

More accurate models

Opportunities and **pitfalls** in automated calibration

Ocean Model Development Workshop

Gregory Wagner (MIT) and the Clima-Ocean team

- Incorporate comprehensive, creative error estimation
- Faster, more innovative parameterization development

Overfitting and compensating error



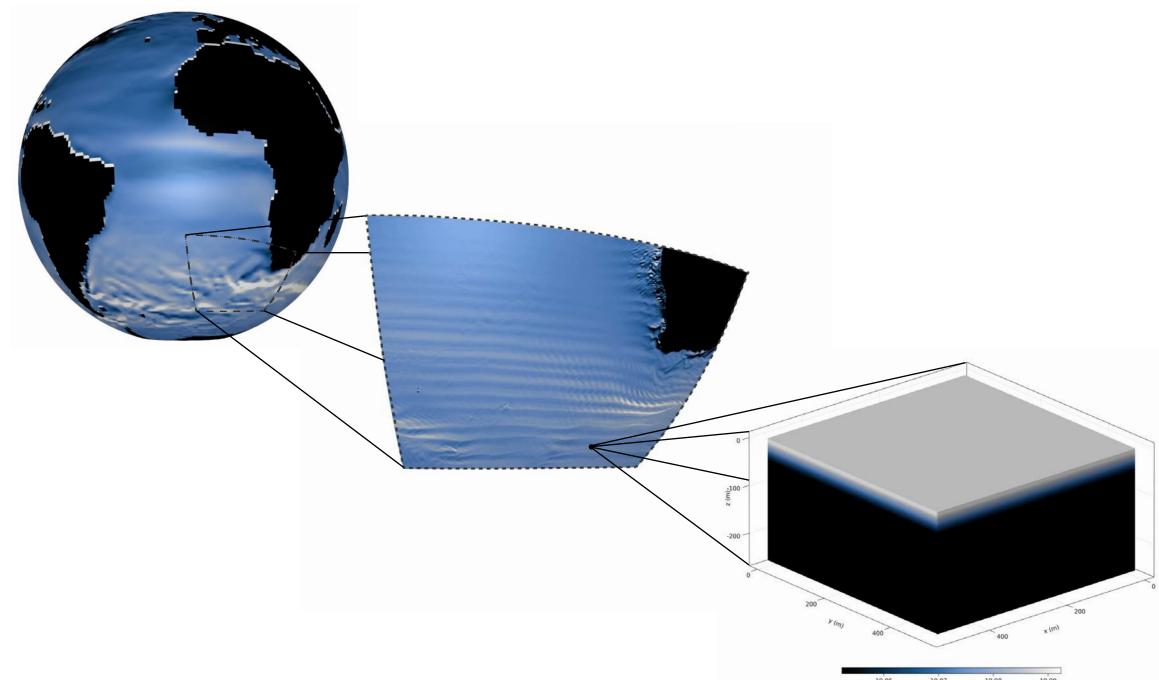




Automated calibration of parameterizations

Finding parameters by minimizing error with a **computational method**

- Methods: stochastic gradient descent, Ensemble Kalman Inversion
- Repeatable and reproducible
- "Error" can be formulated flexibly
- Can include uncertainty quantification as an additional step



