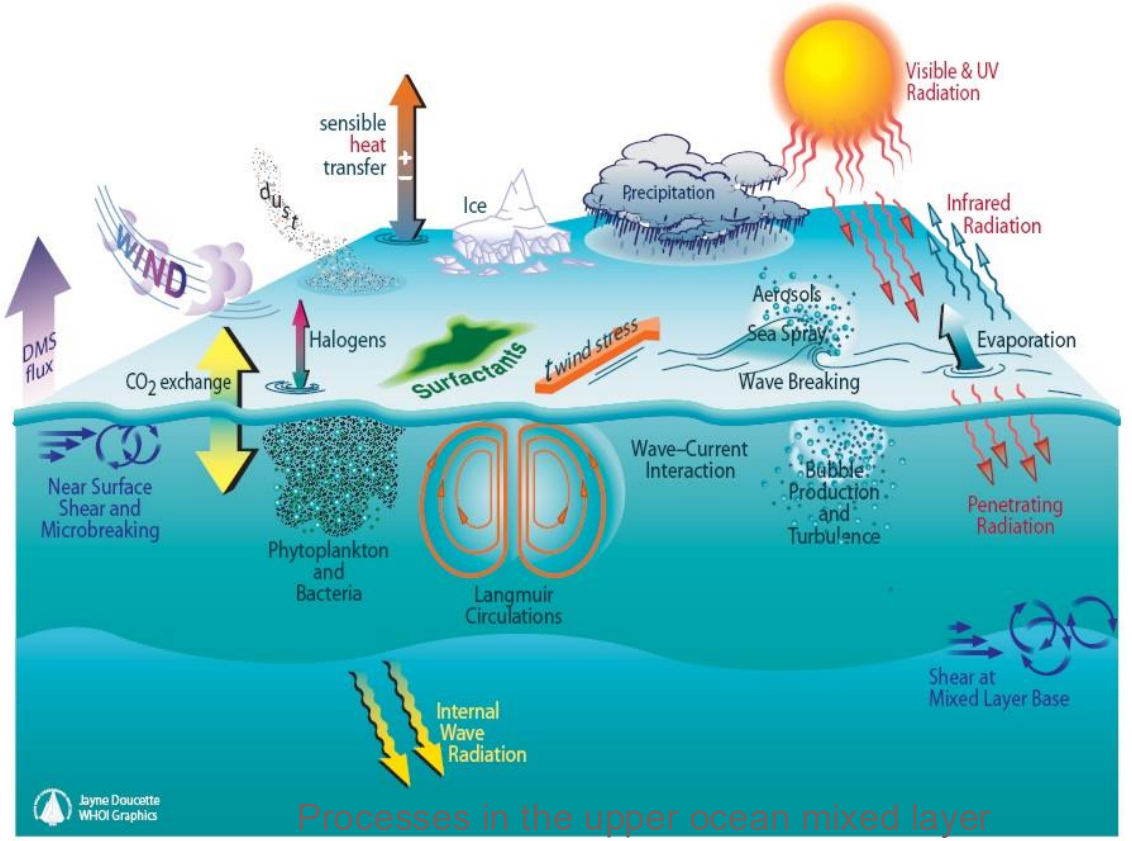


Most of the heat is in the upper ocean!

Ocean Mixed Layer

- Mixing and turbulence controls atmosphere-ocean interactions
- Accurate representation of fluxes is crucial for climate simulations
- Small, fast and complex processes
- Unresolved in General Circulation Models





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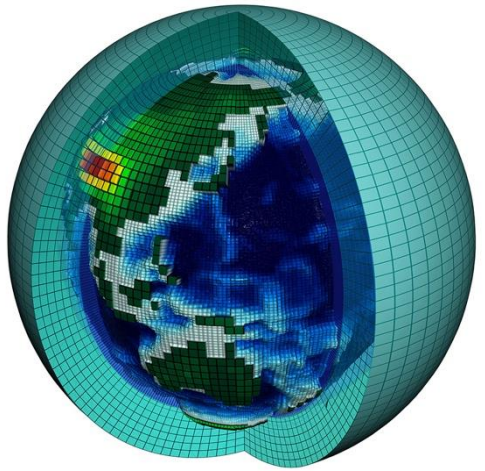

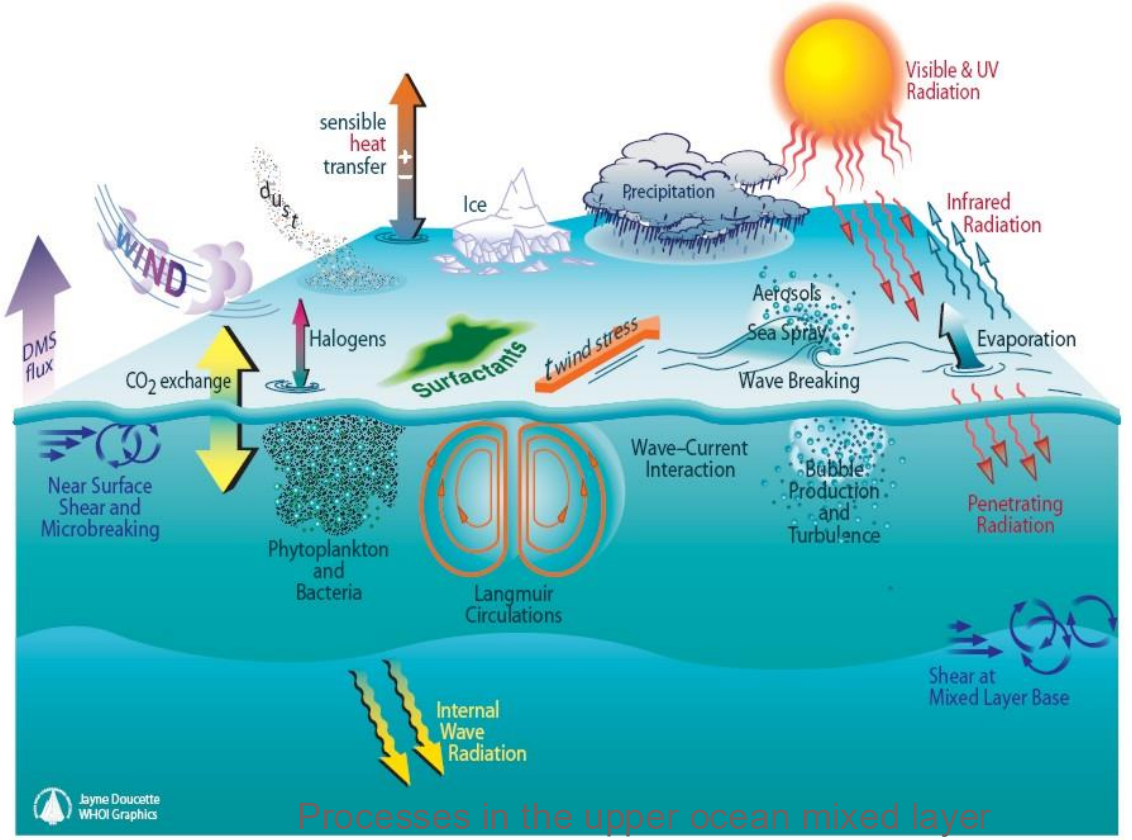

Buoyancy equation

$$\frac{\partial \bar{b}}{\partial t} + \nabla \cdot (\bar{\mathbf{u}}\bar{b}) = \nabla \cdot (\overline{\mathbf{u}'b'})$$

subgrid fluxes of b' (parameterizations)

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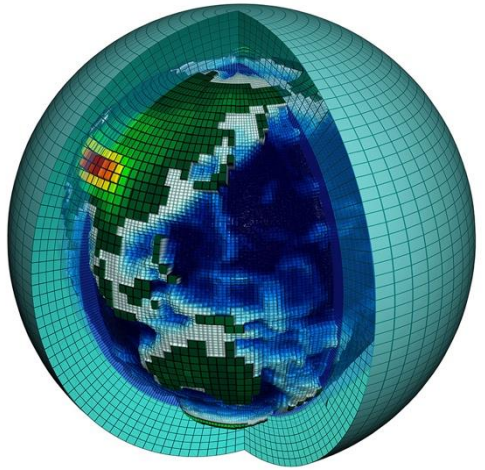

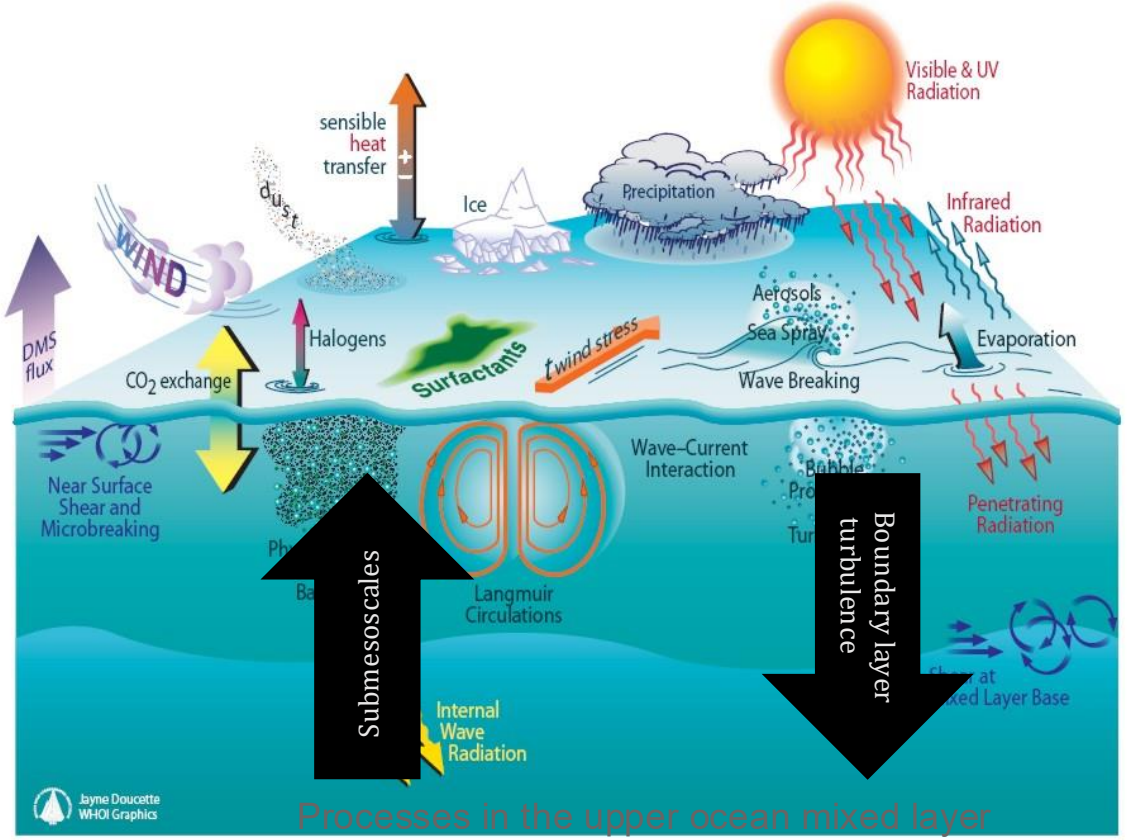

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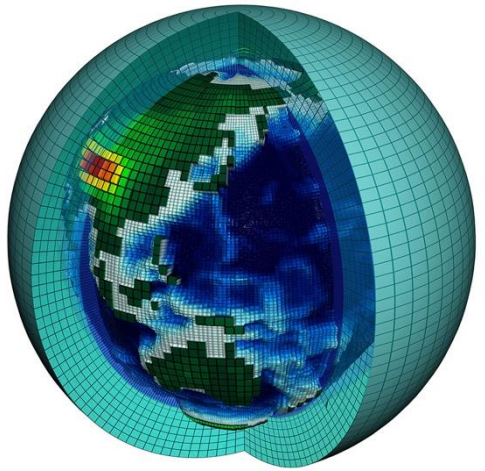

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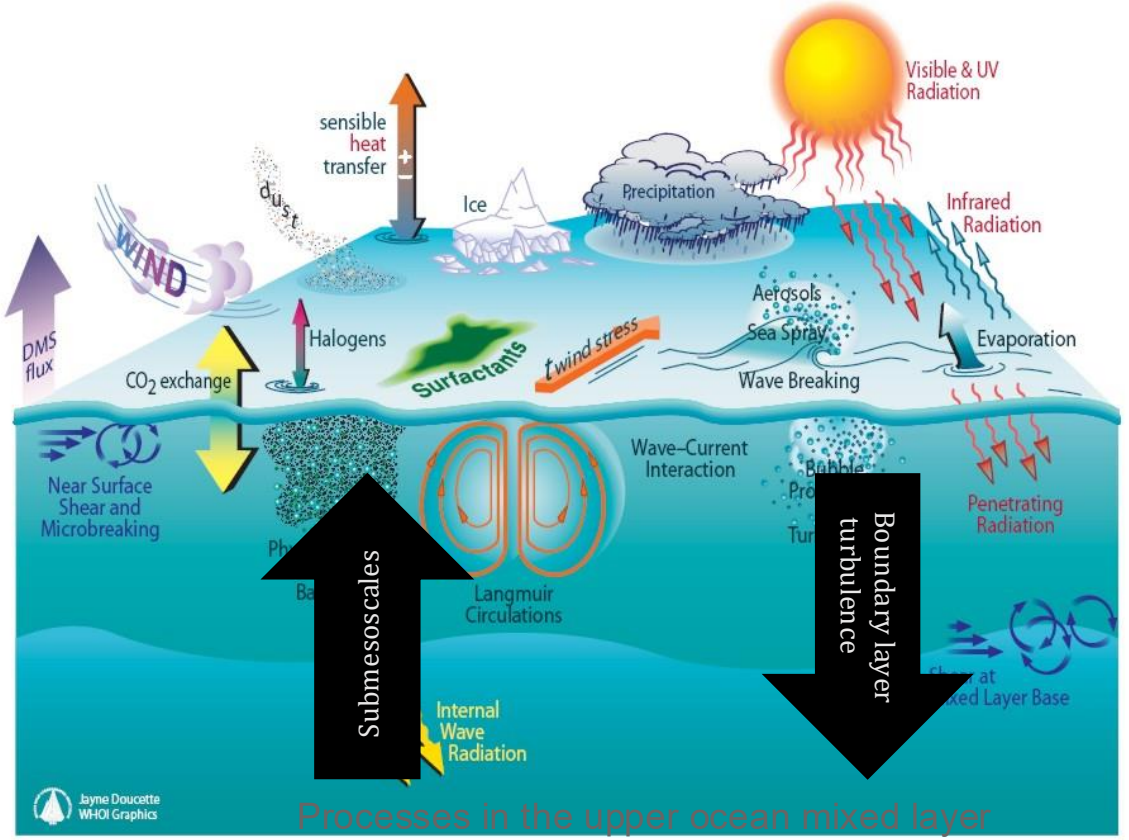
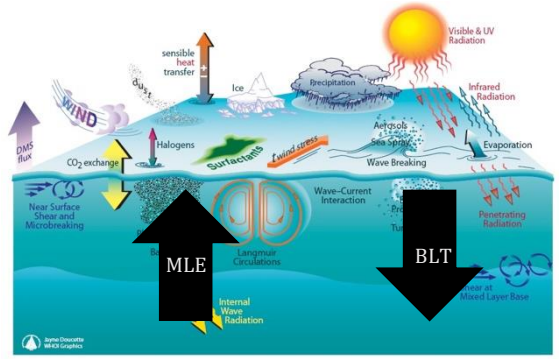
Vertical fluxes $\overline{w'b'}^z$



Submesoscale flows O(1km)
Boundary layer turbulence O(1m)

Ocean Mixed Layer Parameterizations



- Equations solved by GCM:

$$\frac{\partial \overline{\phi}}{\partial t} + \overline{\mathbf{u}} \cdot \nabla \overline{\phi} = -\nabla \cdot \overline{\mathbf{u}'\phi'}$$

unresolved fluxes of ϕ' (parameterizations)

