



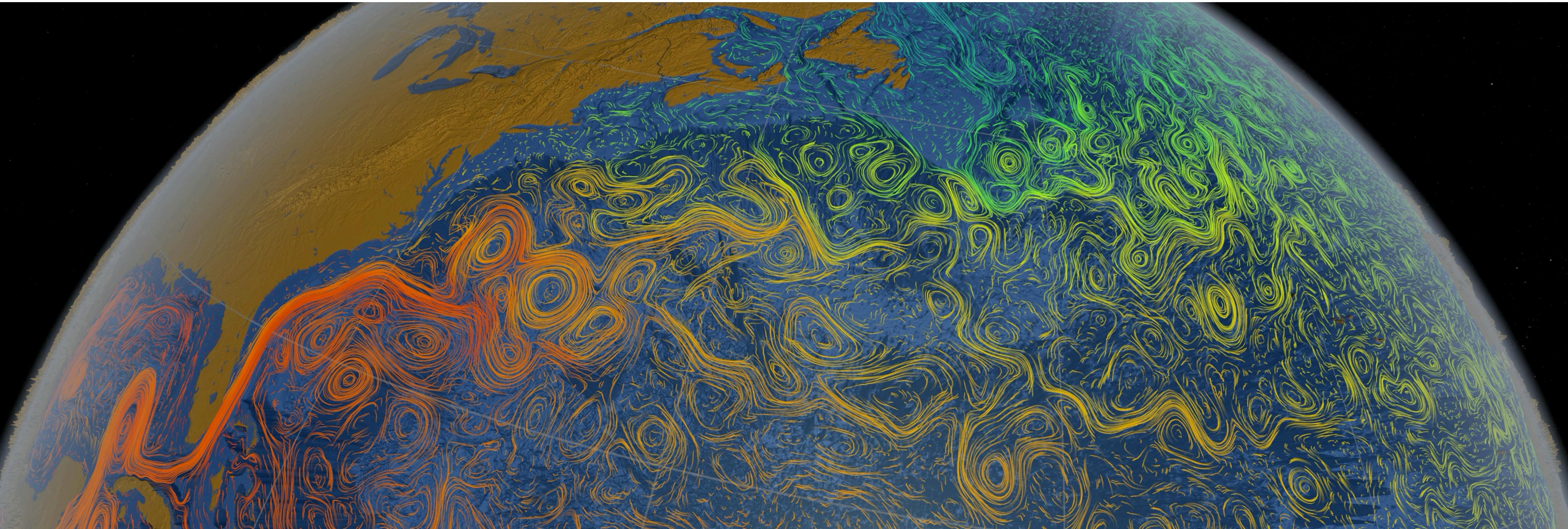
Australian
National University

A data-driven approach for developing and calibrating a parameterization of the ocean mesoscale eddy fluxes



Australian Government
Australian Research Council

Navid Constantinou



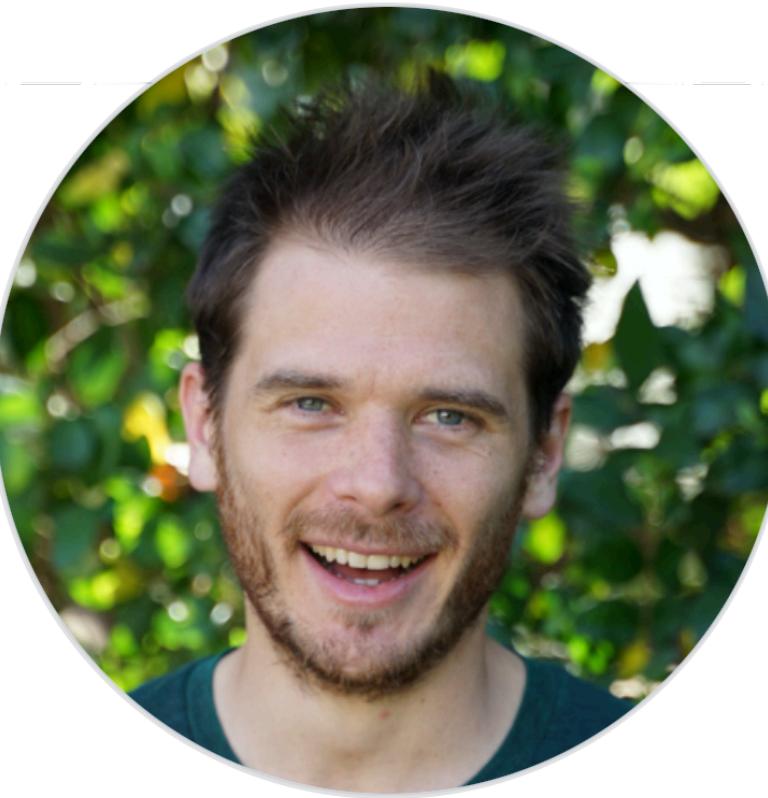
Remark: Not to be confused with Van Gogh's "Starry Night"

KITP, ML for Climate
November 1st, 2021

Visualization using output from the MIT/JPO project
Estimating the Circulation and Climate of the Ocean, Phase II (ECCO2)

Credit: NASA/Goddard Space Flight
Center Scientific Visualization Studio

special thanks go to my pals at MIT



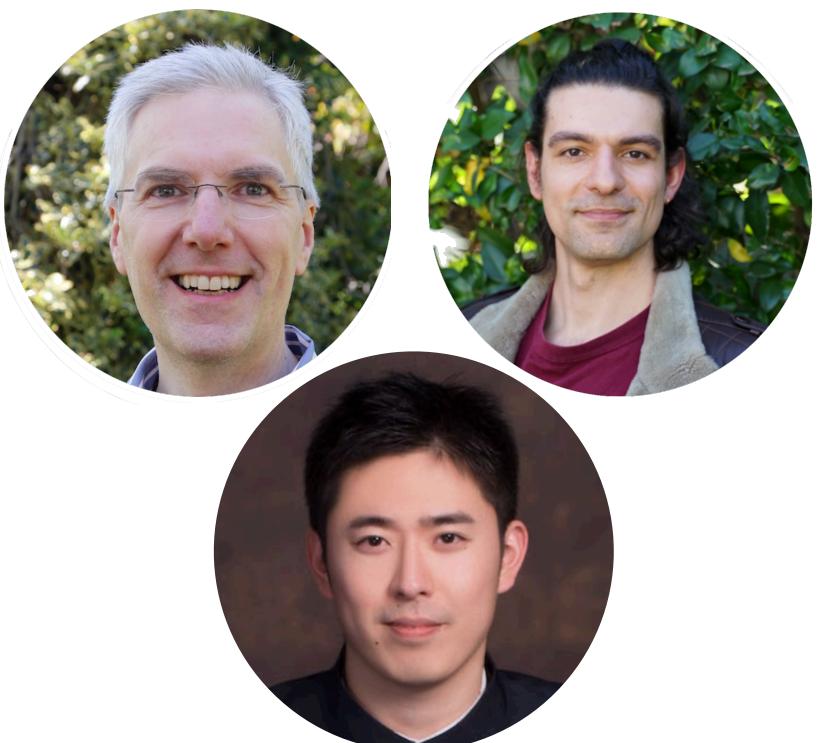
Gregory L. Wagner
glwagner



Adeline Hillier
adelinehillier

Oceans + Julia
 122 followers · 76 following · ⭐ 109
 Massachusetts Institute of Technology
 Salt Lake City, Utah
 gregory.leclaire.wagner@gmail.com
 glwagner.github.io

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also Raffaele Ferrari, Andre Souza, Xiaozhou Ruan (MIT)
and Stephen Griffies (GFDL)

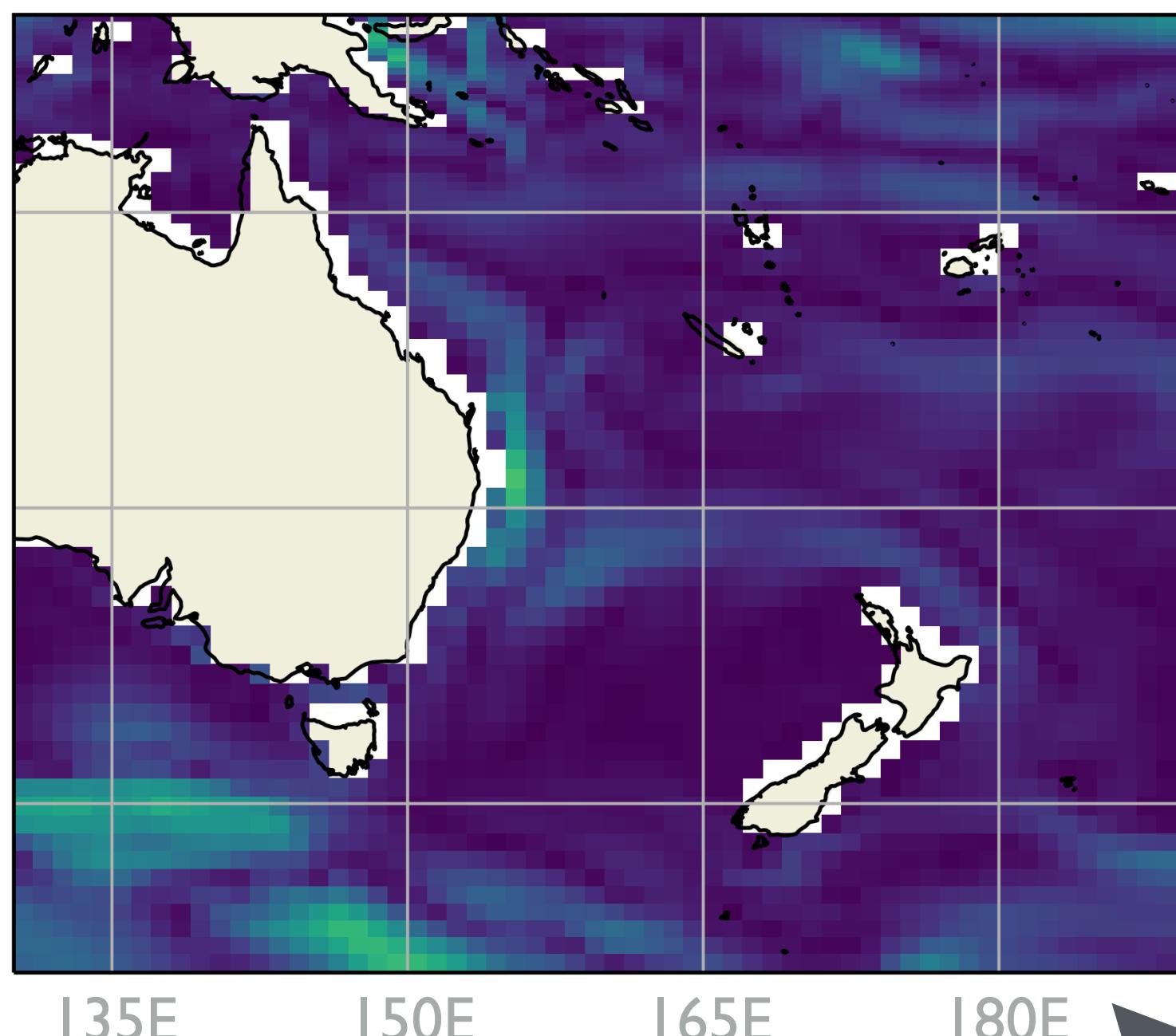


ocean currents modelled at different horizontal resolutions

(why ocean eddies give headaches to climate scientists?)