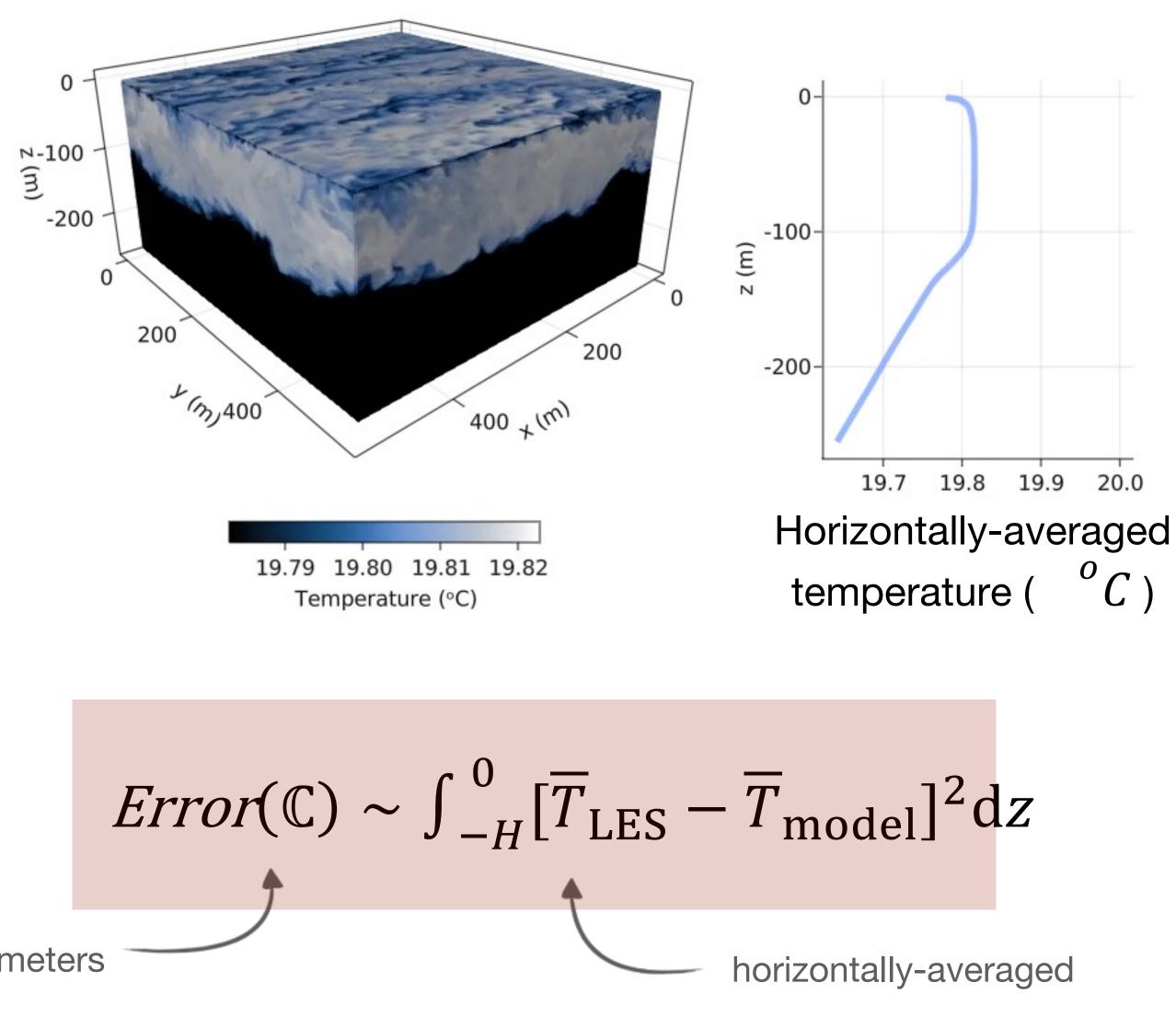
19.96 19.97 19.98 19.99 Temperature (°C)

Automated calibration of mixing parameterizations

- High-fidelity LES = "truth"
- Parameterization embedded in a "single column model"

$$\partial_t \overline{T} = -\partial_z \overline{w'T'}(\mathbb{C})$$

• Error = difference between horizontally-averaged LES and model T, U, V





20.0

CATKE: a one-equation parameterization

Based on Convective Adjustment and Turbulent Kinetic Energy

Single-column temperature equation

 $\partial_t \overline{T} \\= \partial_z \left(\kappa_c \, \partial_z \overline{T} \right)$

Single-column TKE equation $\partial_t e$ $= \partial_z (\kappa_e \ \partial_z e) + \kappa_u |\partial_z \overline{u}|^2 - \kappa_c \ \partial_z \overline{b}$ $= \frac{e^{3/2}}{\ell_D}$ Eddy diffusivity