- Boundary layer turbulent fluxes:

$$\overline{w'\phi'} = K\frac{\partial \overline{\phi}}{\partial z} + \Gamma$$

Diffusivity and nonlocal effects

- Submesoscale eddy fluxes:

$$\overline{\mathbf{u}'b'} = \Psi_{MLE} \times \nabla \overline{b},$$

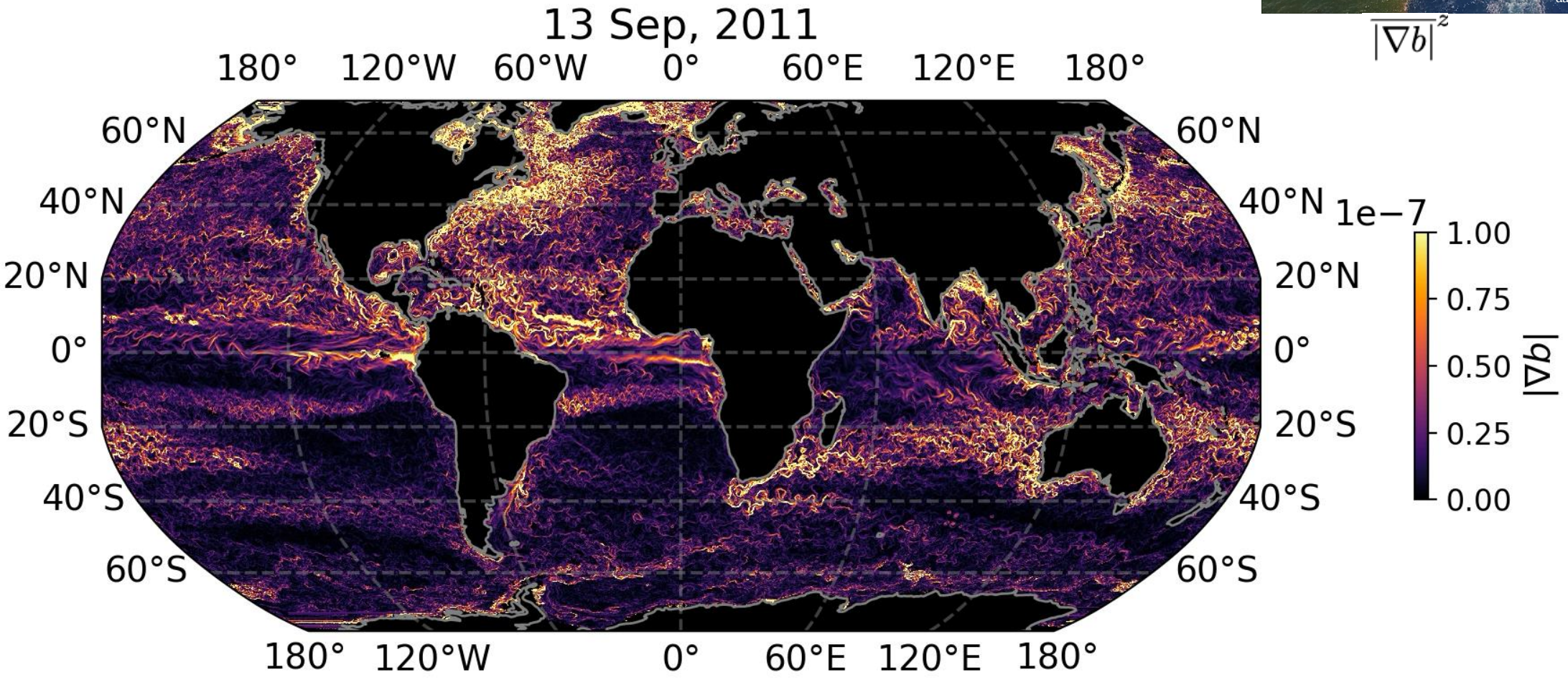
Eddy fluxes define streamfunction

$$\mathbf{u}^{MLE} = \nabla \times \Psi_{MLE}$$

Bolus velocity represents stirring

Challenges in studying the upper ocean

$\overline{|\nabla b|^2}$



Challenges in studying the upper ocean

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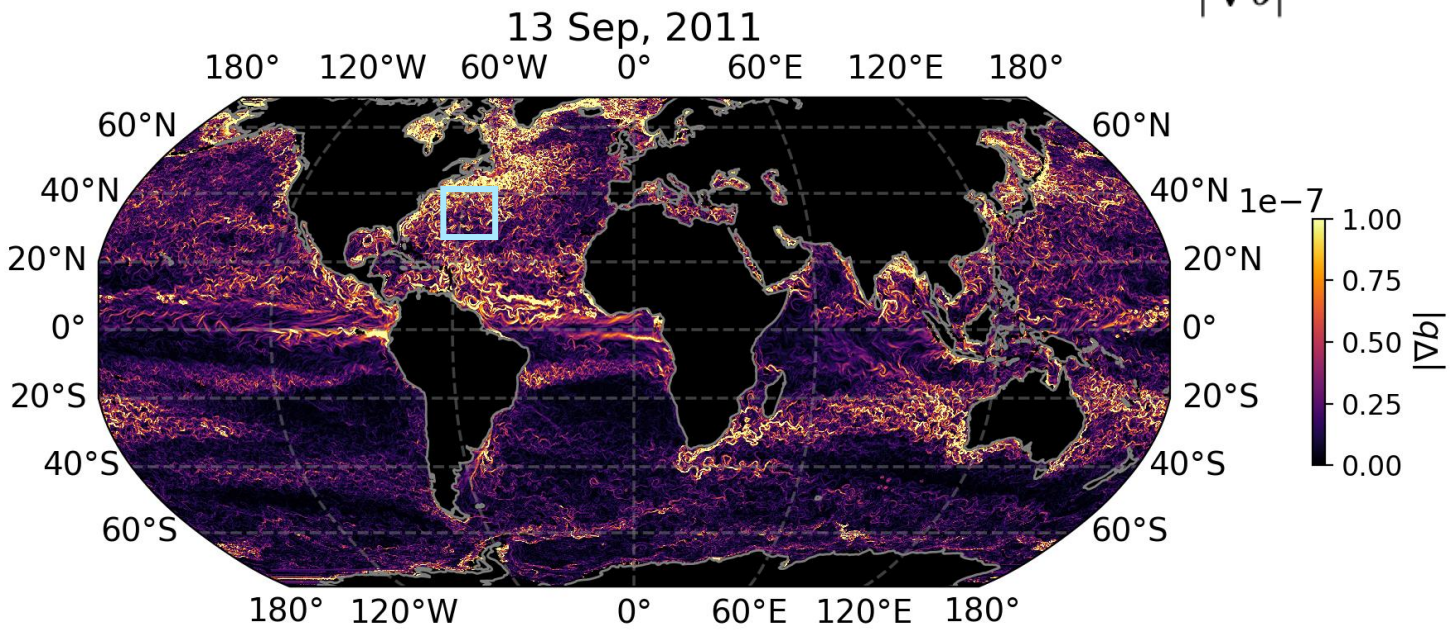
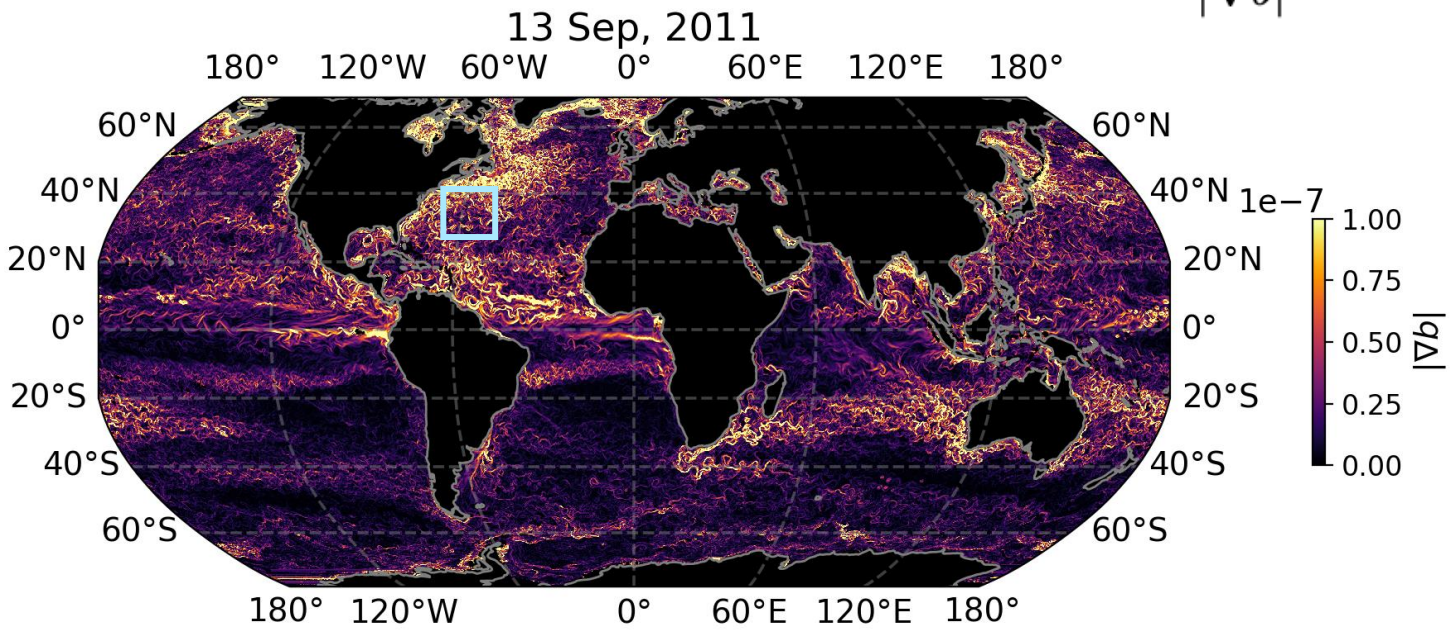


Challenges in studying the upper ocean

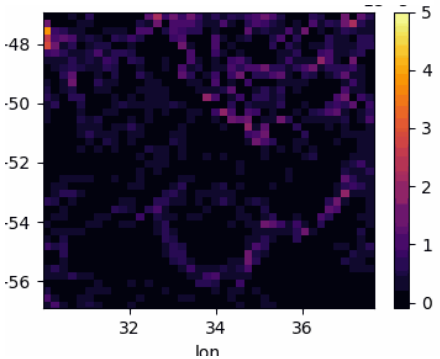
$\overline{|\nabla b|}^z$

vertical fluxes

$$\overline{w'b'}^z \propto \overline{|\nabla b|}^z$$



"truth" from high-res model

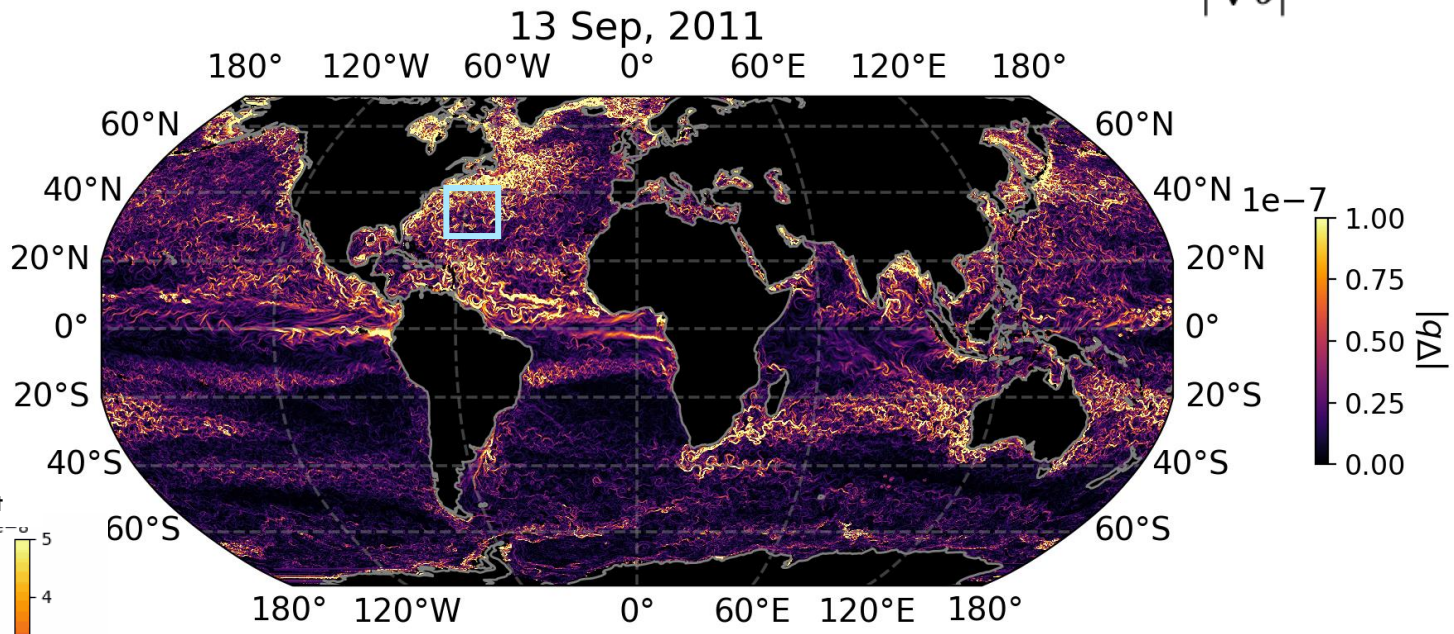


Challenges in studying the upper ocean

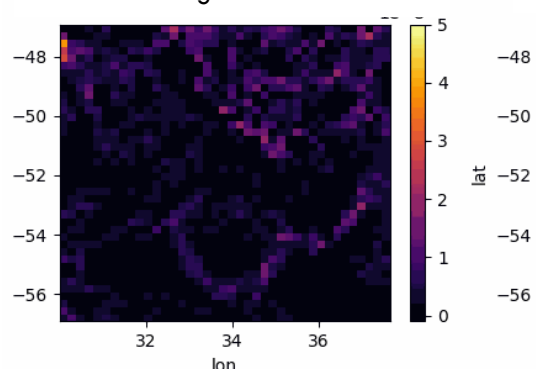
$$\overline{|\nabla b|}^{z}$$

vertical fluxes

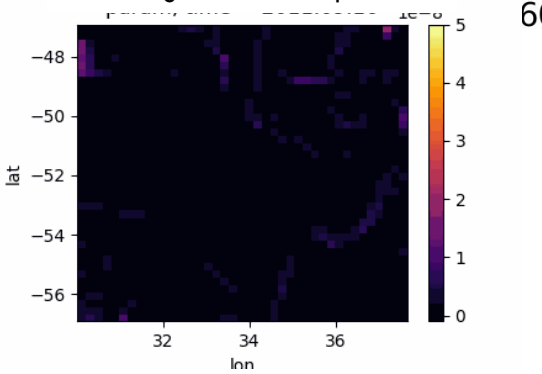
$$\overline{w'b'}^{z} \propto \overline{|\nabla b|}^{z}$$



"truth" from high-res model



What global models predict



Mixed layer eddy parameterization
(Fox-Kemper et al 2008, 2011)

The submesoscale parameterization

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

Bodner, & Fox-Kemper (2020).

Bodner, et al. (2023)

vertical fluxes

Mixed layer eddy parameterization
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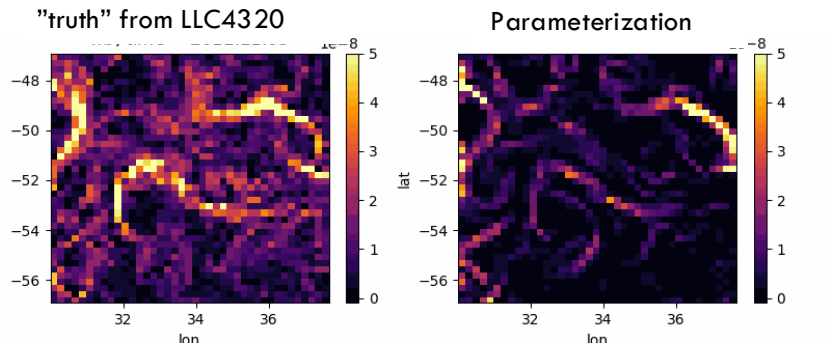
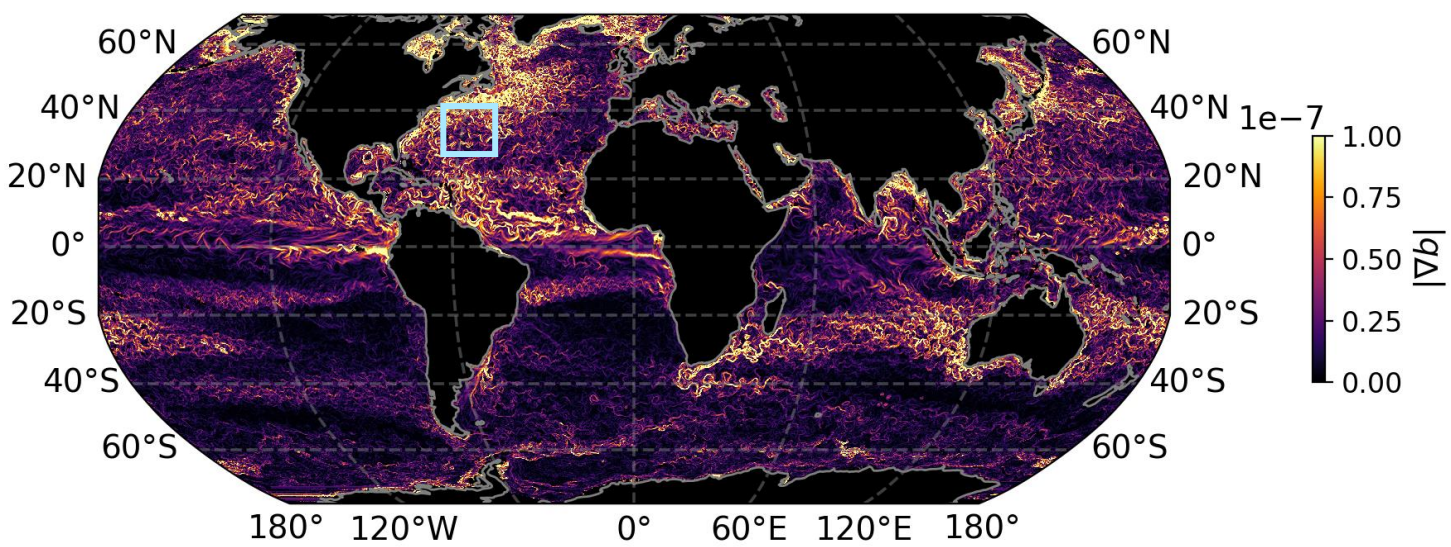
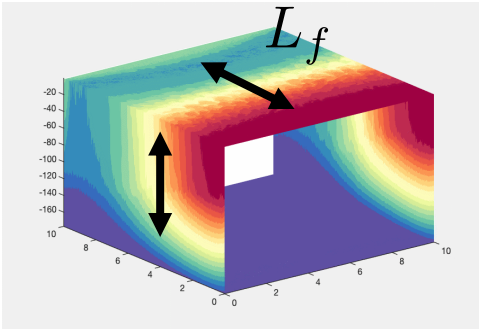
$$\cdot \overline{w'b'}^z \propto \overline{|\nabla b|}^z$$





Frontal width rescaling factor

L_f



What determines frontal width?