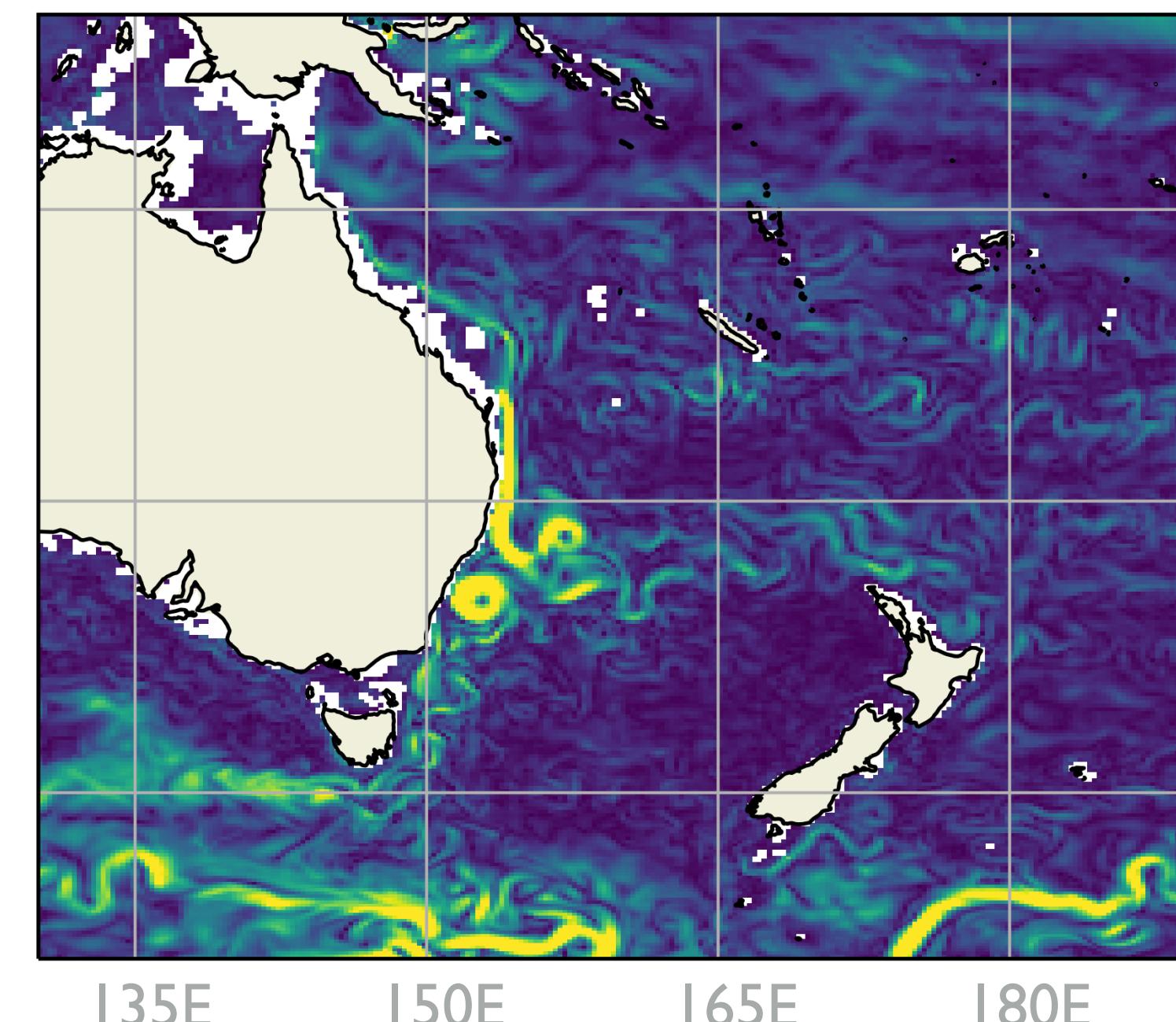


1°

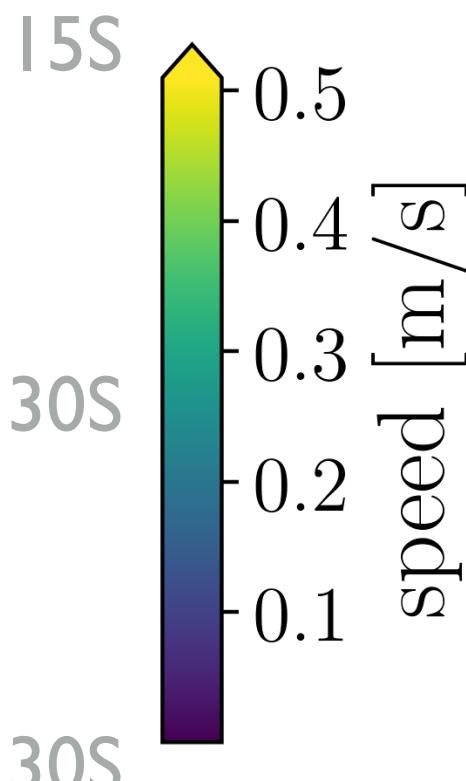
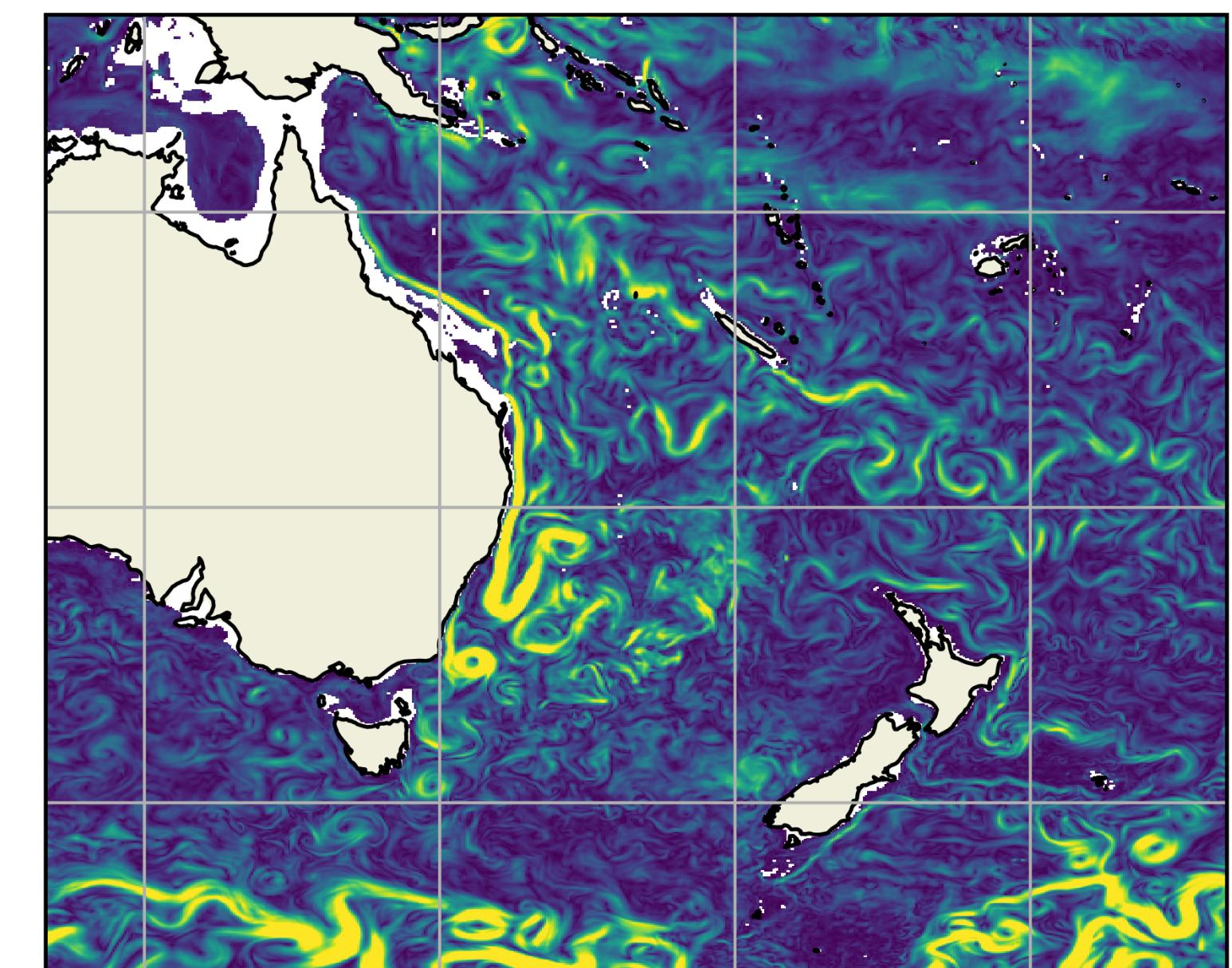


typically used
for climate predictions
IPCC, etc...