Turbulent parameters

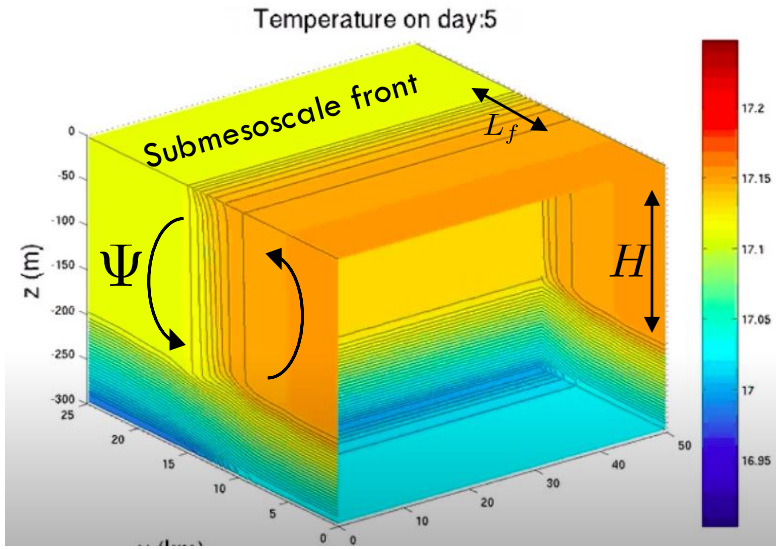
$\vec{u_*}, w_*$ h_{BL}

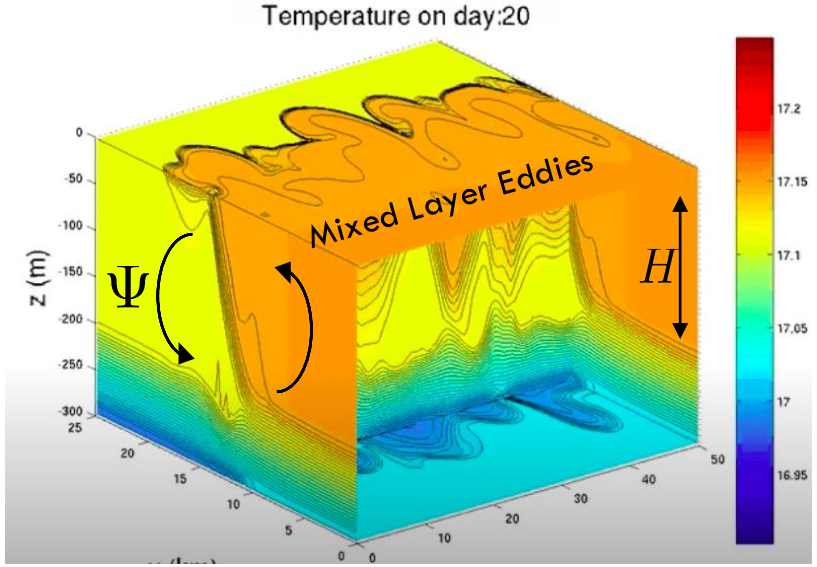
Improved theory

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

The Mixed Layer (Submesoscale) Eddy parameterization

- Represents the **restratification** effect of mixed layer eddies acting to slump submesoscale fronts





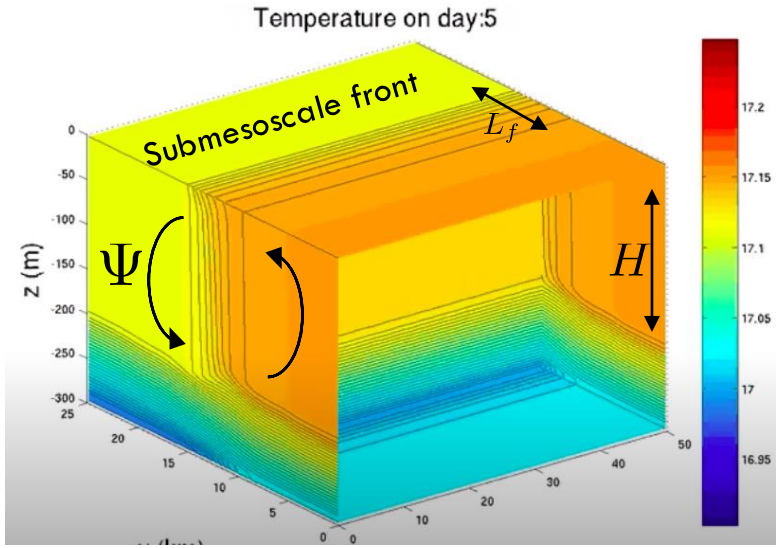
Fox-Kemper et. al. 2011

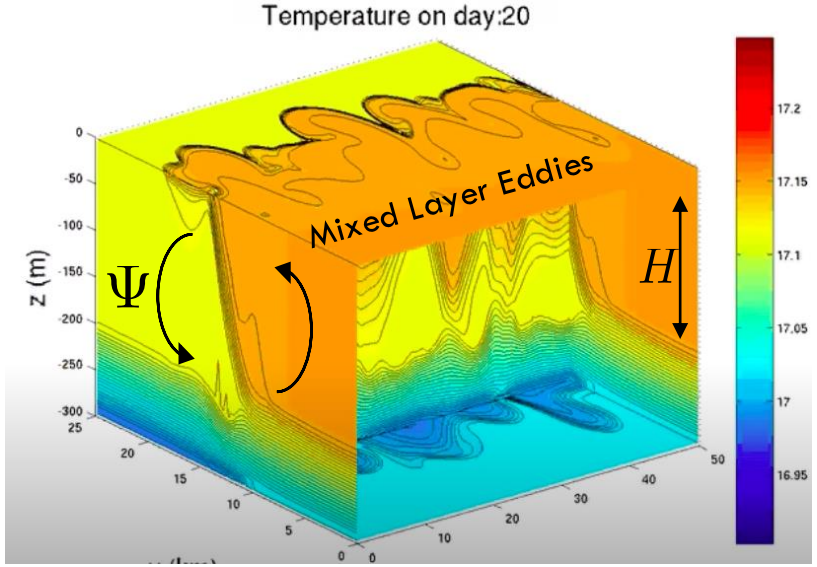
The Mixed Layer (Submesoscale) Eddy parameterization

- Represents the **restratification** effect of mixed layer eddies acting to slump submesoscale fronts

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

- Strength depends on **frontal width** L_f
- Previously set as deformation radius $L_f = \frac{NH}{f}$





Fox-Kemper et. al. 2011

A new scaling for frontal width L_f

Bodner, et al. (2023)

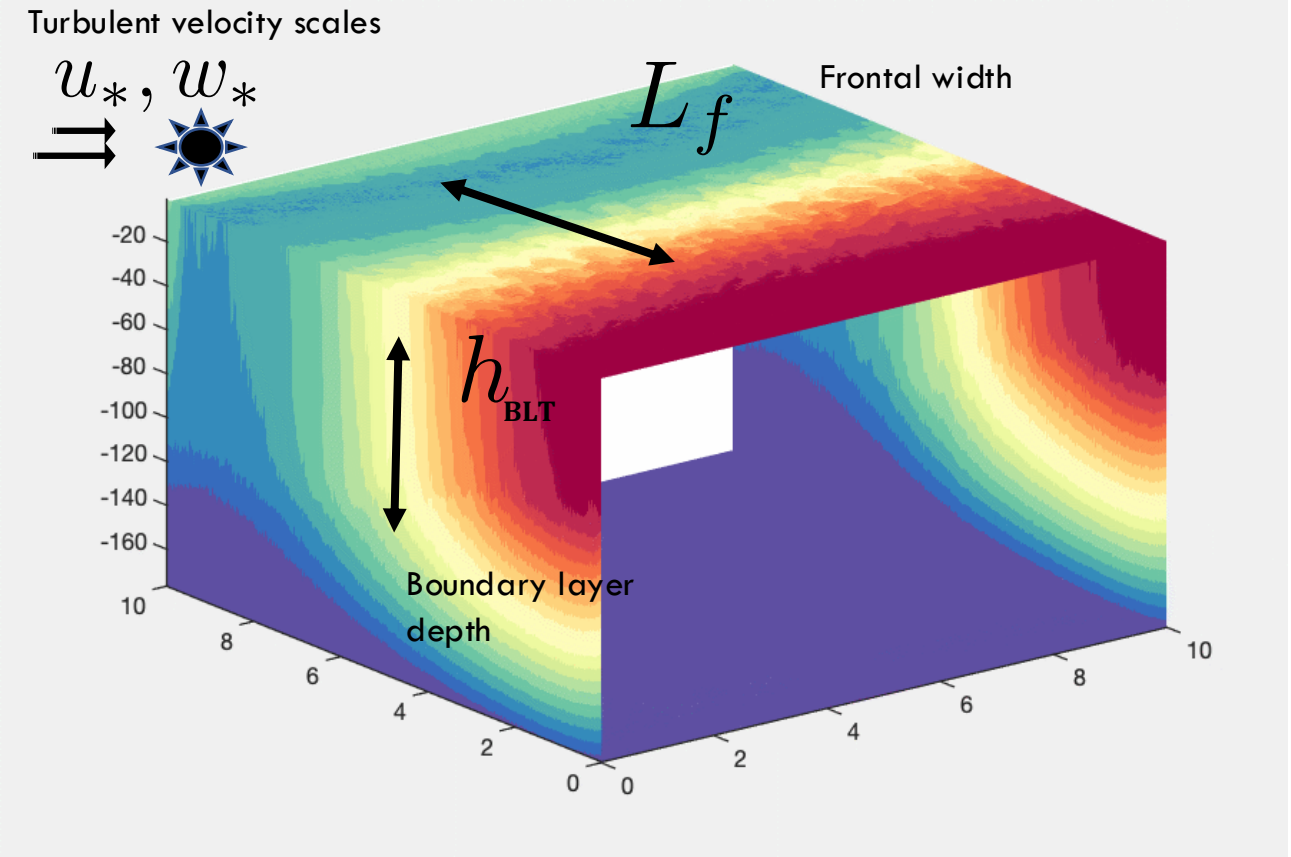
$$L_f = C_L \cdot \frac{(m_* {u_*}^3 + n_* {w_*}^3)^{2/3}}{f^2} \cdot \frac{1}{h}$$

McWilliams (2015)

Turbulent thermal wind balance

$$\nabla_H b = -f\hat{\mathbf{z}} \times \mathbf{s} + \frac{\partial^2(\nu \mathbf{s})}{\partial z^2}$$

Buoyancy gradient | Vertical shear | Vertical eddy viscosity



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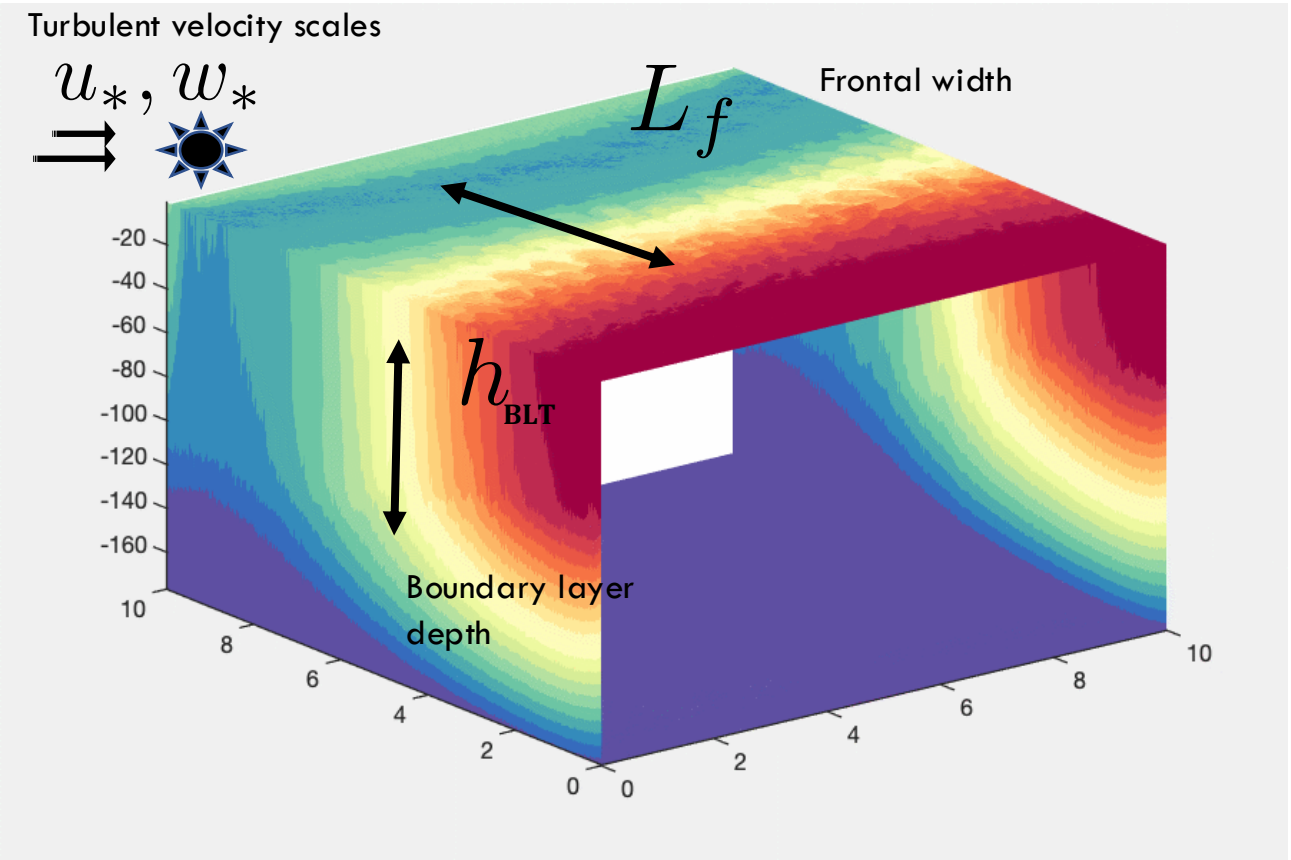
C_L: $Ri_T \approx 0.25$ — Horizontal shear instability

From boundary layer turbulence schemes (KPP, ePBL)

Turbulent velocity scales u_*, w_*



BFF11

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

$\Rightarrow$

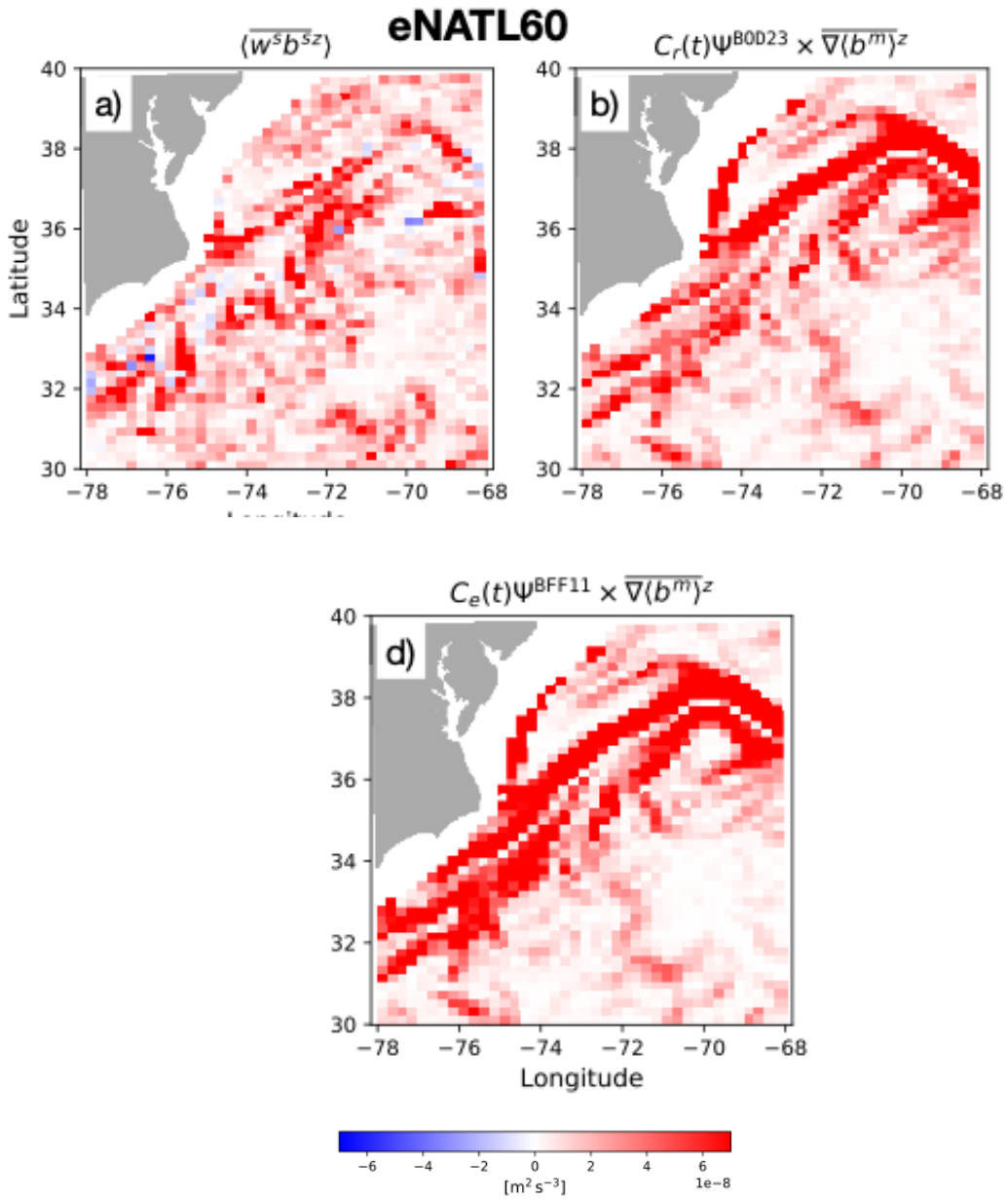
BOD23

$$C_r \frac{\Delta s |f| h H^2 \nabla \overline{b}^z \times \mathbf{z}}{(m_* {u_*}^3 + n_* {w_*}^3)^{2/3}} \mu(z)$$

$$C_r \approx \frac{0.07}{0.25} \approx 0.28$$

New parameterization estimates stronger submesoscale fluxes

Uchida, Bodner et al (2026)