0.25°



0.10°



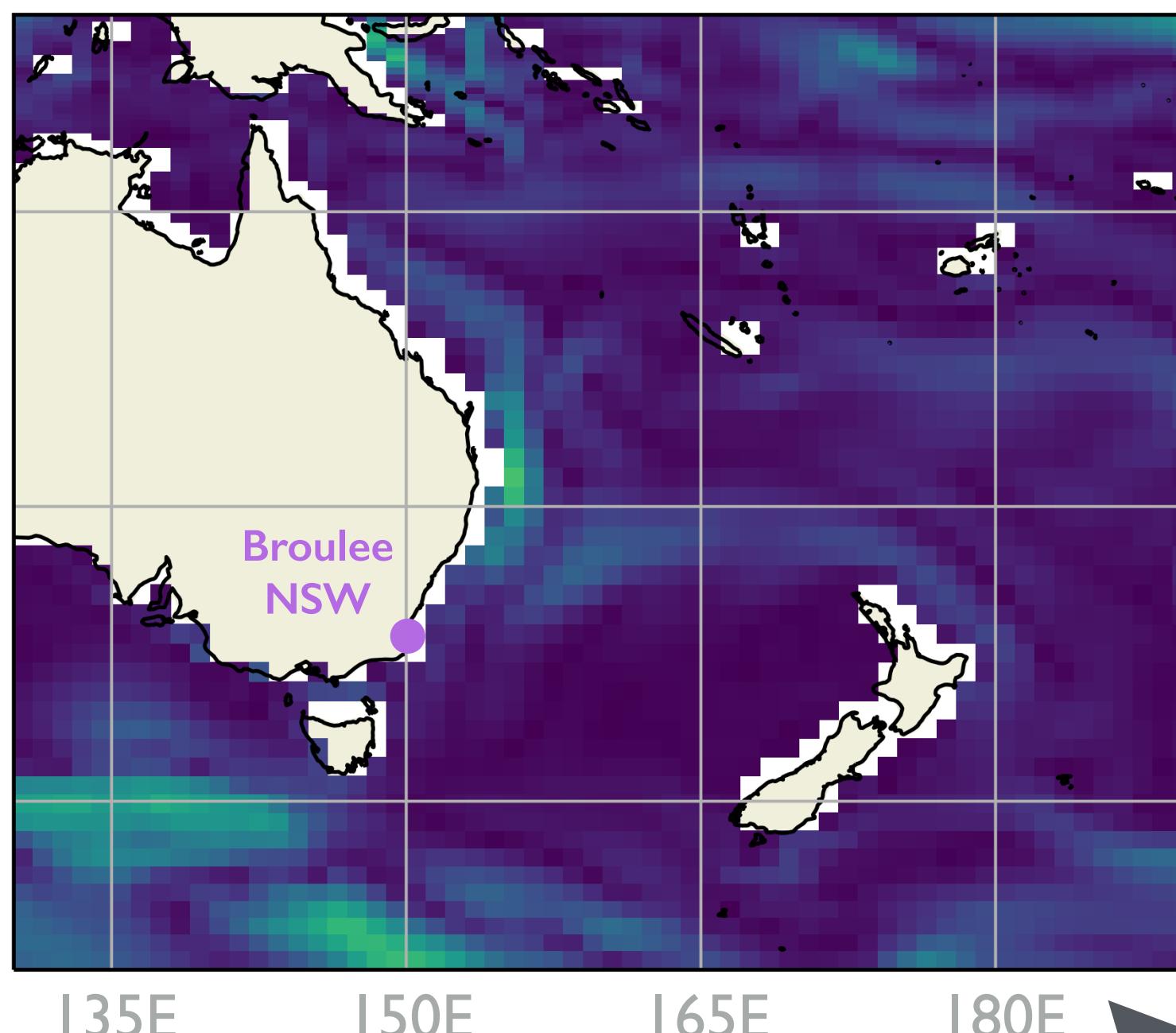
state-of-the-art
ocean—sea-ice model

ocean currents modelled at different horizontal resolutions

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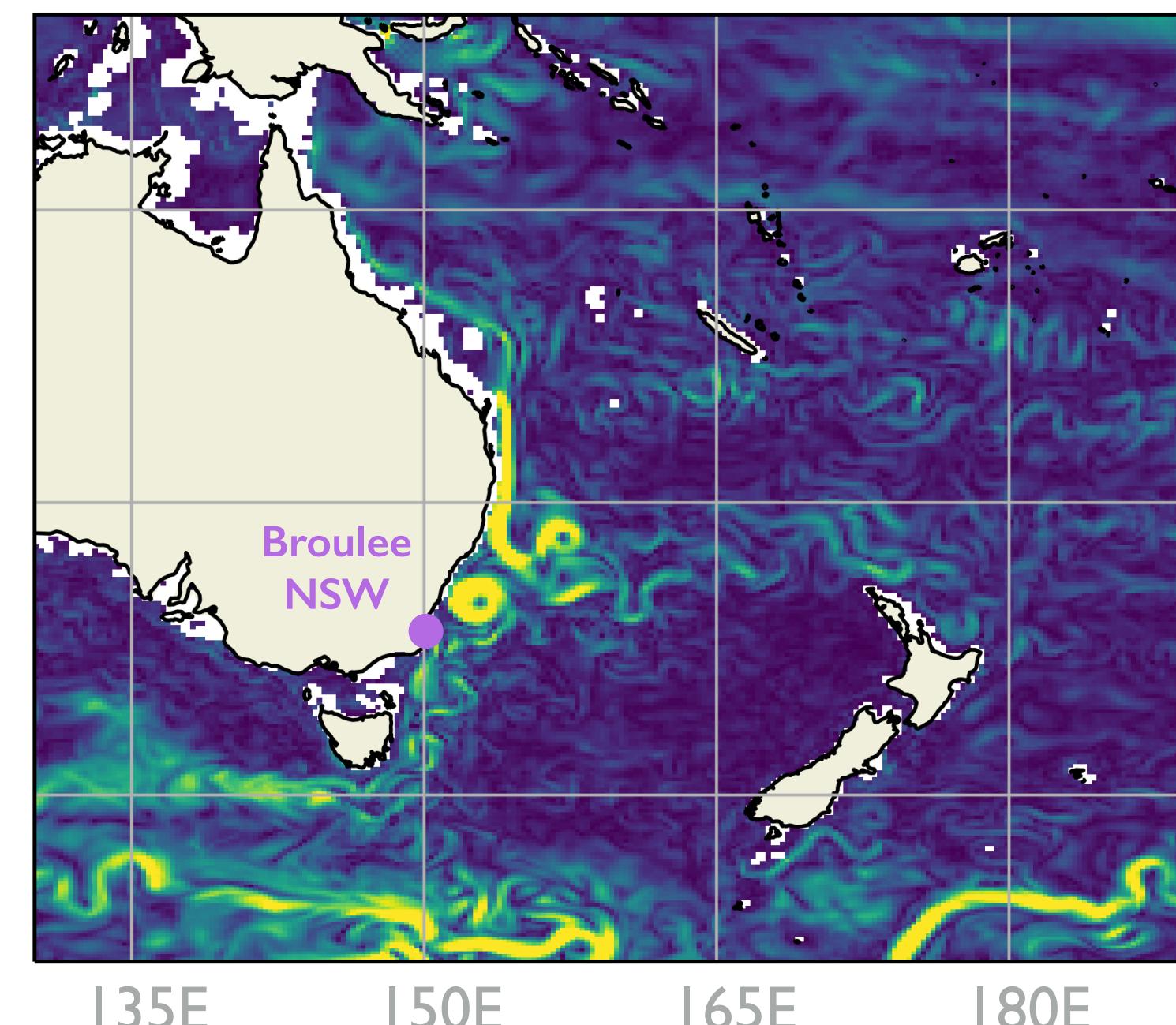


1°

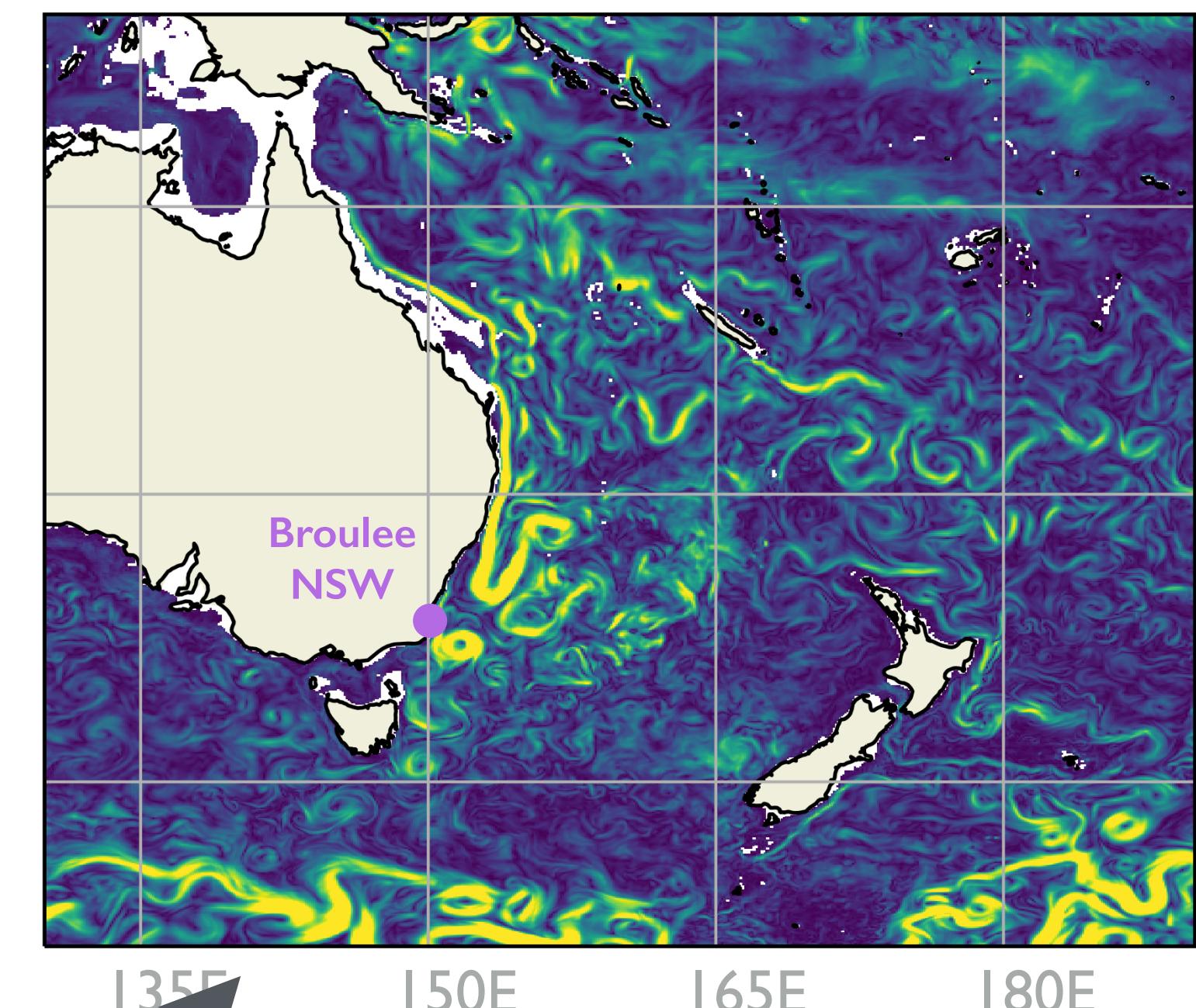


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ocean currents modelled at different horizontal resolutions



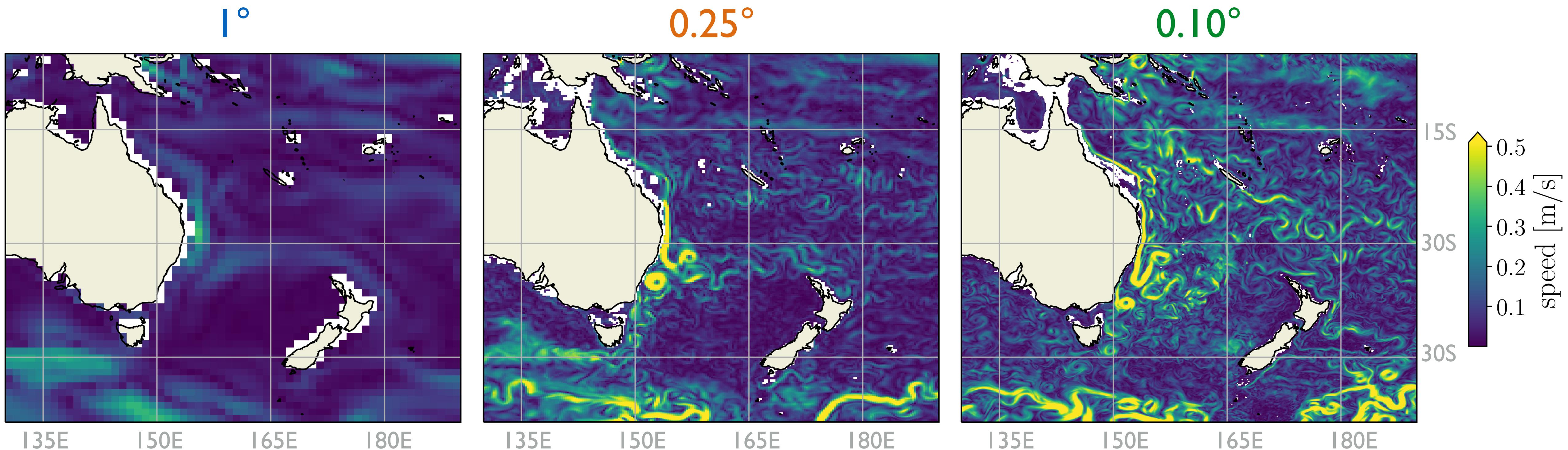
typically used
for climate predictions
IPCC, etc...



state-of-the-art
ocean—sea-ice model

can we make the **coarse model** feel the effect
of the flow details that it does not resolve?

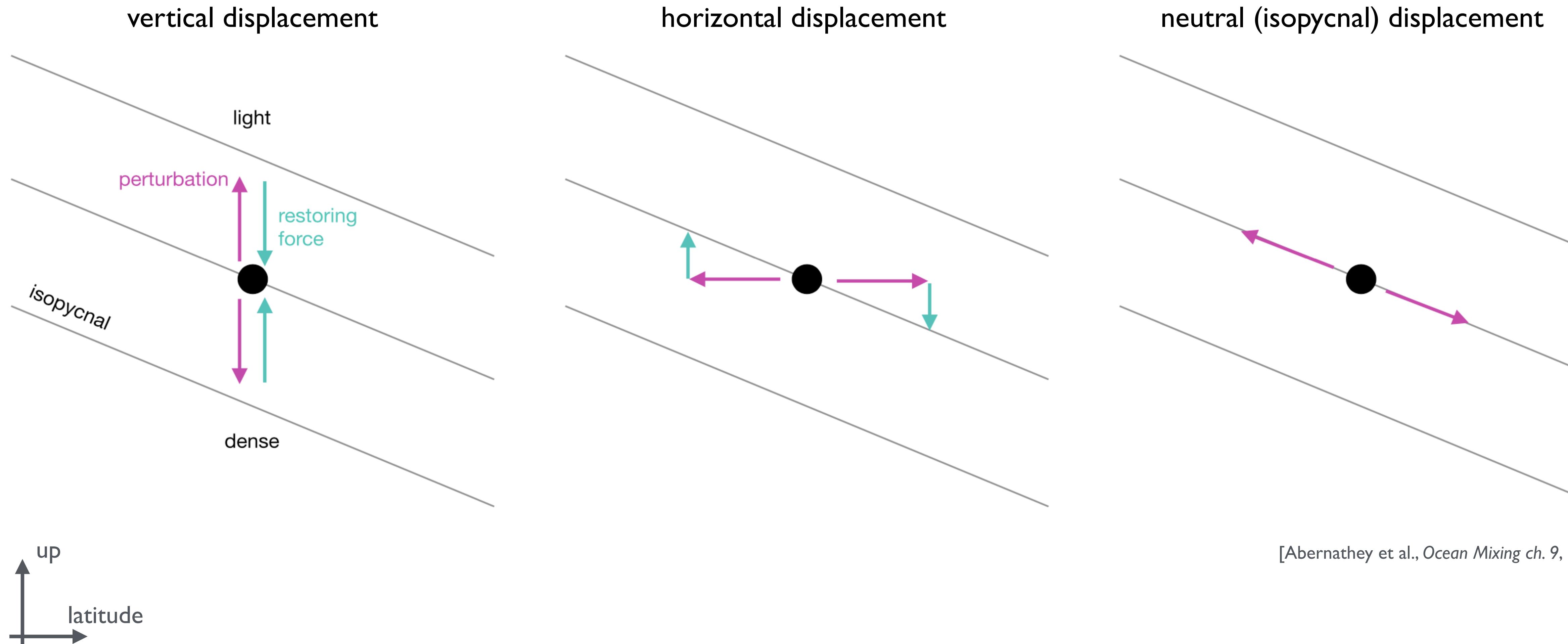
[in technical terms: “eddy parameterisation”]



we don't need to know what each eddy is doing!
we care for the low-order, long-time statistics of the system
(climate vs weather)

a small primer on how eddies
affect the large-scales

eddies move tracers along neutral directions



isopycnal/neutral direction = along isopycnal
diapycnal = across isopycnal (costs potential energy)

[Abernathy et al., Ocean Mixing ch. 9, 2021]

how eddies affect tracers?



(few equations hardly ever hurt)

tracer (e.g. heat) dynamics

$$\frac{\partial c}{\partial t} + \mathbf{u} \cdot \nabla c = \kappa \nabla^2 c$$

$$c = \bar{c} + c'$$

resolved unresolved

how eddies affect tracers?



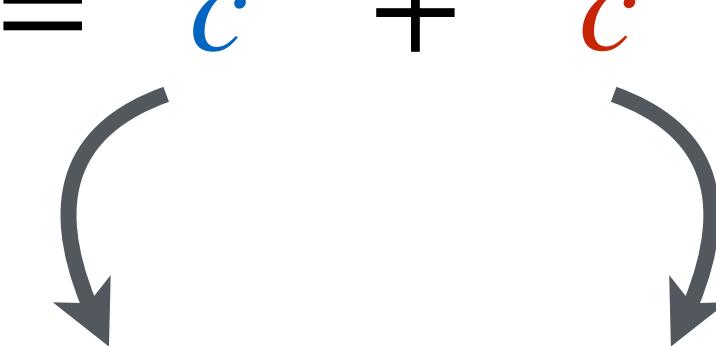
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tracer (e.g. heat) dynamics

$$\frac{\partial c}{\partial t} + \mathbf{u} \cdot \nabla c = \kappa \nabla^2 c$$

$$c = \bar{c} + c'$$

resolved unresolved



}

$$\frac{\partial \bar{c}}{\partial t} + \bar{\mathbf{u}} \cdot \nabla \bar{c} = \kappa \nabla^2 \bar{c} - \nabla \cdot (\bar{\mathbf{u}}' c')$$

the dynamics the
model solves for

subgrid
eddy fluxes

$\bar{\mathbf{u}}' c'$ eddy tracer flux

parametrization

express **eddy tracer flux** in terms of the **resolved fields**

$$\overline{u'c'} = \mathcal{F}(\bar{u}, \bar{c}, \dots)$$

eddy tracer eddy tracer flux
flux parametrization



isoneutral diffusion

eddies mix tracers, therefore

$$\overline{u'c'} \approx -\kappa_{\text{eddy}} \nabla \bar{c}$$

downgradient flux

$$\implies -\nabla \cdot (\overline{u'c'}) = \kappa_{\text{eddy}} \nabla^2 \bar{c}$$

“eddy diffusivity”



isoneutral diffusion

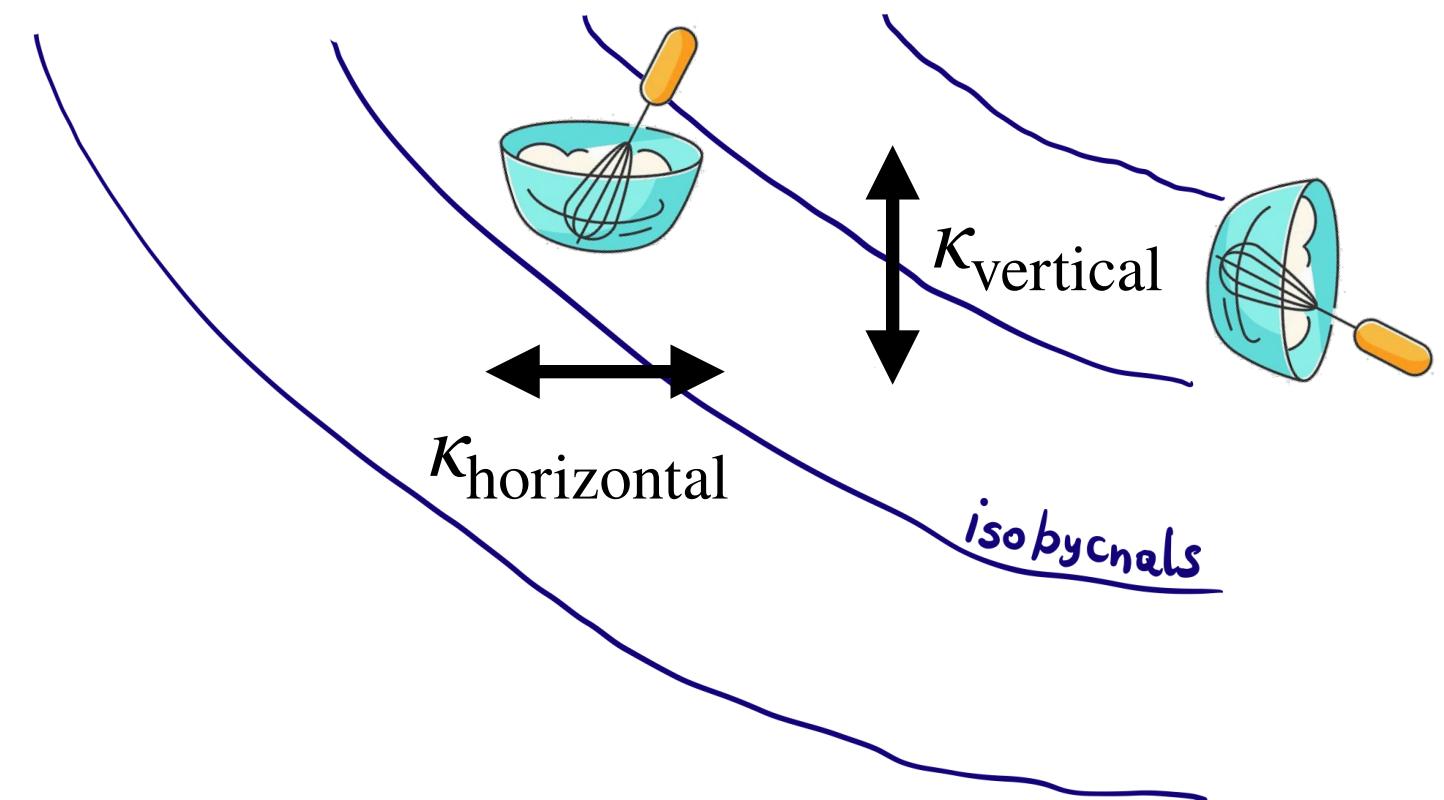
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$$\implies -\nabla \cdot (\overline{u'c'}) = \kappa_{\text{eddy}} \nabla^2 \bar{c}$$

downgradient flux

“eddy diffusivity”



$$\overline{u'c'} \approx - \begin{pmatrix} \kappa_h & 0 & 0 \\ 0 & \kappa_h & 0 \\ 0 & 0 & \kappa_v \end{pmatrix} \cdot \nabla \bar{c}$$