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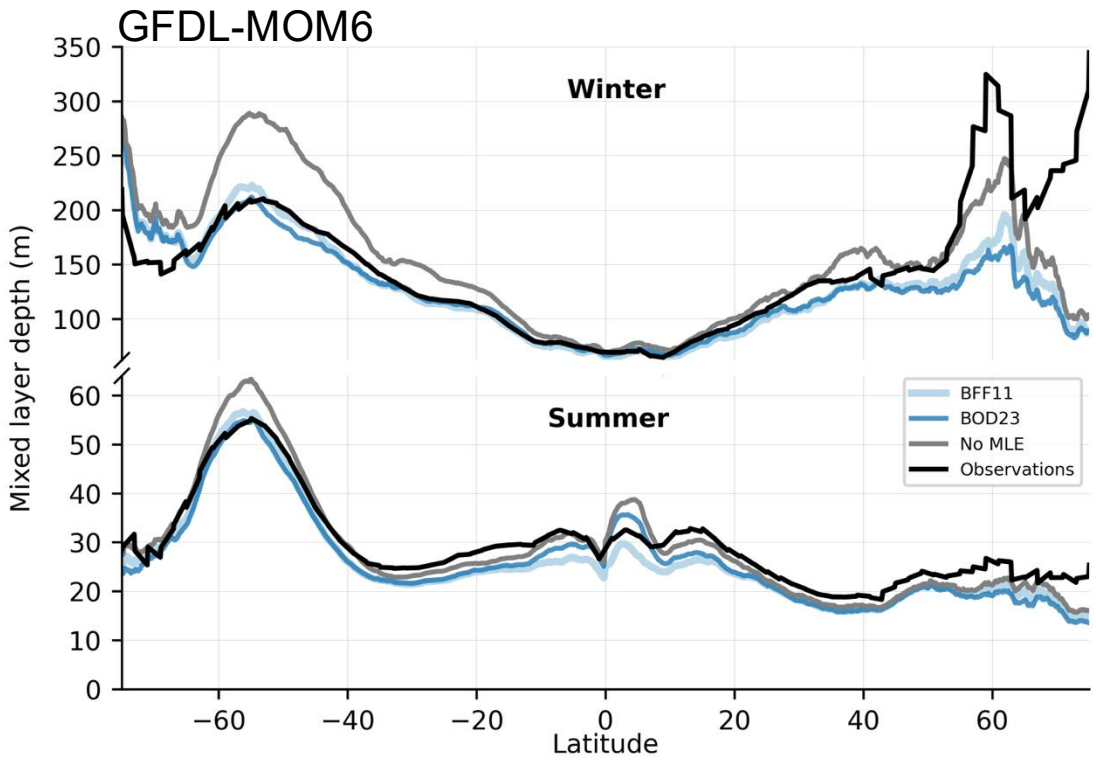
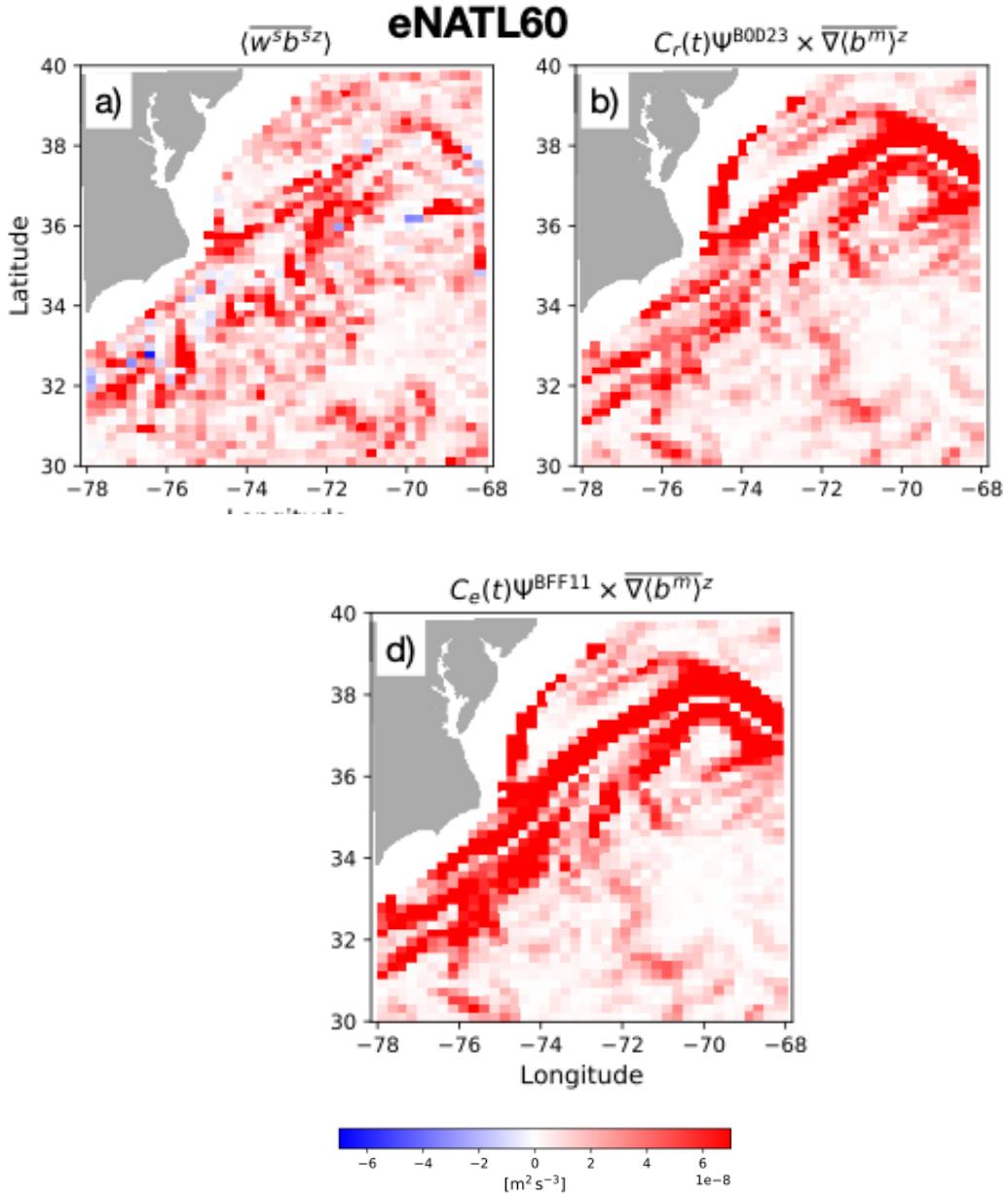
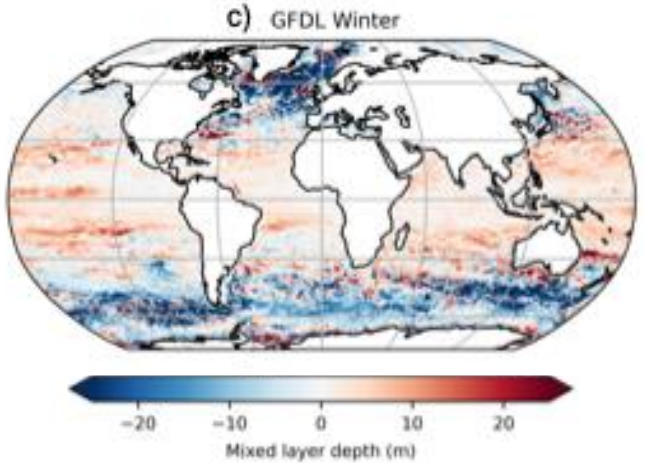
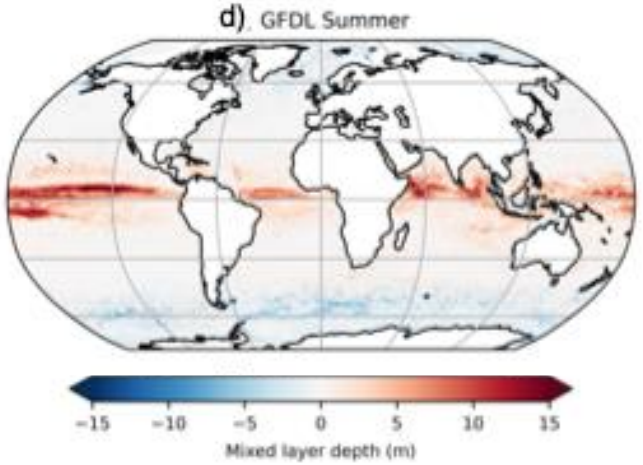


differences in zonal mean MLD are smaller than the biases that arise without any MLE representation







GFDL-MOM6 CESM-MOM6 BLOM

Mixed layer depth

Results from Bodner23 minus results from Fox-Kemper 2011

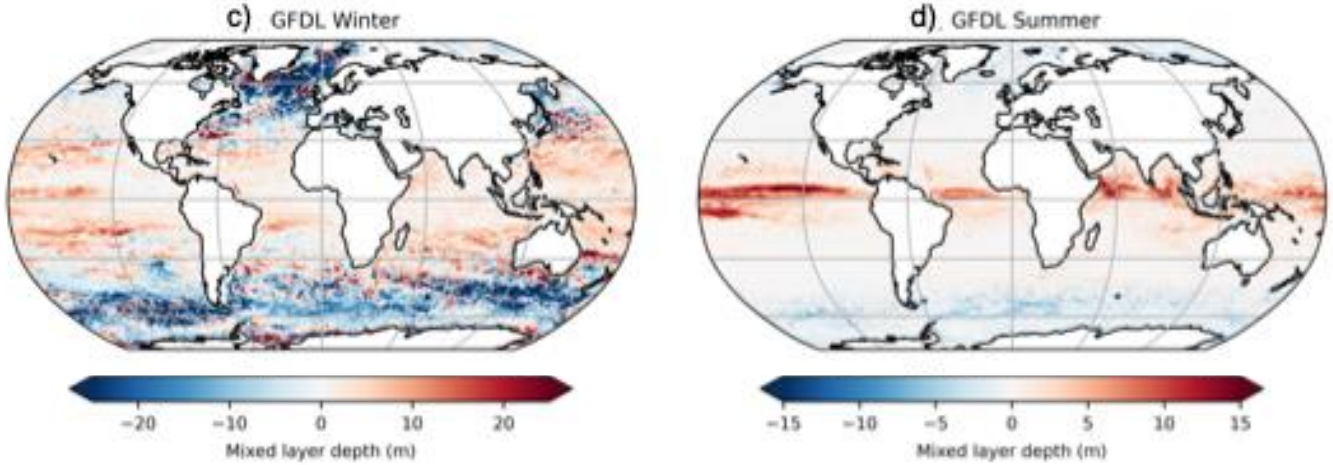
BOD23 reduces restratification

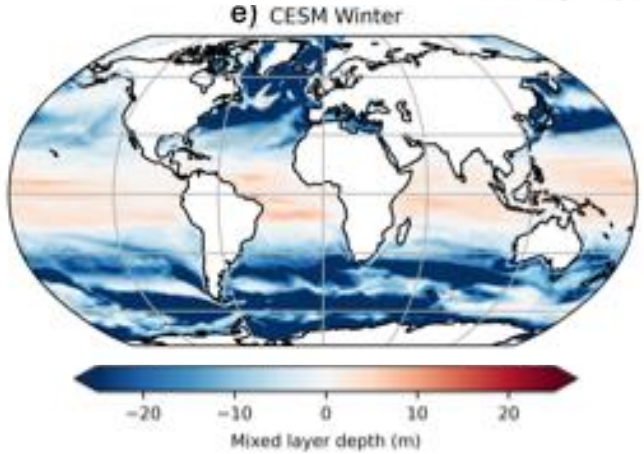
BOD23 Increases restratification

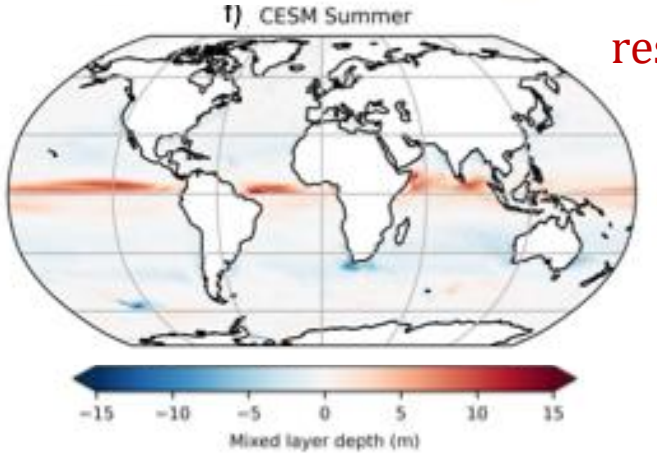
GFDL-MOM6 CESM-MOM6 BLOM

Mixed layer depth

Results from Bodner23 minus results from Fox-Kemper 2011







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GFDL-MOM6 CESM-MOM6 BLOM

Mixed layer depth

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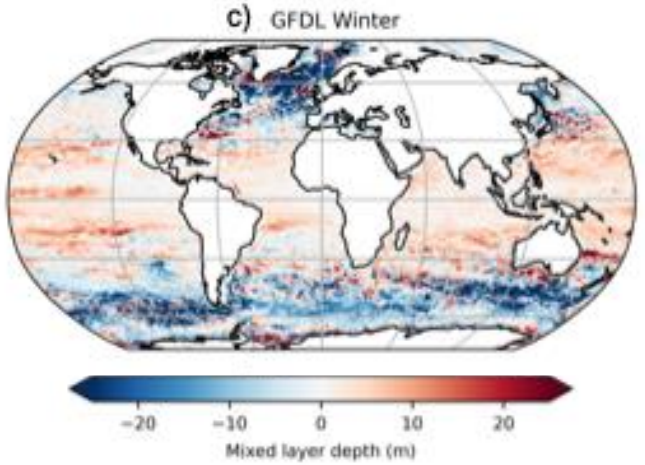