anisotropic
downgradient flux



isoneutral diffusion

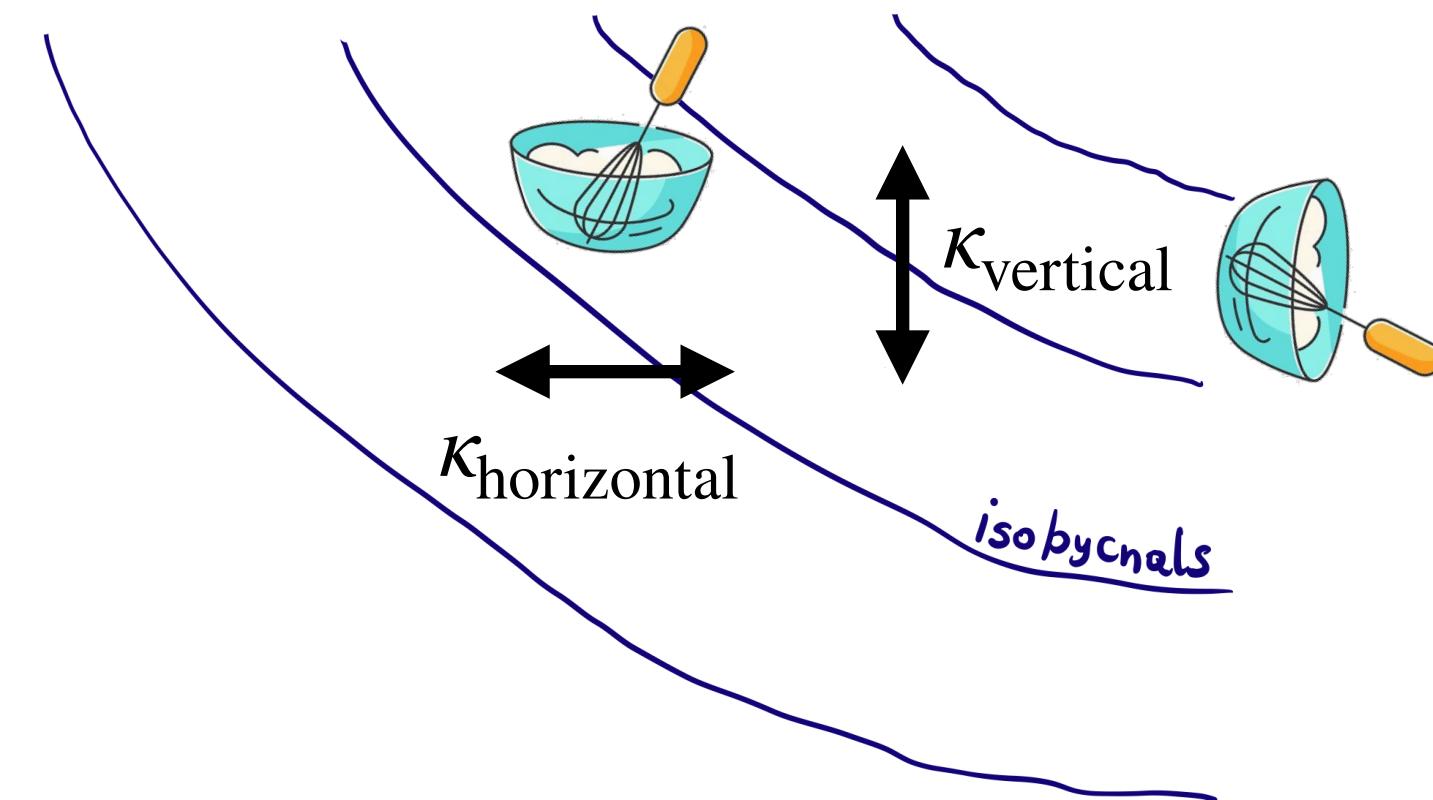
eddies mix tracers, therefore

$$\overline{u'c'} \approx -\kappa_{\text{eddy}} \nabla \bar{c}$$

downgradient flux

$$\implies -\nabla \cdot (\overline{u'c'}) = \kappa_{\text{eddy}} \nabla^2 \bar{c}$$

“eddy diffusivity”



κ_{eddy}

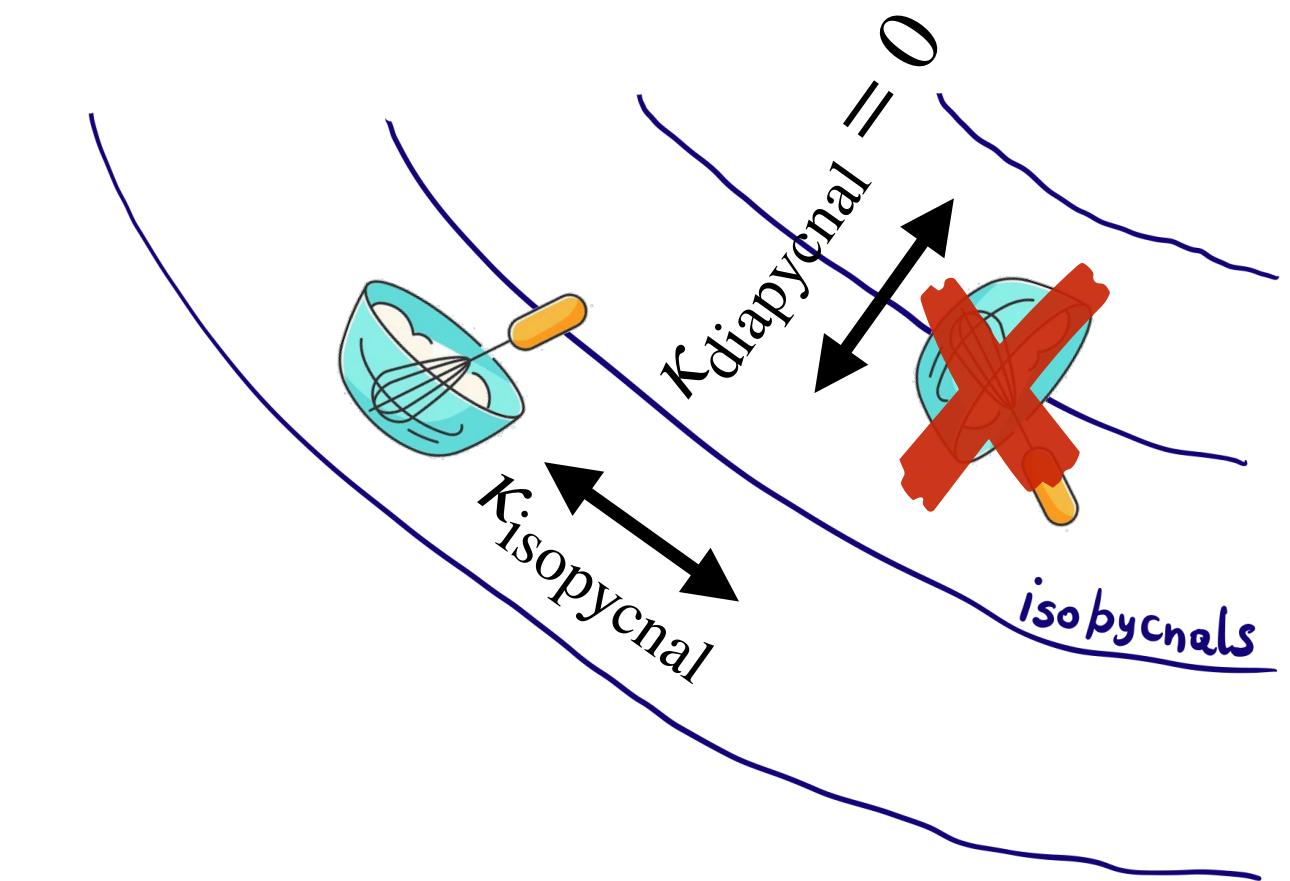
a 3x3 tensor
that rotates coords
to neutral-cross neutral
directions

$$\overline{u'c'} \approx - \begin{pmatrix} \kappa_h & 0 & 0 \\ 0 & \kappa_h & 0 \\ 0 & 0 & \kappa_v \end{pmatrix} \cdot \nabla \bar{c}$$

anisotropic
downgradient flux

$$\overline{u'c'} \approx -\mathbb{K}_{\text{eddy}} \cdot \nabla \bar{c}$$

downgradient flux
locally aligned with
neutral direction





isoneutral diffusion

$$\overline{u'c'} \approx - (\mathbb{K}_{GM} + \mathbb{K}_{Redi}) \cdot \nabla \bar{c}$$



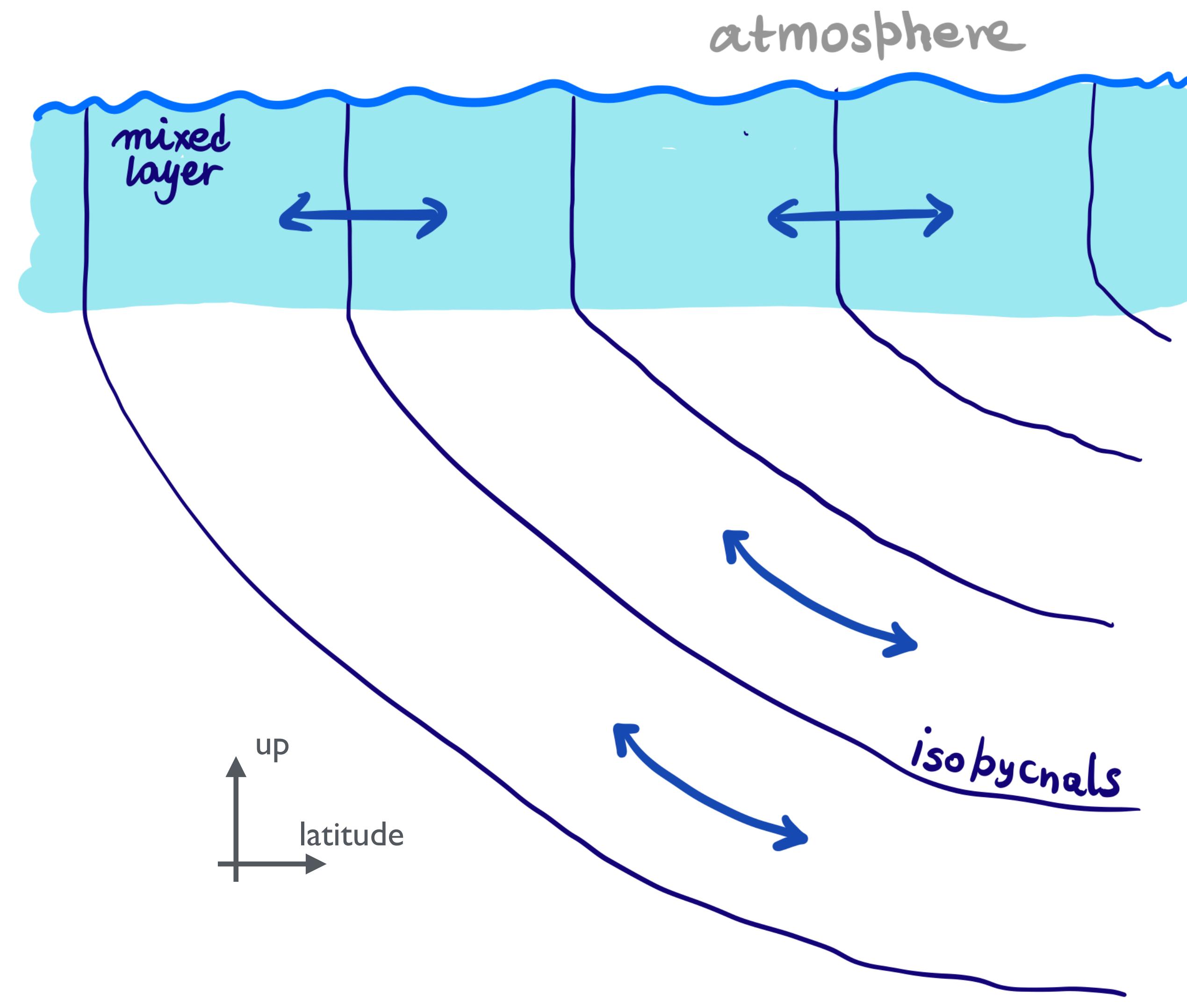
skew flux
modeling
stirring along
isopycnals



tracer
diffusion
along
isopycnals



it was all fun and games until...



towards the surface dominant dynamics change

mesoscale parametrization should “convert” to boundary layer turbulence parametrization

[eg Ferrari et al. 2008]