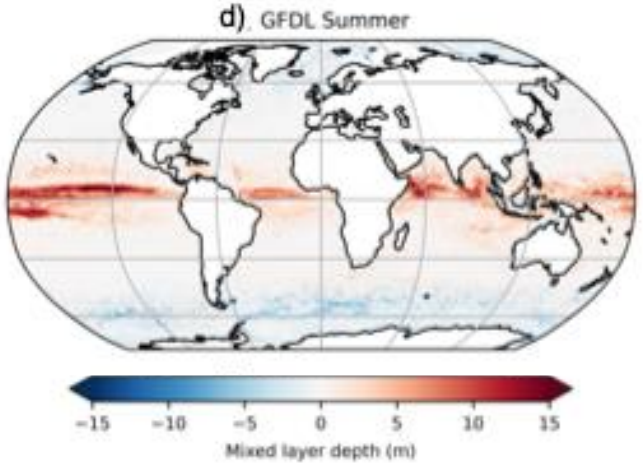

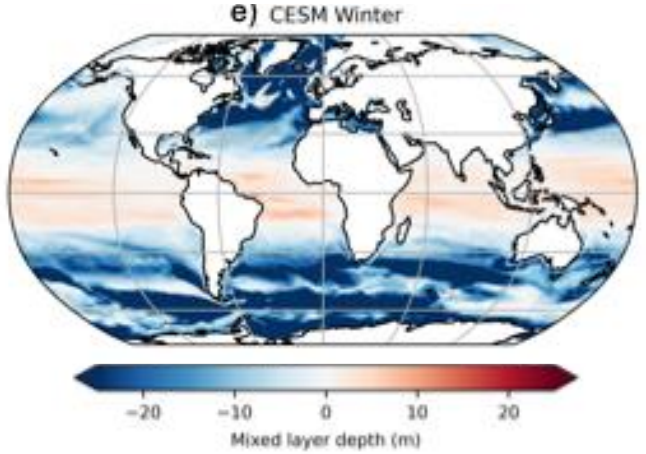

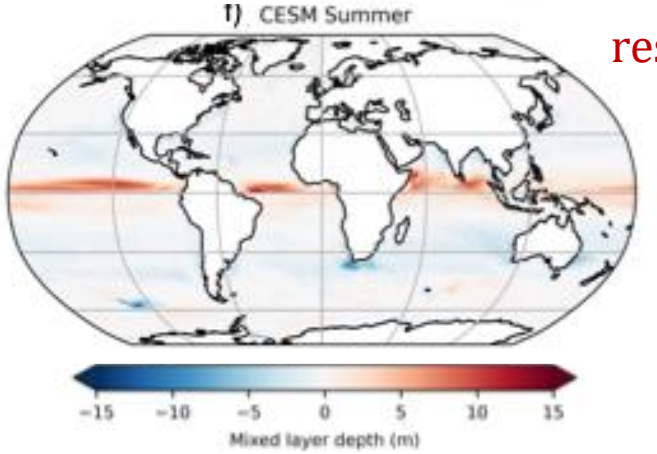

BOD23 reduces restratification

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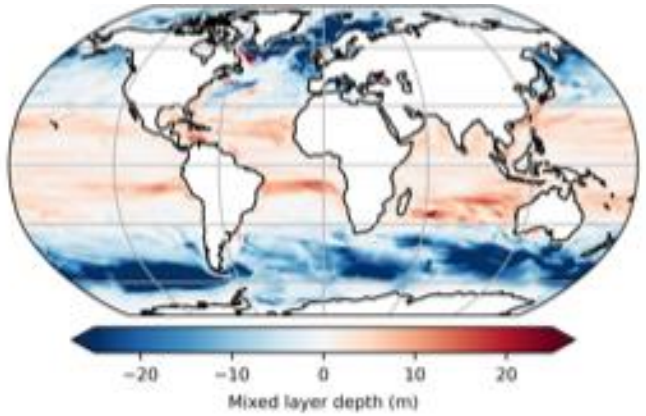
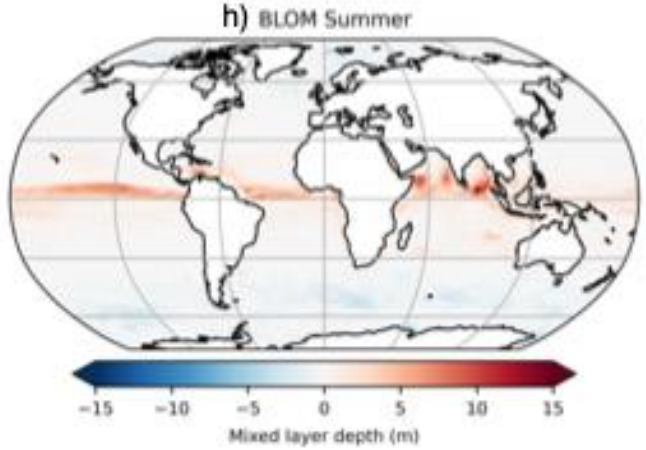
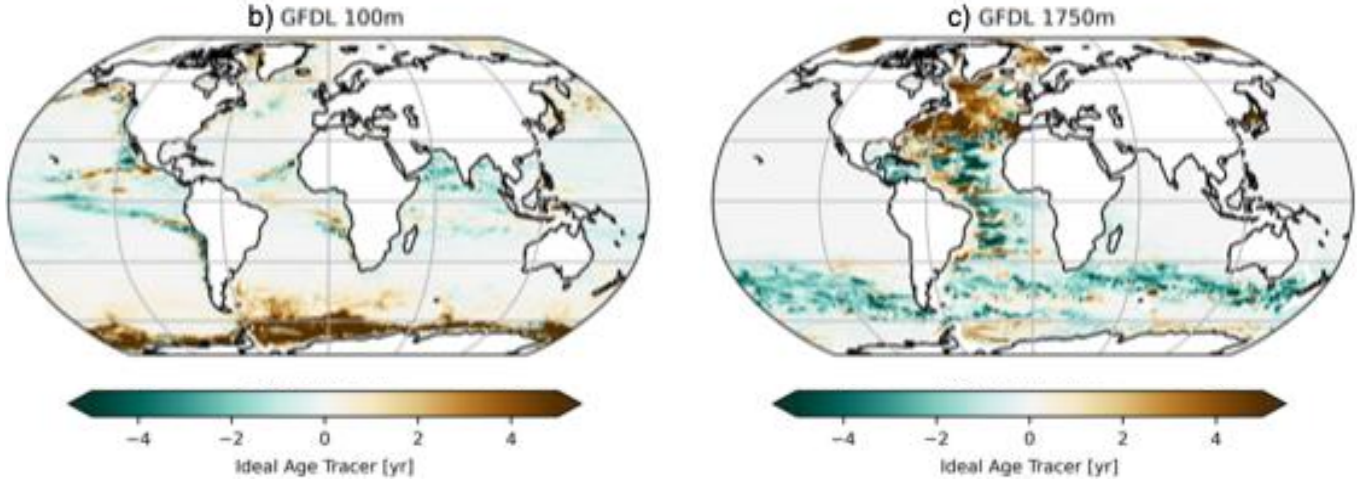




Results from Bodner23 minus
results from Fox-Kemper 2011

GFDL-MOM6 CESM-MOM6 BLOM

Ideal Age



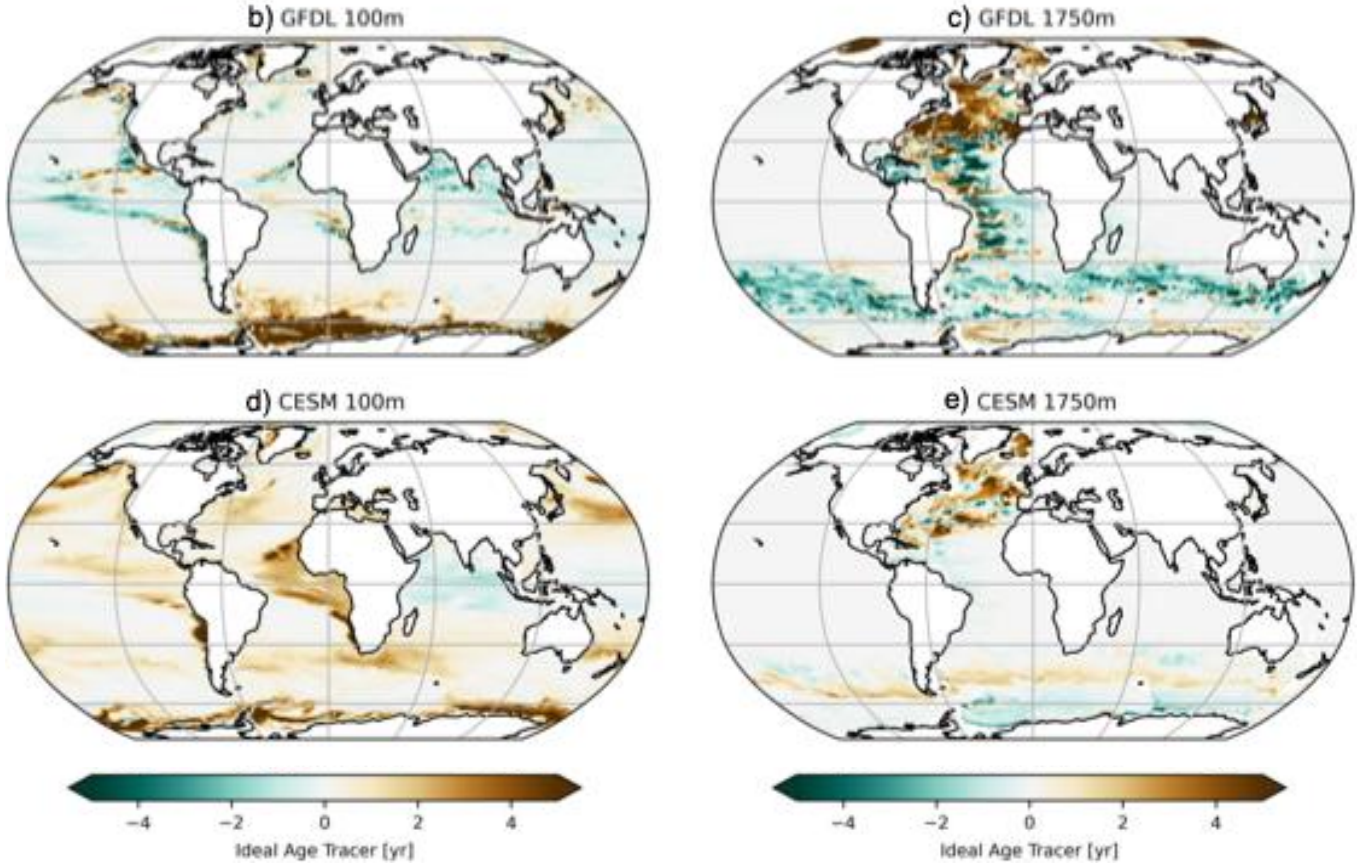
BOD23 reduces ventilation

BOD23 increases ventilation

Results from Bodner23 minus
results from Fox-Kemper 2011

GFDL-MOM6 CESM-MOM6 BLOM

Ideal Age



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GFDL-MOM6 CESM-MOM6 BLOM

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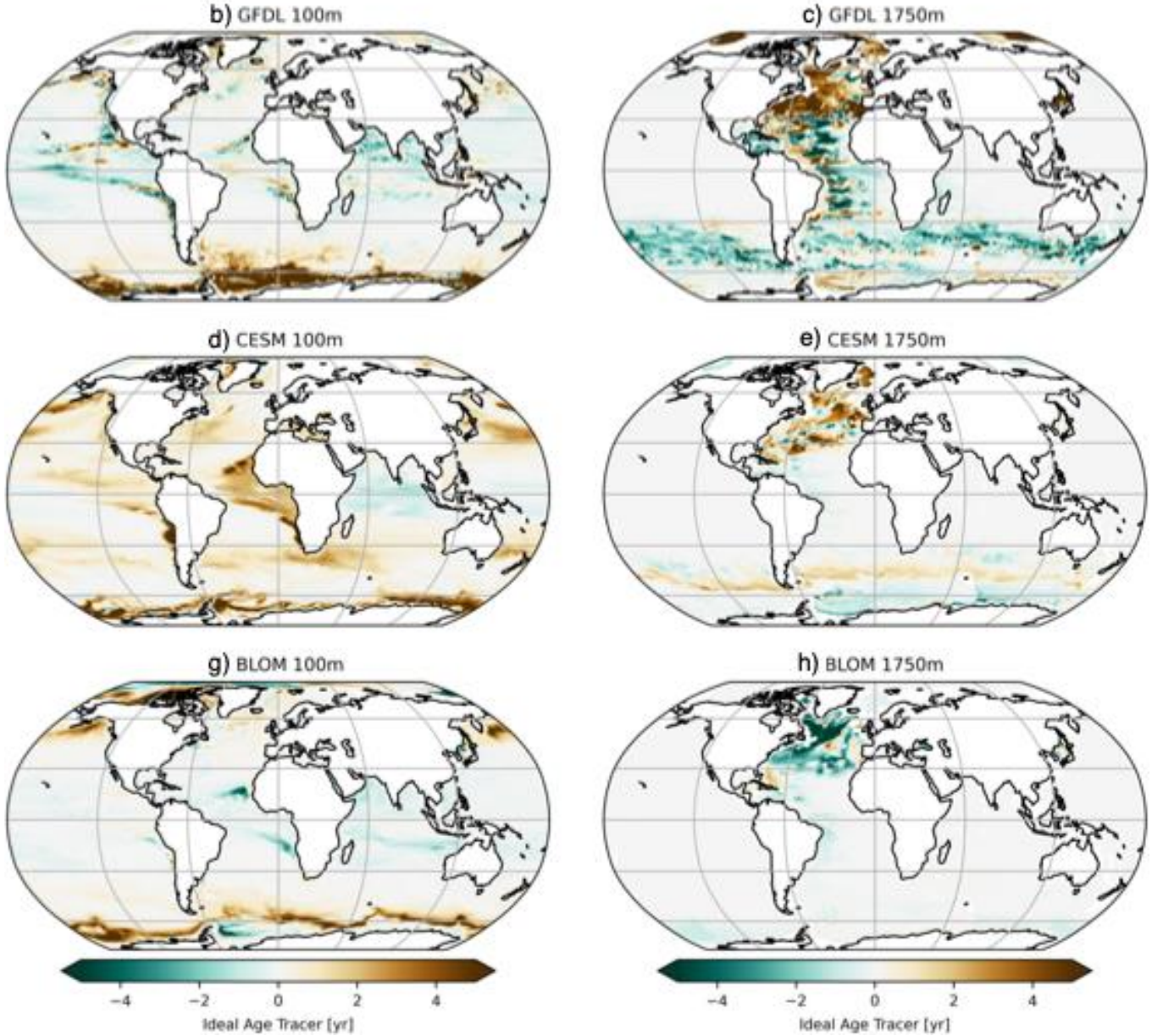

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GFDL-MOM6 CESM-MOM6 BLOM

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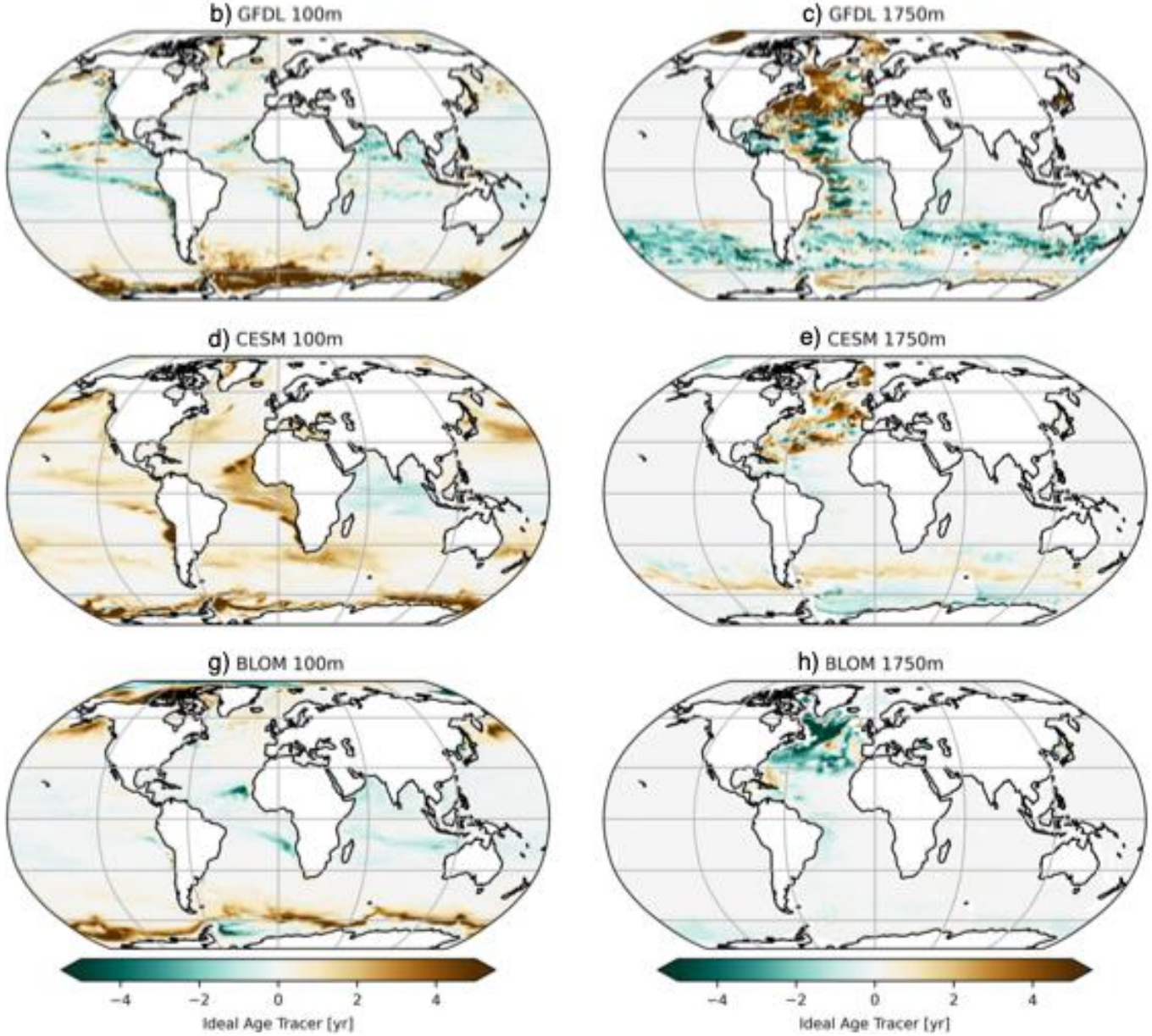
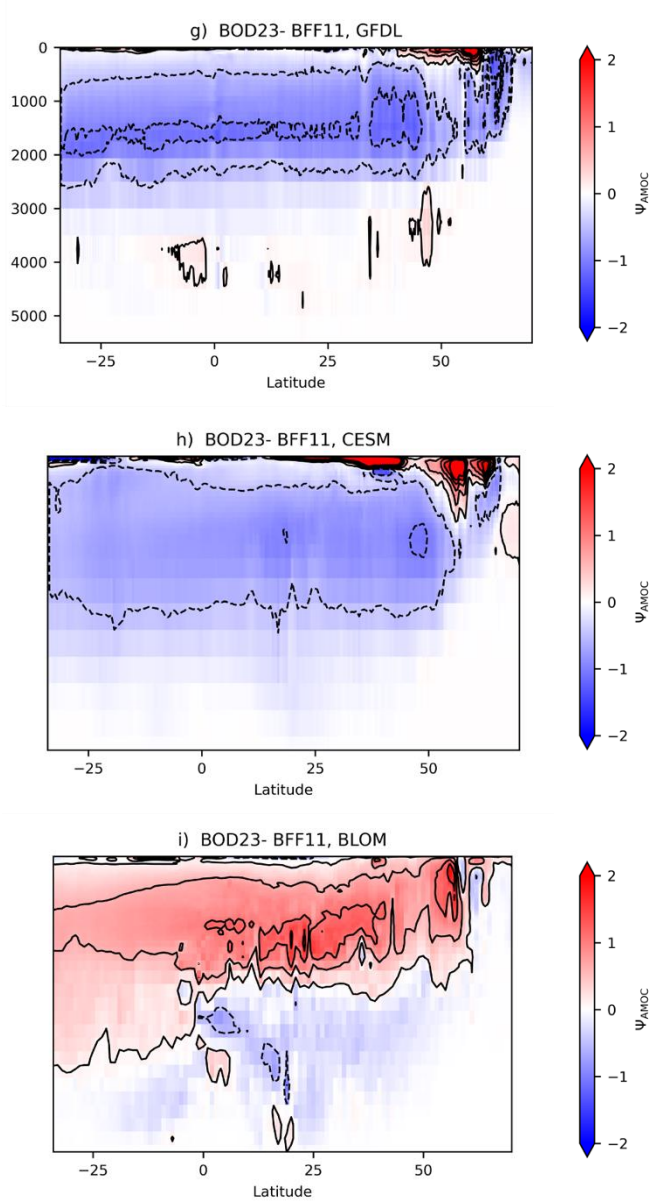