GM-Redi should “turn off” when isopycnal become too steep

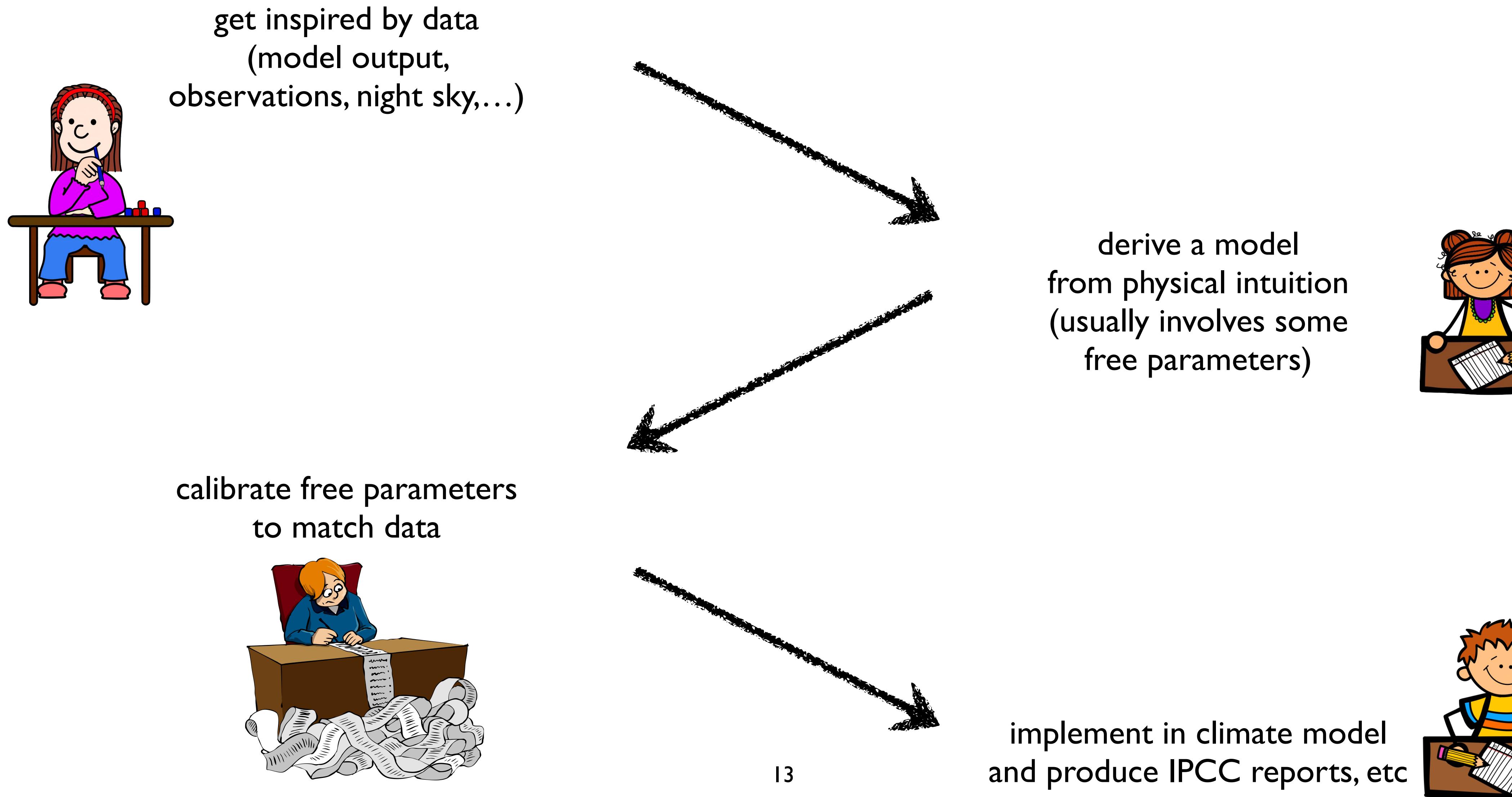
[slope-clipping, slope tapering
Gerdes et al. 1991, Dabanasoglou and McWilliams 1995, Large et al. 1997]

parametrization should “turn off” in places where model is able to resolve eddies (double-counting)

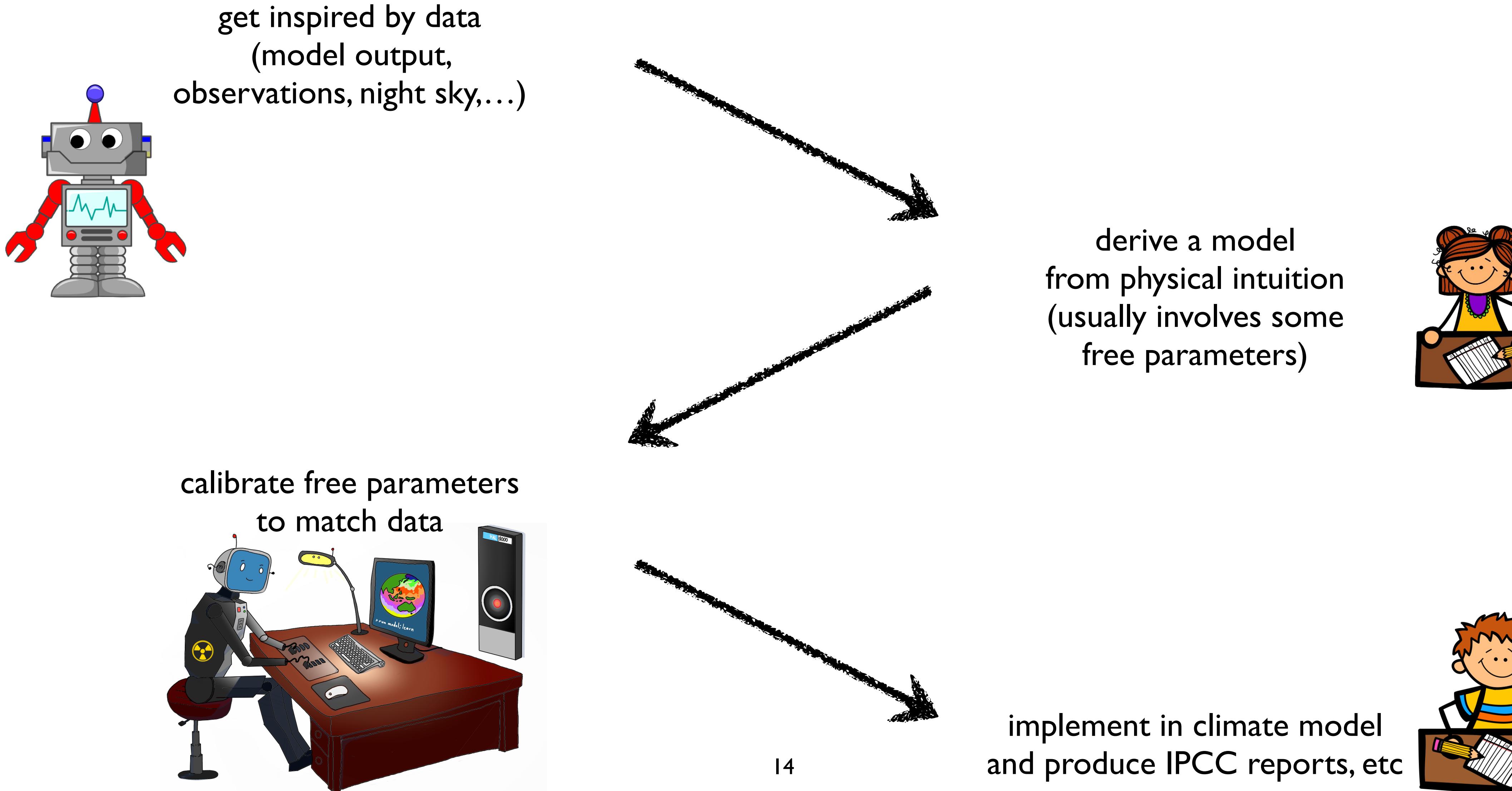
[scale-aware eg Zanna et al. 2017]

eddy activity varies (laterally, vertically, seasonally?)
GM/Redi diffusivities may depend on space/time

how do we come up with new parametrizations?



how do we come up with new parametrizations? and how machines can help?



how about data-driven?
doesn't that involve a neural network?

Newton's laws were, actually, “data-driven”

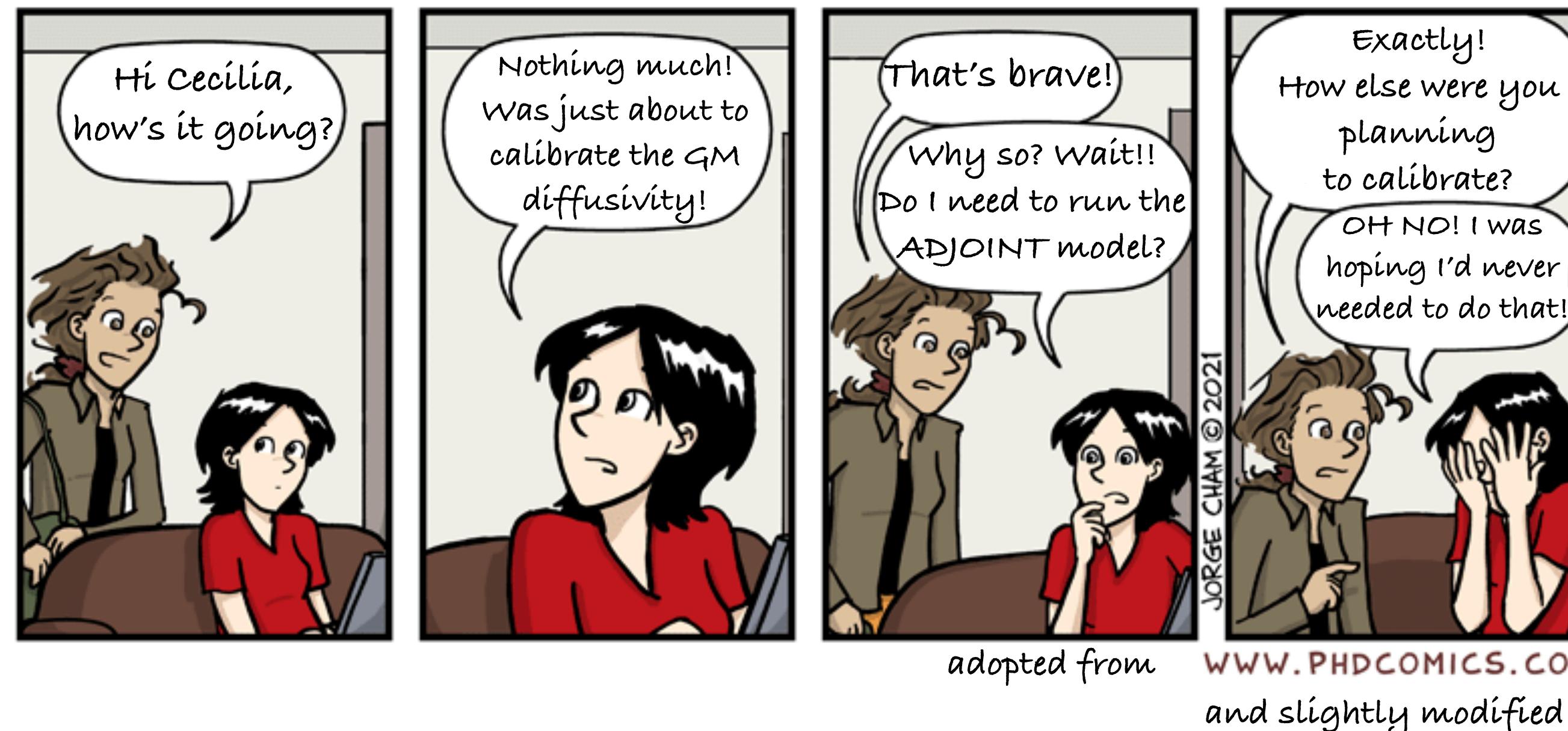
Instead of starting from a neural network
with $O(1e6)$ free parameters
we start from what we currently have
and enhance our physical models adding few more free parameters

calibration is *data-driven*

calibration

*“All agree that calibration is great!
But most don’t do it in a systematic manner
because it is so cumbersome!”*