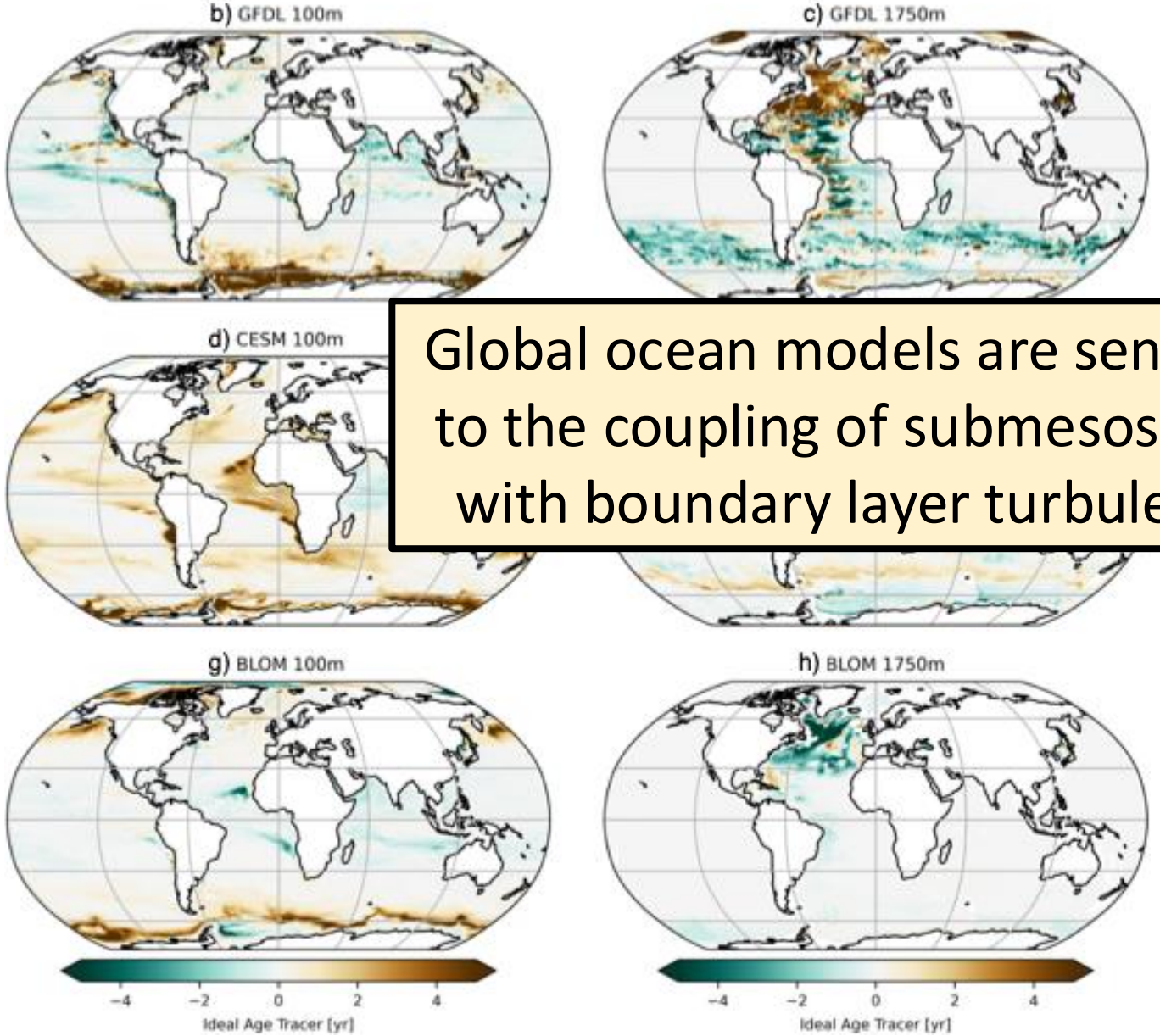
AMOC



Results from Bodner23 minus
results from Fox-Kemper 2011

GFDL-MOM6 CESM-MOM6 BLOM

Ideal Age



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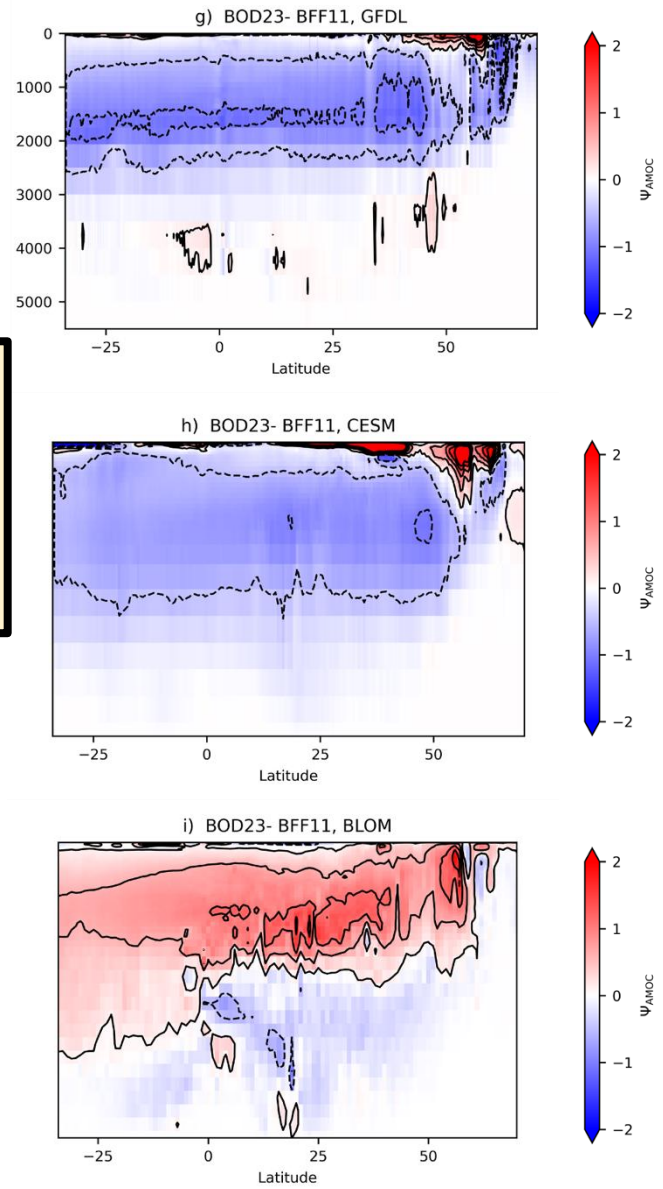
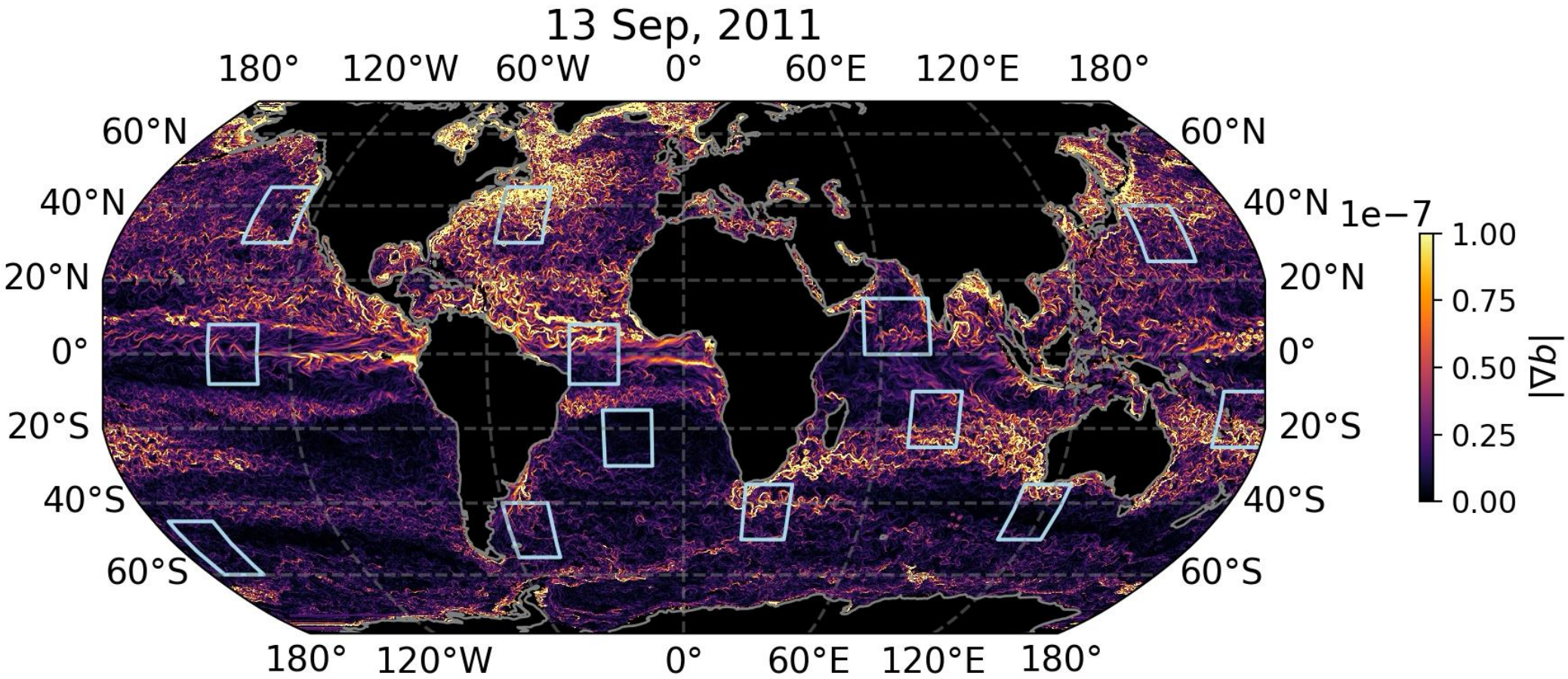


Global ocean models are sensitive to the coupling of submesoscales with boundary layer turbulence

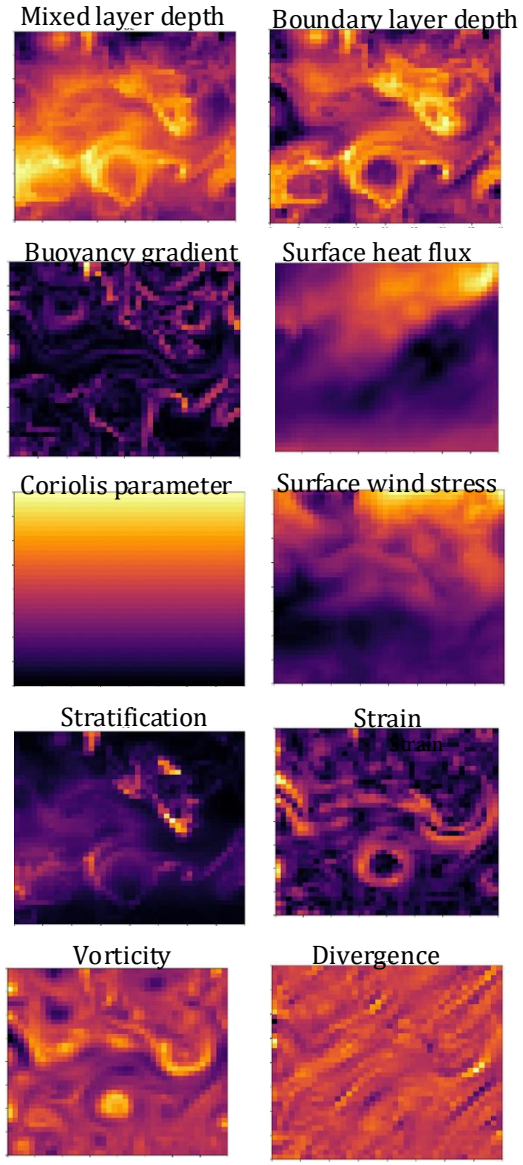
Data-driven submesoscale parameterization

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



Bodner, Balwada, Zanna (2025)

Data-driven submesoscale parameterization



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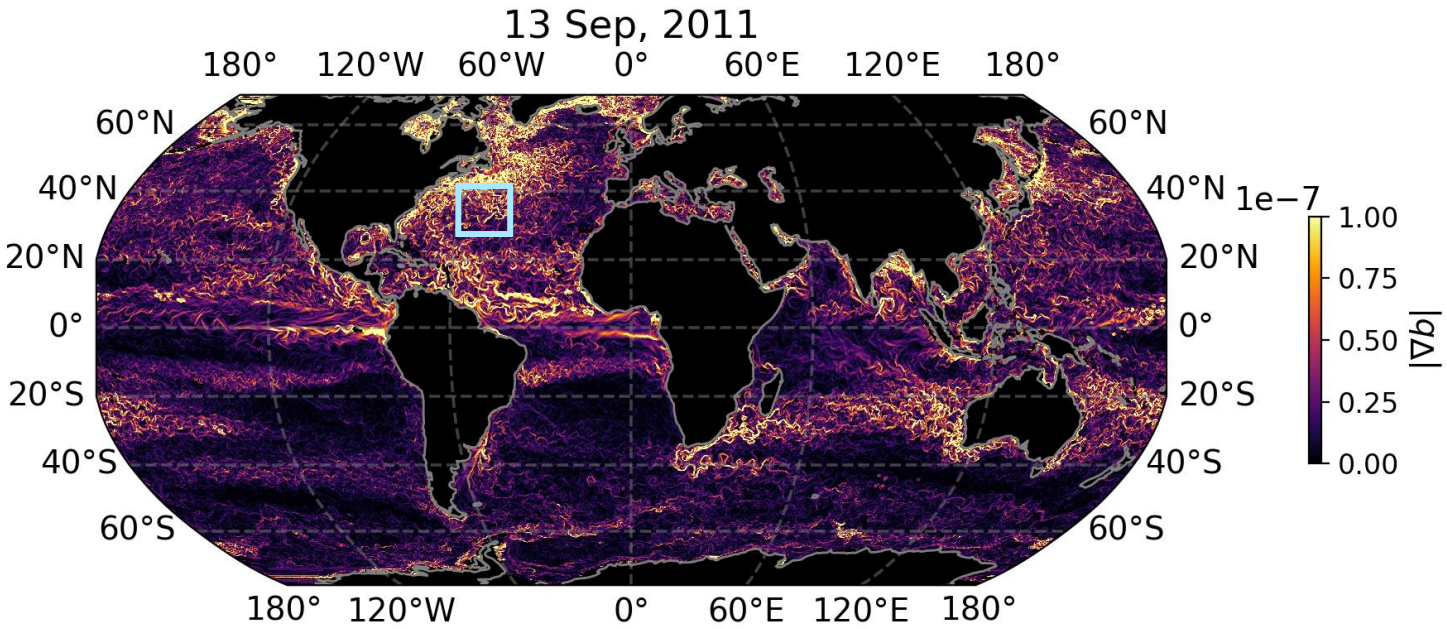
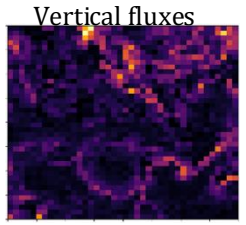


Given a set of relevant variables: predict vertical fluxes directly computed from data