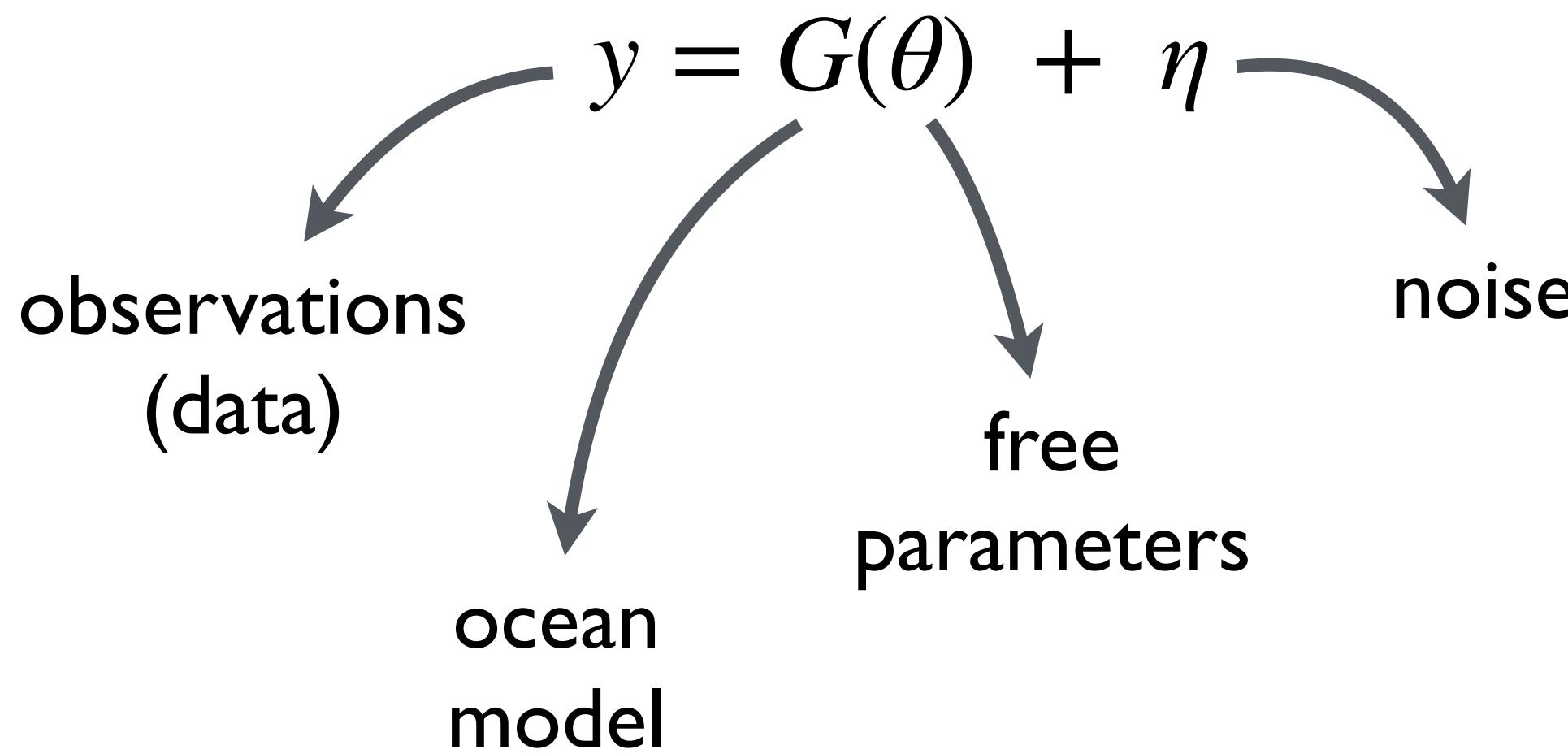
— adage



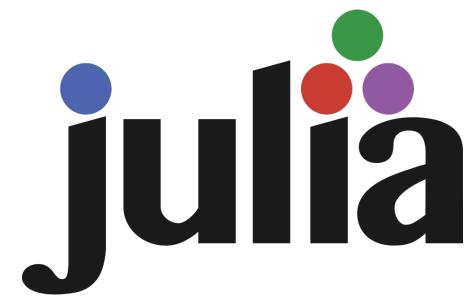
derivative-free Bayesian optimization
using ensemble Kalman filters

Ensemble Kalman Inverse process

Derivative-free ensemble optimization method
that seeks to find the optimal parameters θ for inverse problem



Calibration is done *online* by running ensembles of forward model runs



software enables research



[CliMA / Oceananigans.jl](#) Public

An oceanic library for fast, friendly, data-driven fluid dynamics on CPUs and GPUs

[clima.github.io/oceananigansdocumentation/stable](#)

MIT License

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Oceananigans.jl

Fast and friendly ocean-flavored Julia software for simulating incompressible fluid dynamics in Cartesian and spherical shell domains on CPUs and GPUs.

[CliMA / EnsembleKalmanProcesses.jl](#) Public

Implements Optimization and approximate uncertainty quantification algorithms, Ensemble Kalman Inversion, and Ensemble Kalman Processes.

[clima.github.io/ensemblekalmanprocesses.jl/dev](#)

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EnsembleKalmanProcesses.jl

Implements Optimization and approximate uncertainty quantification algorithms, Ensemble Kalman Inversion, and Ensemble Kalman Processes.

[adelinehillier / OceanTurbulenceParameterEstimation.jl](#) Public

Parameter estimation for column models of the ocean surface boundary layer.

MIT License

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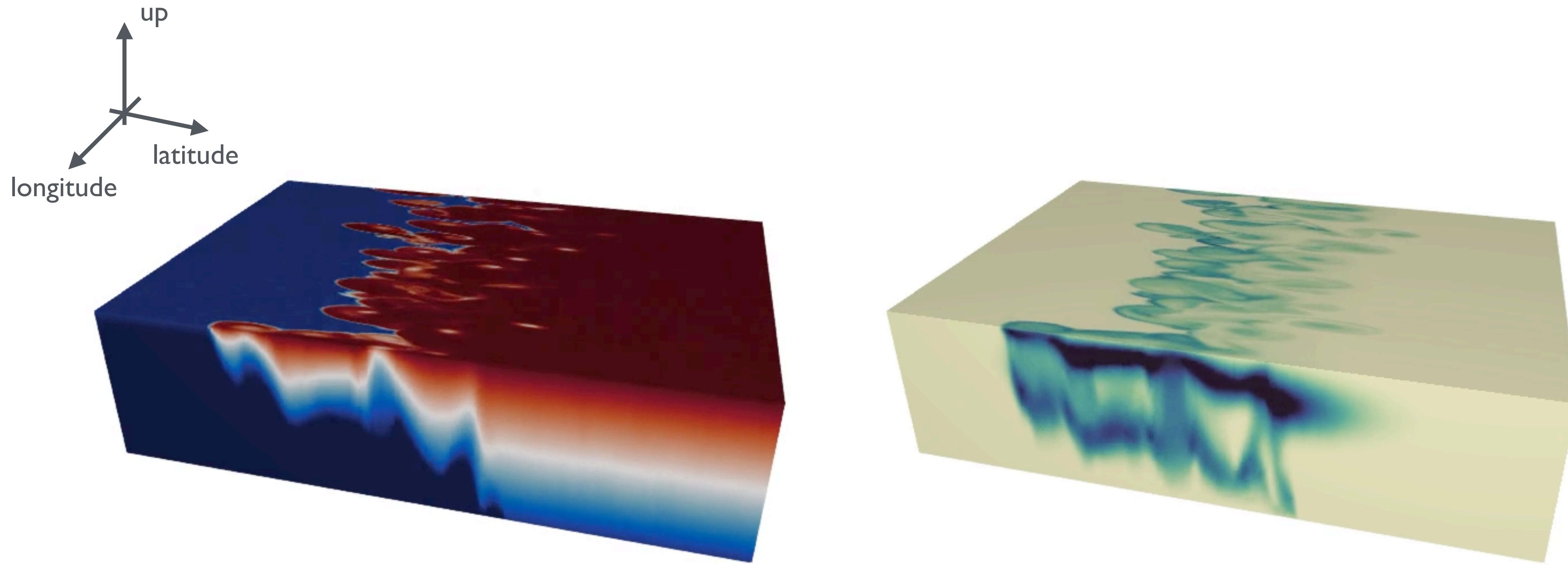
[README.md](#) [...](#)

OceanTurbulenceParameterEstimation.jl

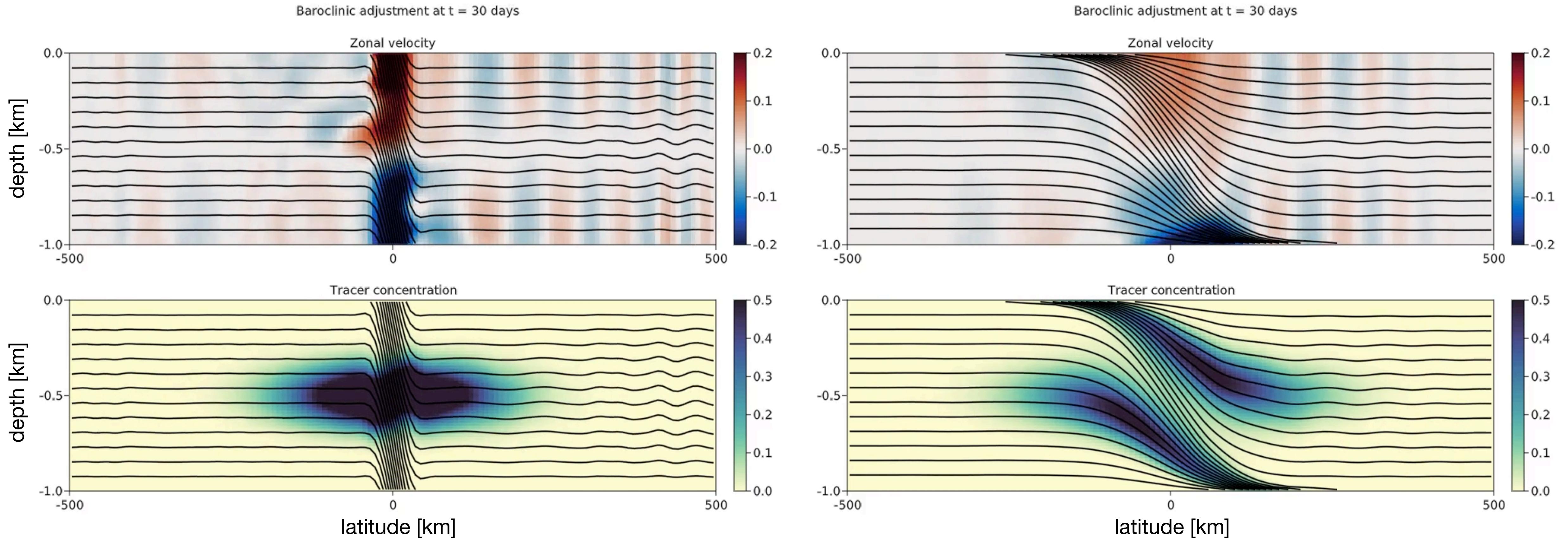
A Julia package designed to leverage [Oceananigans.jl](#) and [EnsembleKalmanProcesses.jl](#) to allow for calibration of ocean turbulence parametrizations.