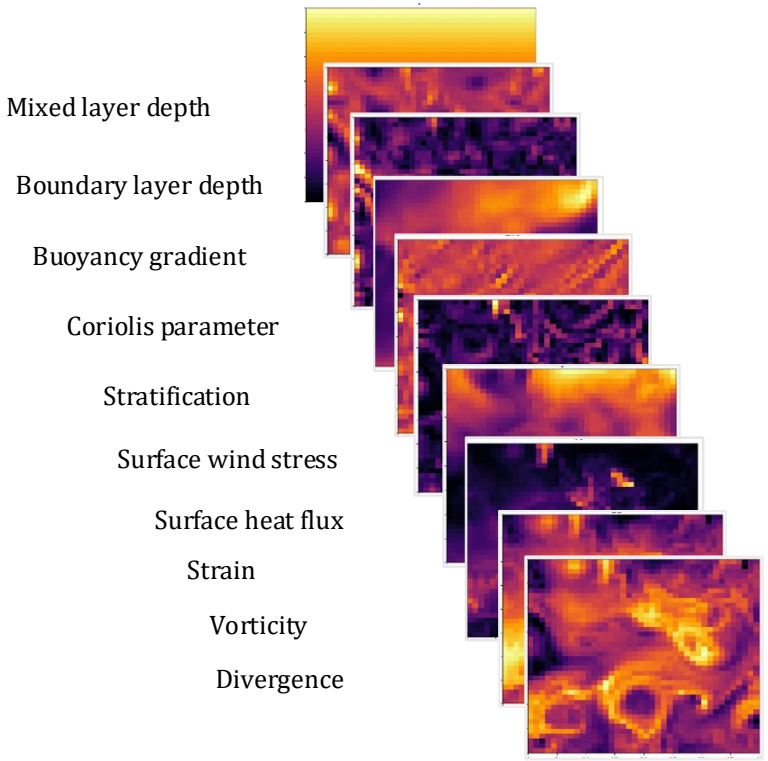
Bodner, Balwada, Zanna (2025)

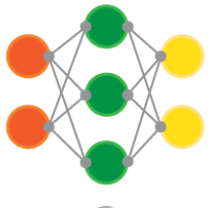
Data-driven submesoscale parameterization

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

Inputs

Variables resolved by General Circulation Models



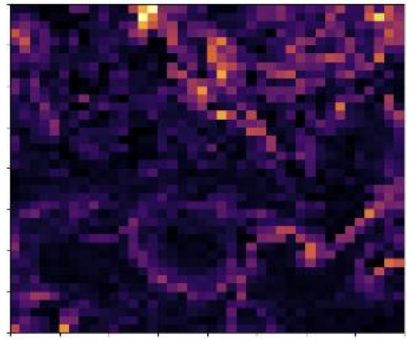


Fully Convolutional Neural Network

Output

Submesoscale vertical buoyancy fluxes

$\overline{w'b'}$



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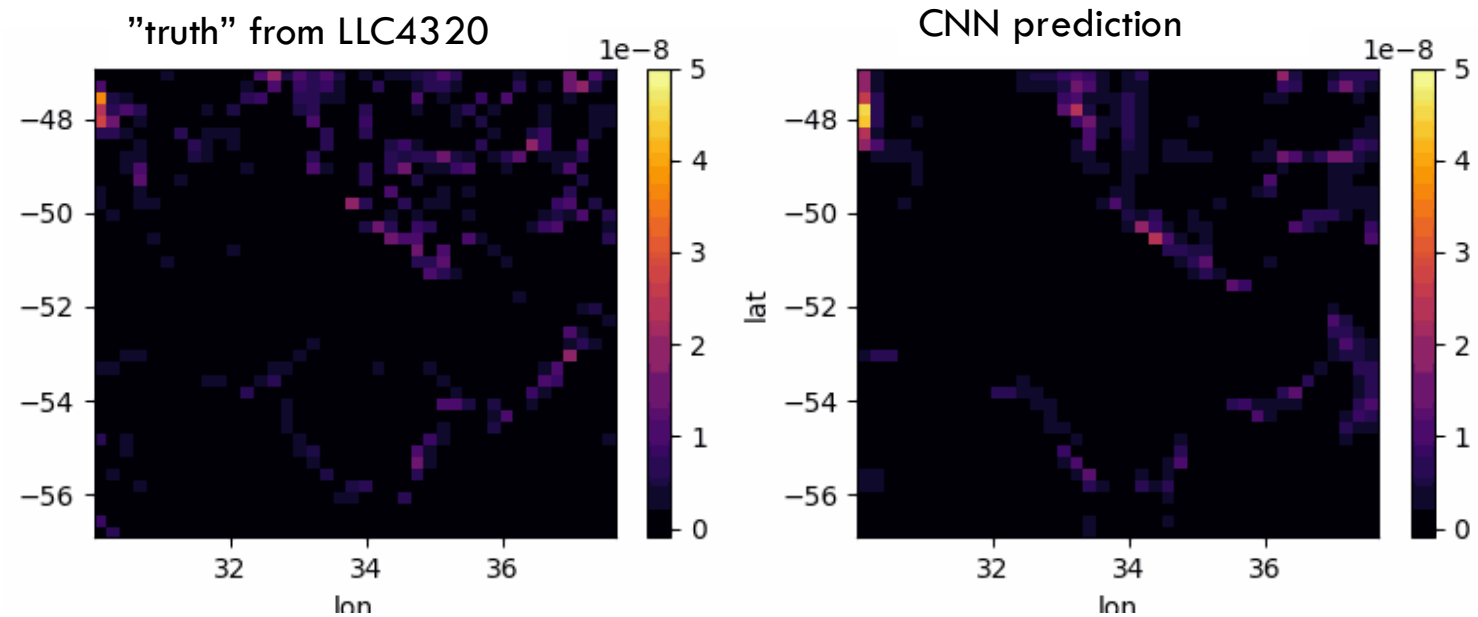
Bodner, Balwada, Zanna (2025)

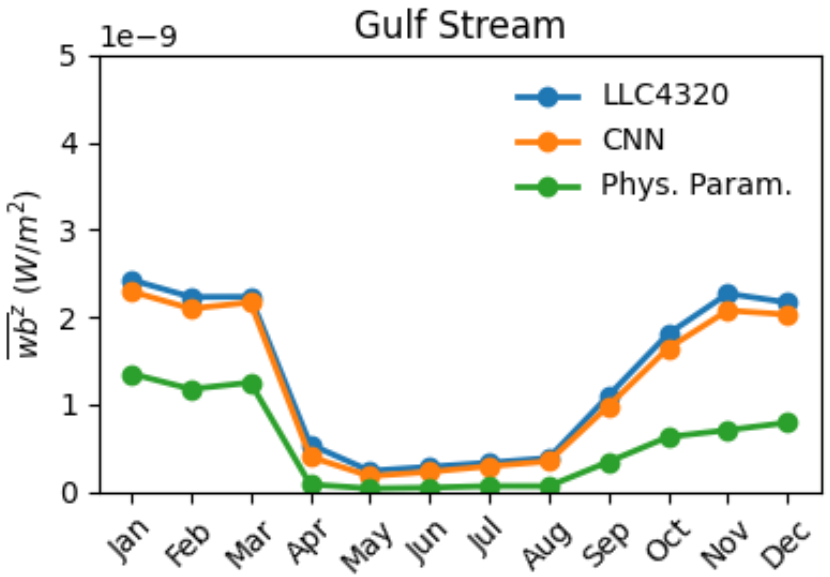
Prediction on unseen data

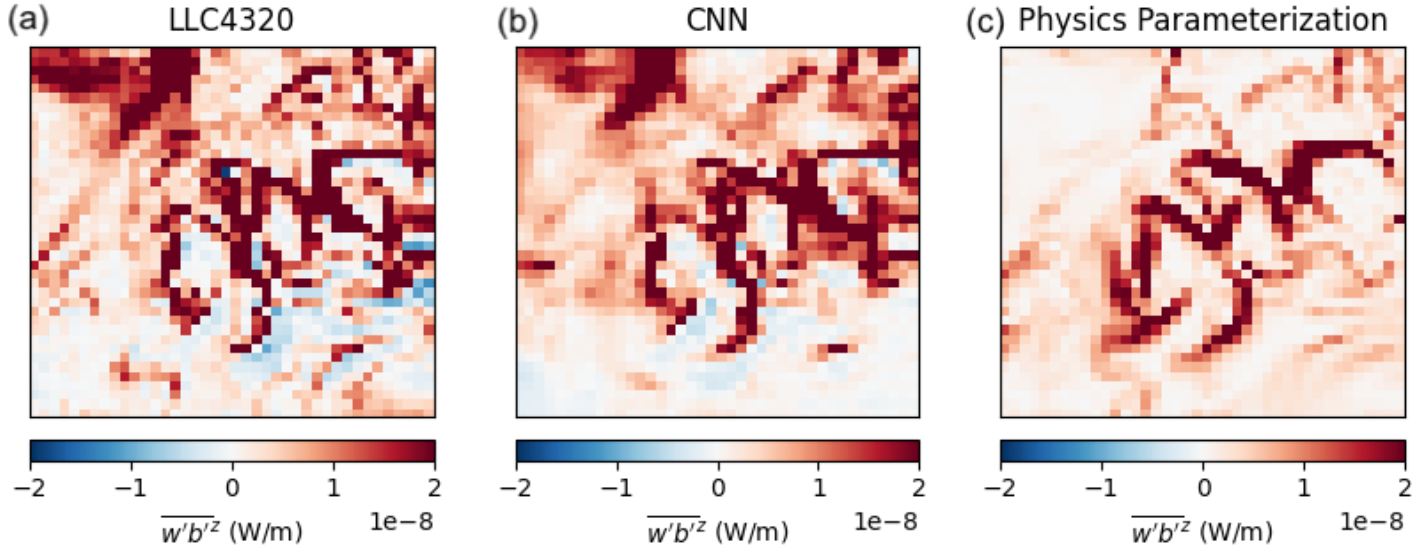
- The CNN captures the overall structure, including negative fluxes

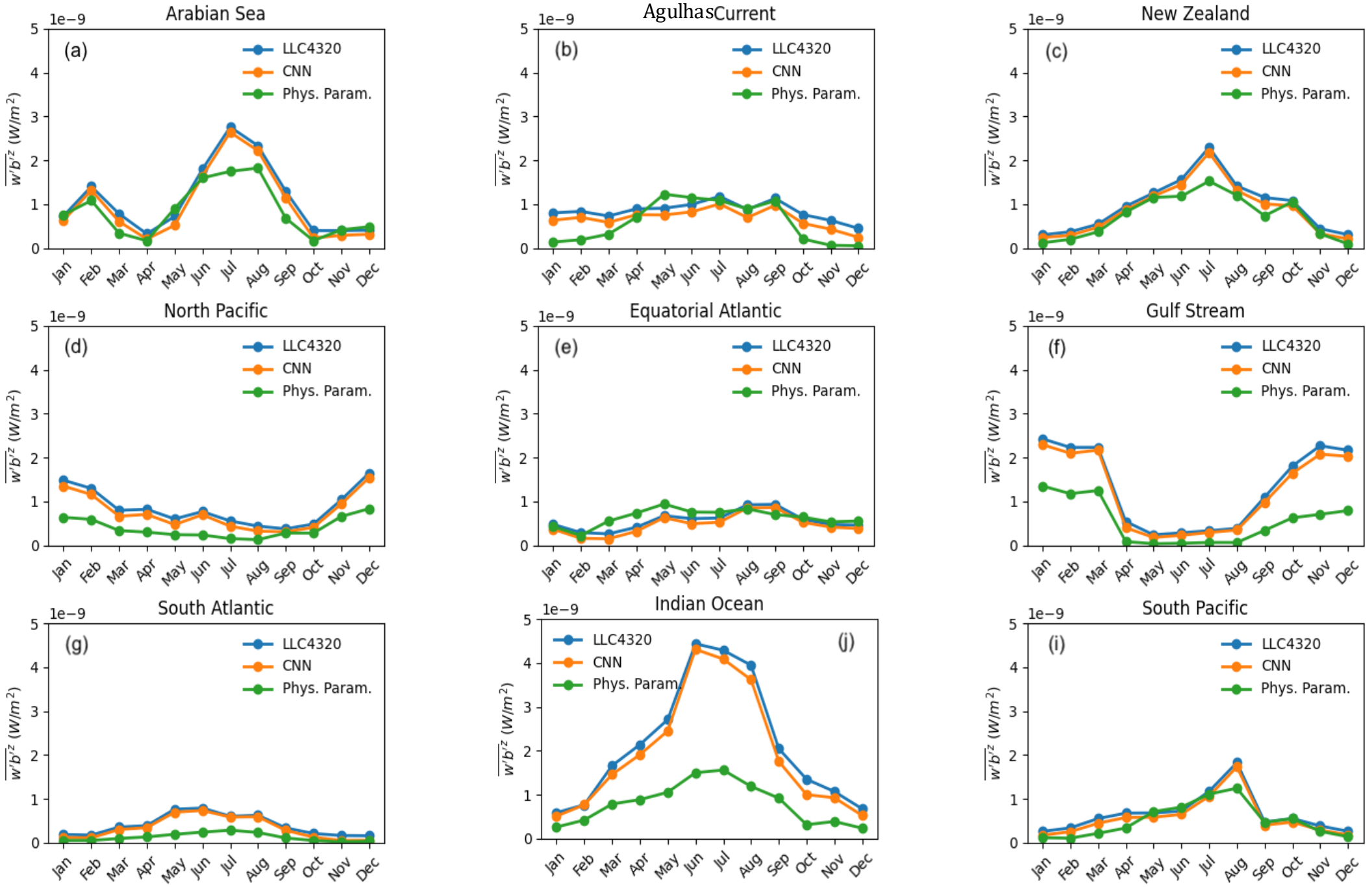


Prediction on unseen data

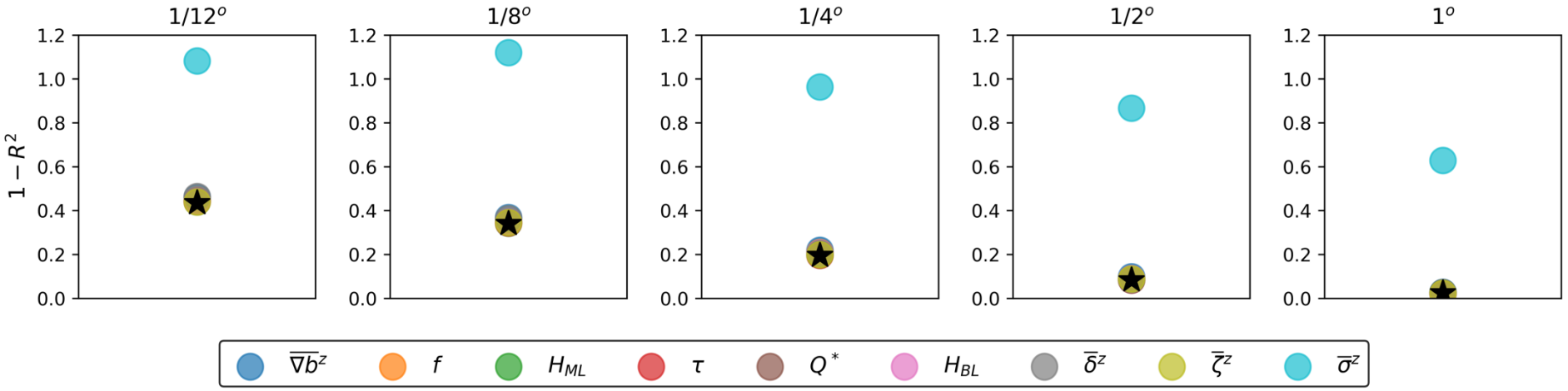
- The CNN captures the overall structure, including negative fluxes
- the CNN predictions outperforms the physics-based parameterization, particularly during months of strong submesoscale fluxes.



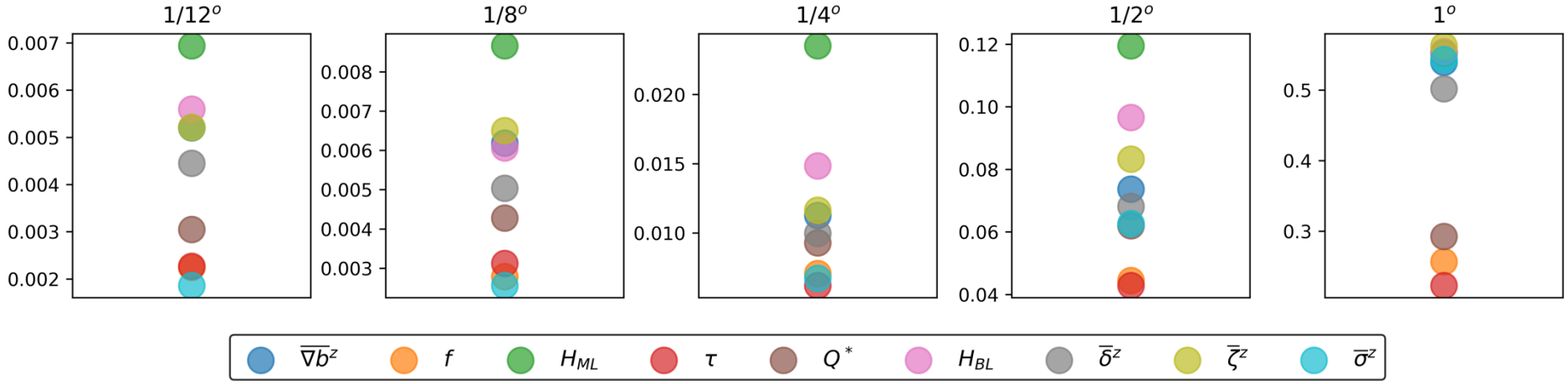



Arabian Sea
AgulhasCurrent
New Zealand
North Pacific
Equatorial Atlantic
Gulf Stream
South Atlantic
Indian Ocean
South Pacific
(a)
(b)
(c)
(d)
(e)
(f)
(g)
(j)
(i)
LLC4320
CNN
Phys. Param.
1e−9
$\overline{w'b'^z}$ (W/m²)
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec

But why so good?

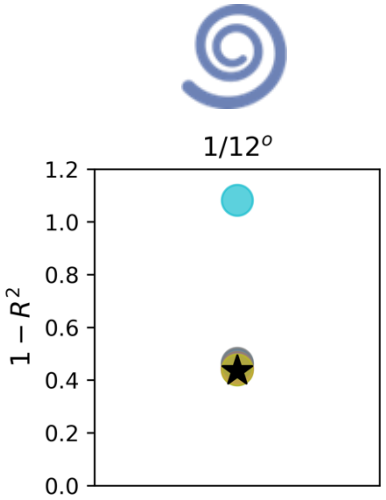


Remove input feature

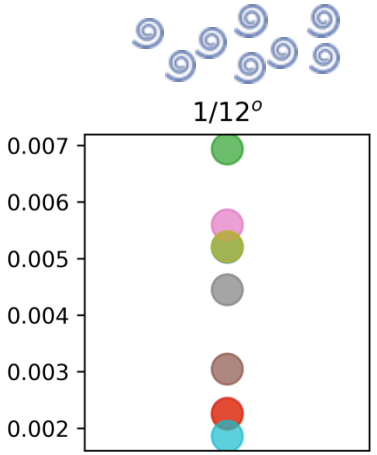


Sensitivity (gradients) relative to input feature

But why so good?

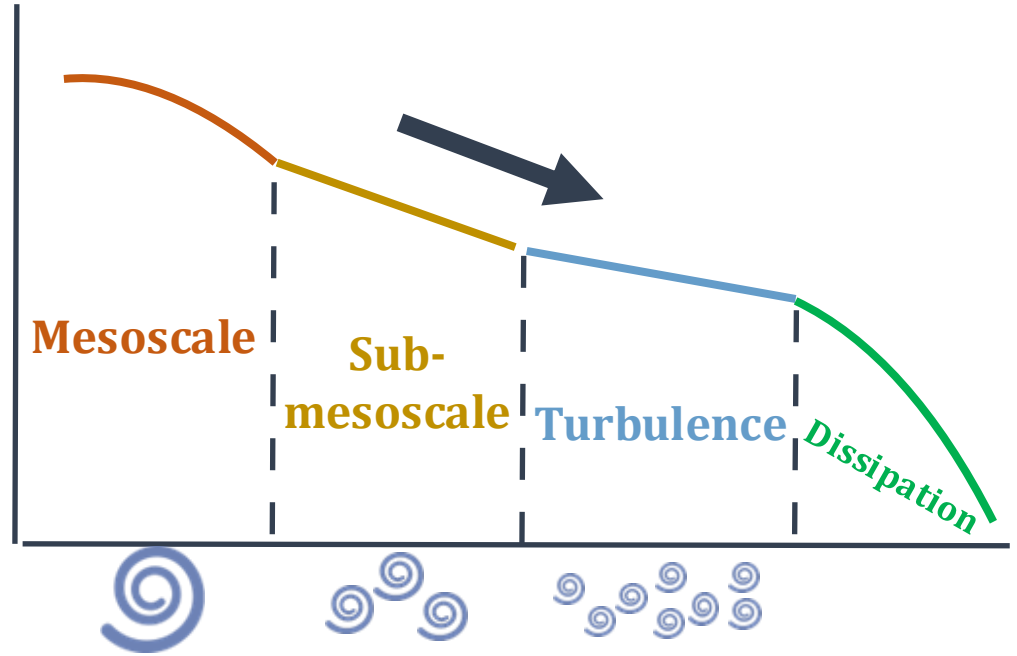


Remove input feature



Sensitivity (gradients) relative to input feature

Multiscale interactions determine submesoscale flux!



CNN submesoscale parameterization

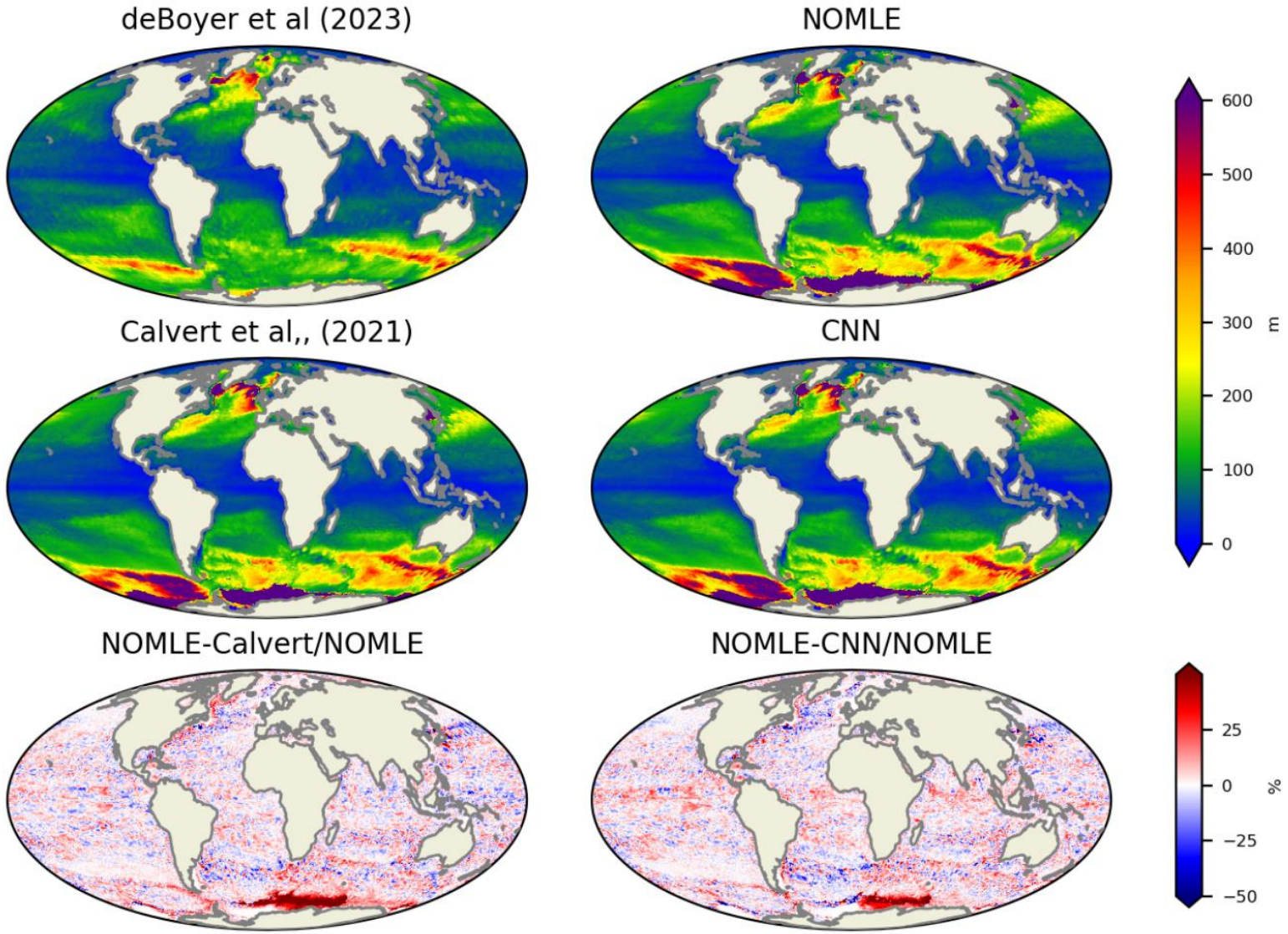
Bodner, Balwada, Zanna (2025)

Contreras et al. (in prep.)

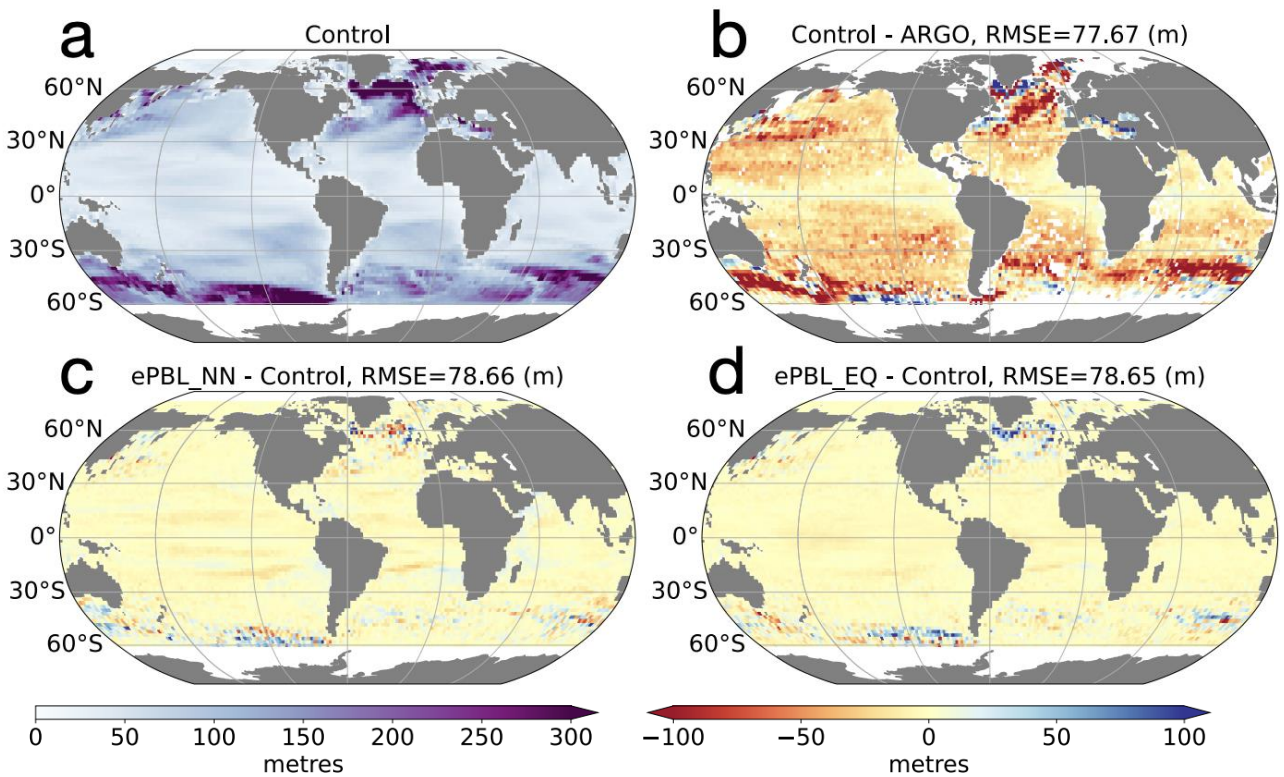
- CNN implemented in NEMO
- Streamfunction inverted from predicted fluxes

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

- Online performance compared with Calvert MLE parameterization reveals limited change



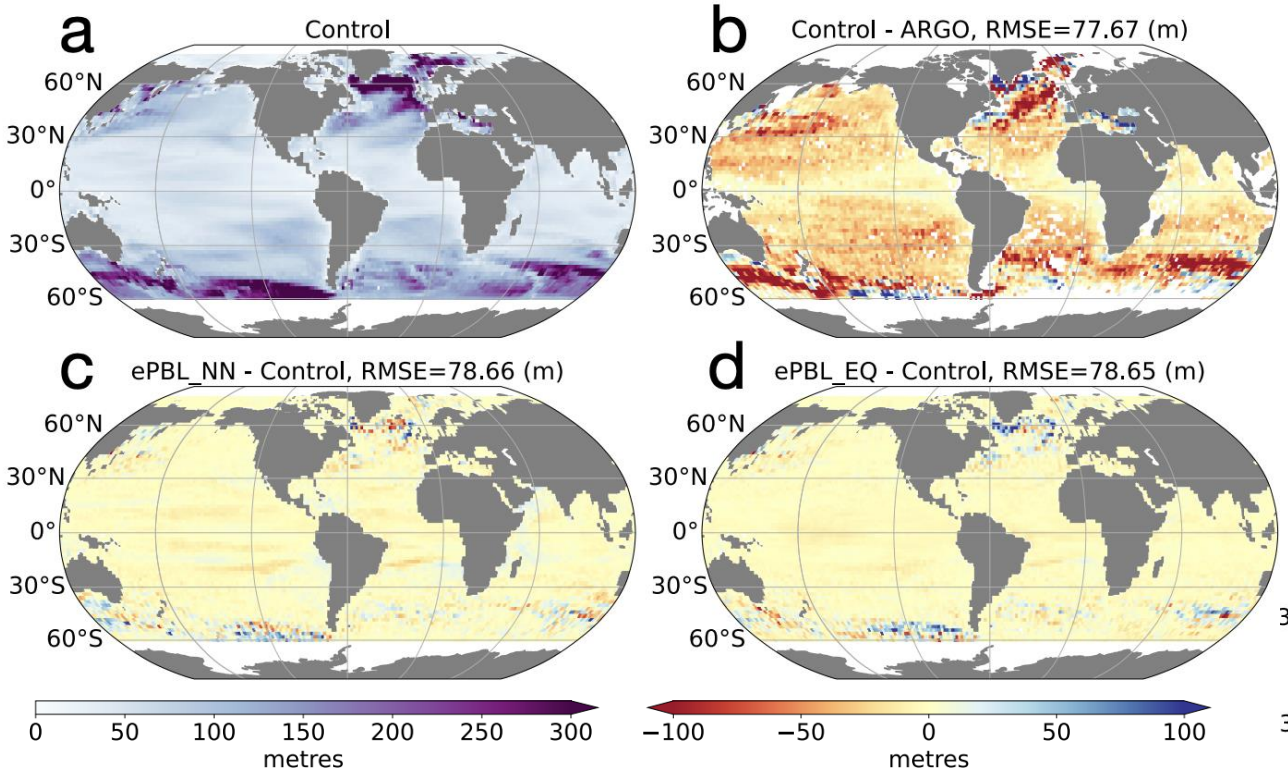
Vertical mixing parameterizations



Winter mixed layer depth

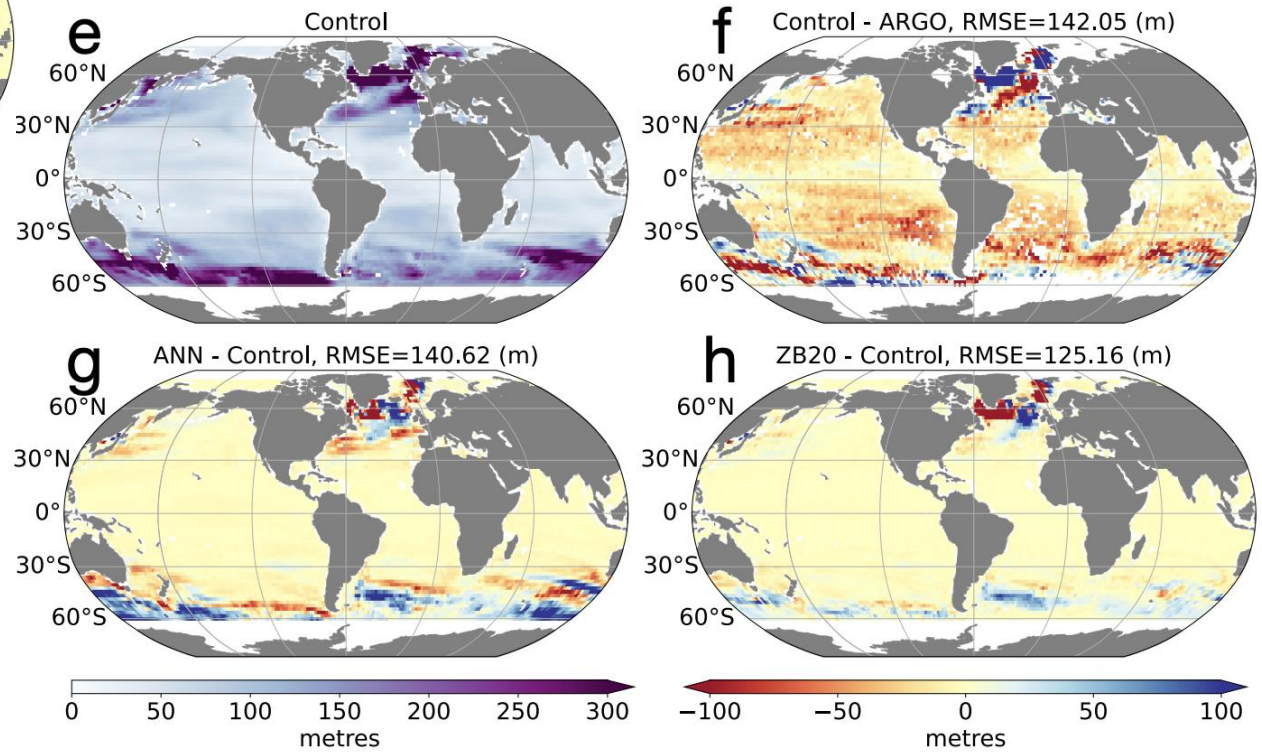
Zanna et al (2025)

Vertical mixing parameterizations



Winter mixed layer depth

Mesoscale parameterizations



Winter mixed layer depth

Zanna et al (2025)

Summary

- Subgrid effects of climate models are inferred via parameterizations , meant to correct the large-scale resolved motioned by important unresolved processes.
- Data-driven parameterizations have the potential to obtain higher-level accuracy than purly physics-based.
- Implementation strategies in large-scale models should considerthe cost-benefit of many parameters vs bias reduction.
- Other strategies include hard-coding conservation laws and equation discovery to reduce number of parameters.