baroclinic adjustment of a front

Buoyancy and tracer concentration at $t = 30$ days



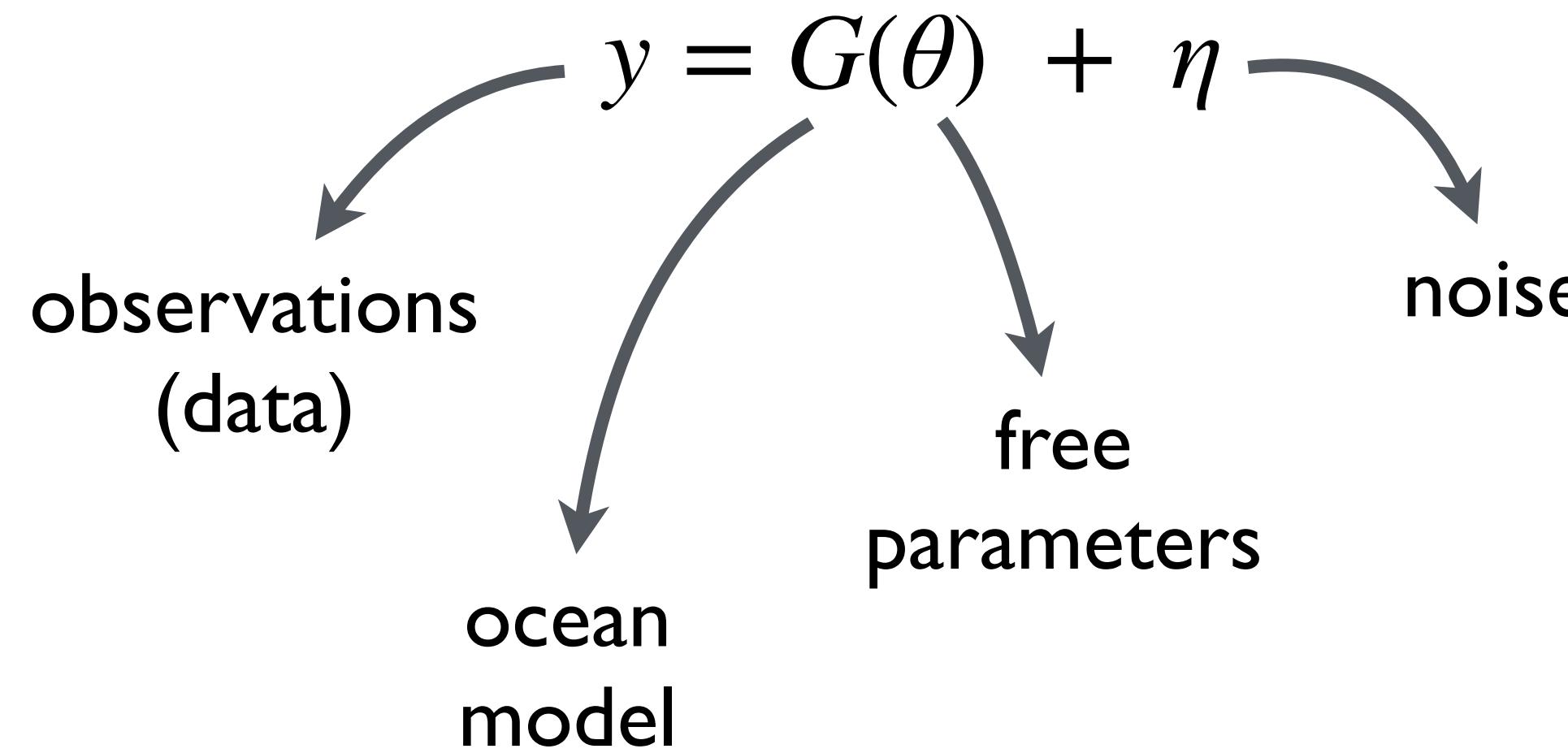
zonally-averaged baroclinic adjustment of a front



with GM + Redi diffusion

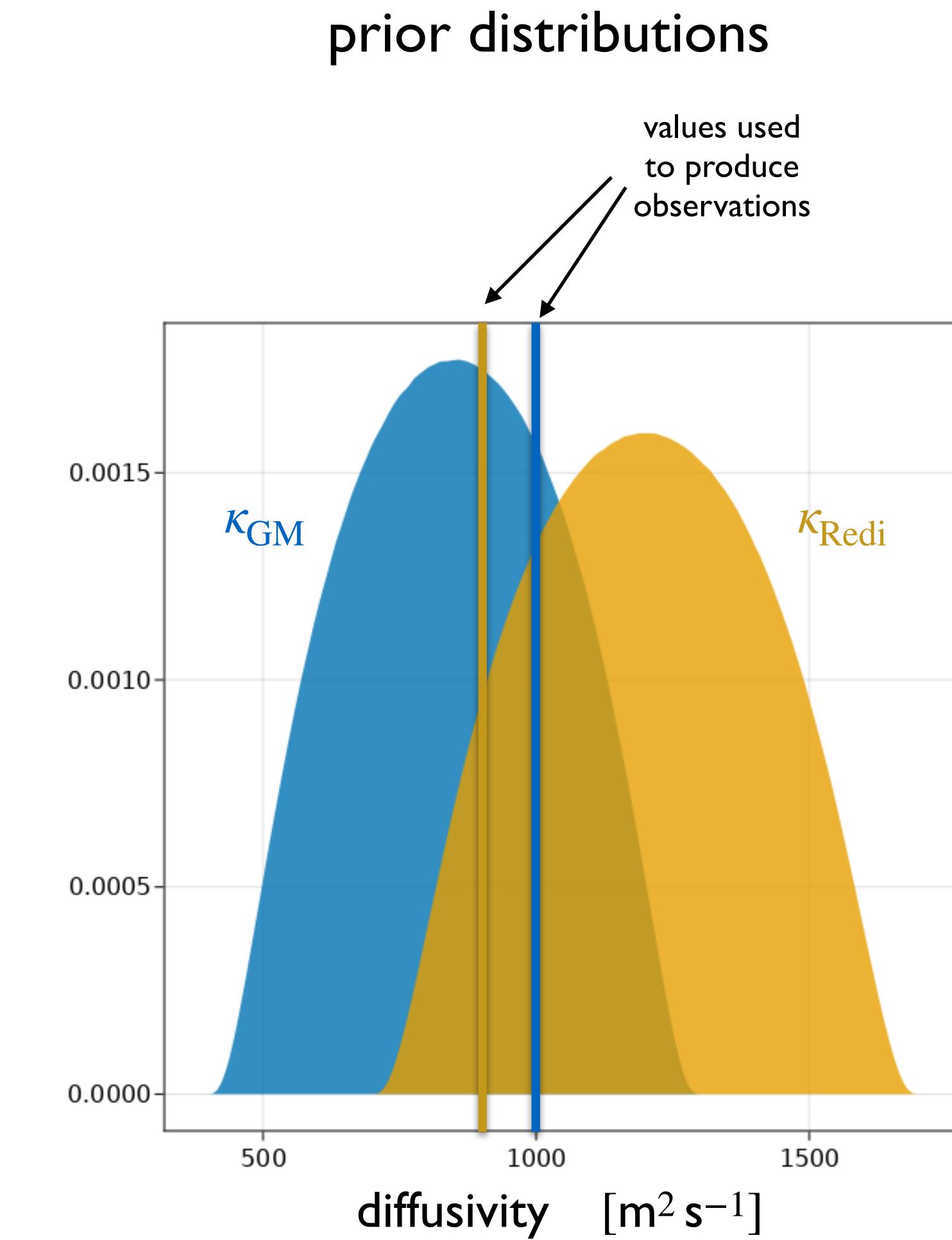
$$\kappa_{\text{GM}} = 1000 \text{ m}^2 \text{ s}^{-1} \quad \kappa_{\text{Redi}} = 900 \text{ m}^2 \text{ s}^{-1}$$

perfect model calibration (proof-of-concept) using Ensemble Kalman Inverse process

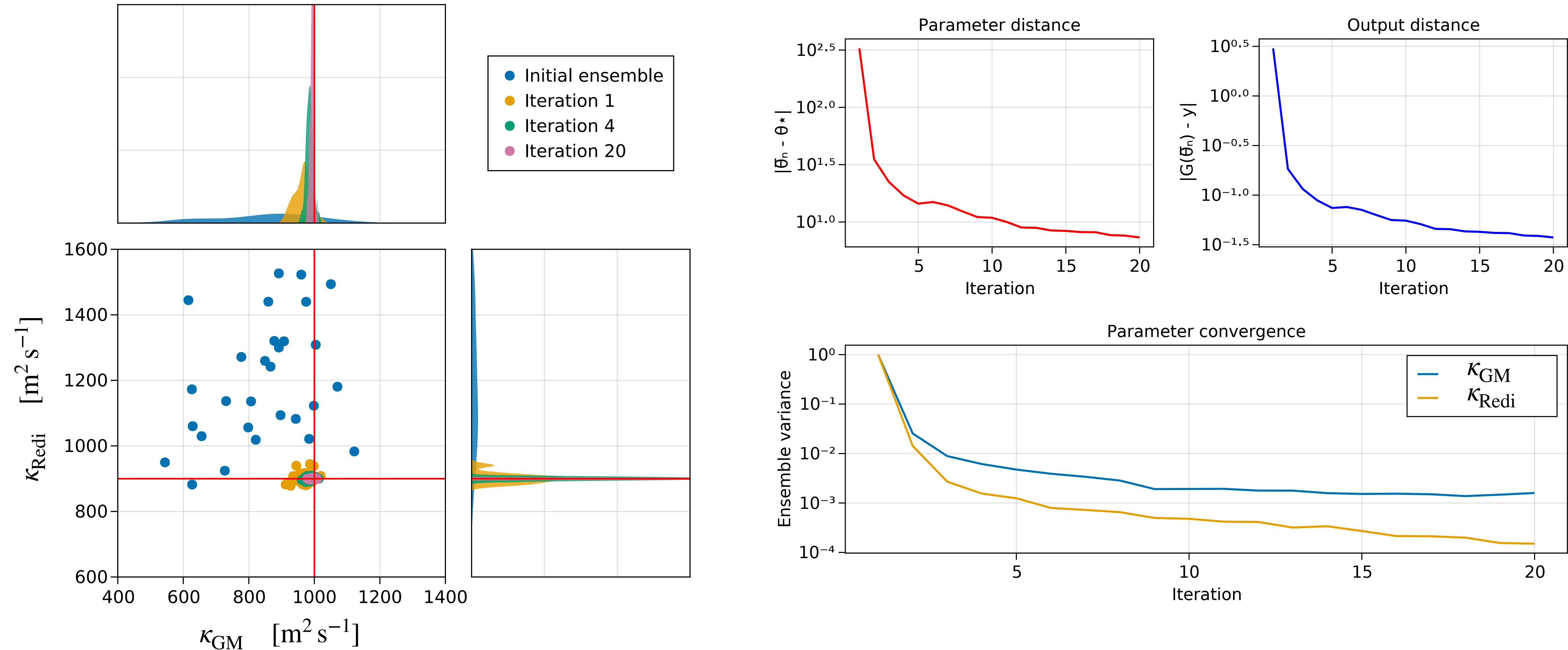


1. produce observations with given GM and Redi diffusivities
2. “close eyes” and see if EKI can converge figure out the values

(“perfect model calibration” = obs y were generated by model G)



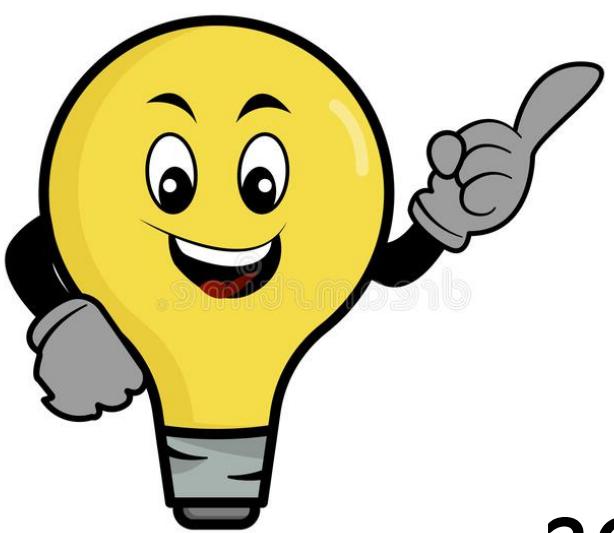
perfect model calibration (proof-of-concept) using Ensemble Kalman Inverse process



OK, so what?

we can easily calibrate free parameters of a turbulence closure

we can even calibrate *simultaneously* across various scenarios
and find optimal parameters that are robust



add depth/time/anything dependence in diffusivities is trivial

any parametrization obtain this ways
is, *by construction*, numerically stable
when added back to the model



but that's only the beginning