 $\kappa_c = \ell_c \sqrt{e}$

Mixing length

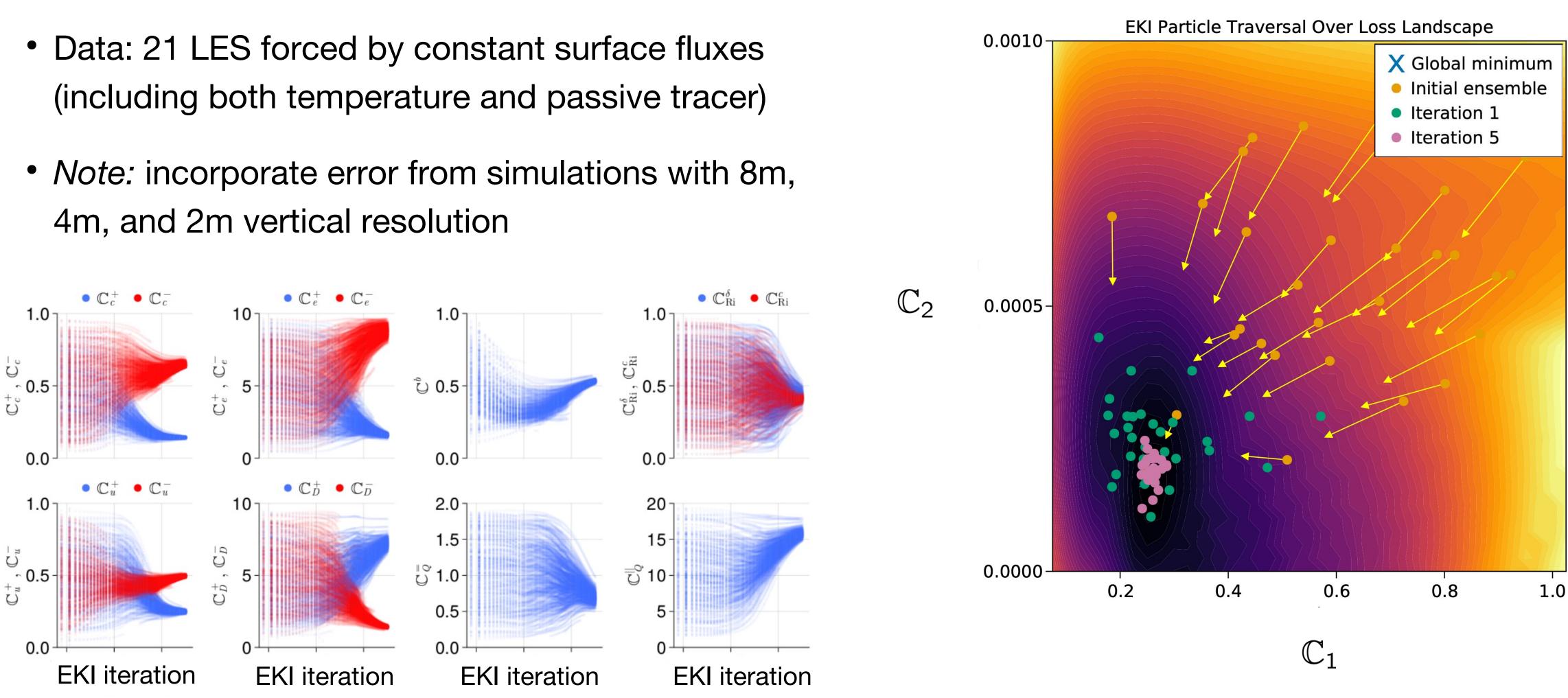
$$\ell_{c} = \ell_{c}^{\text{conv}} + \sigma_{c}(Ri)\min\left(d, \mathbb{C}^{b}\right)$$

Convective mixing length $\ell_c^{\text{conv}} \sim \frac{e^{3/2}}{J^b} ifN^2 > 0$



Calibration with Ensemble Kalman Inversion

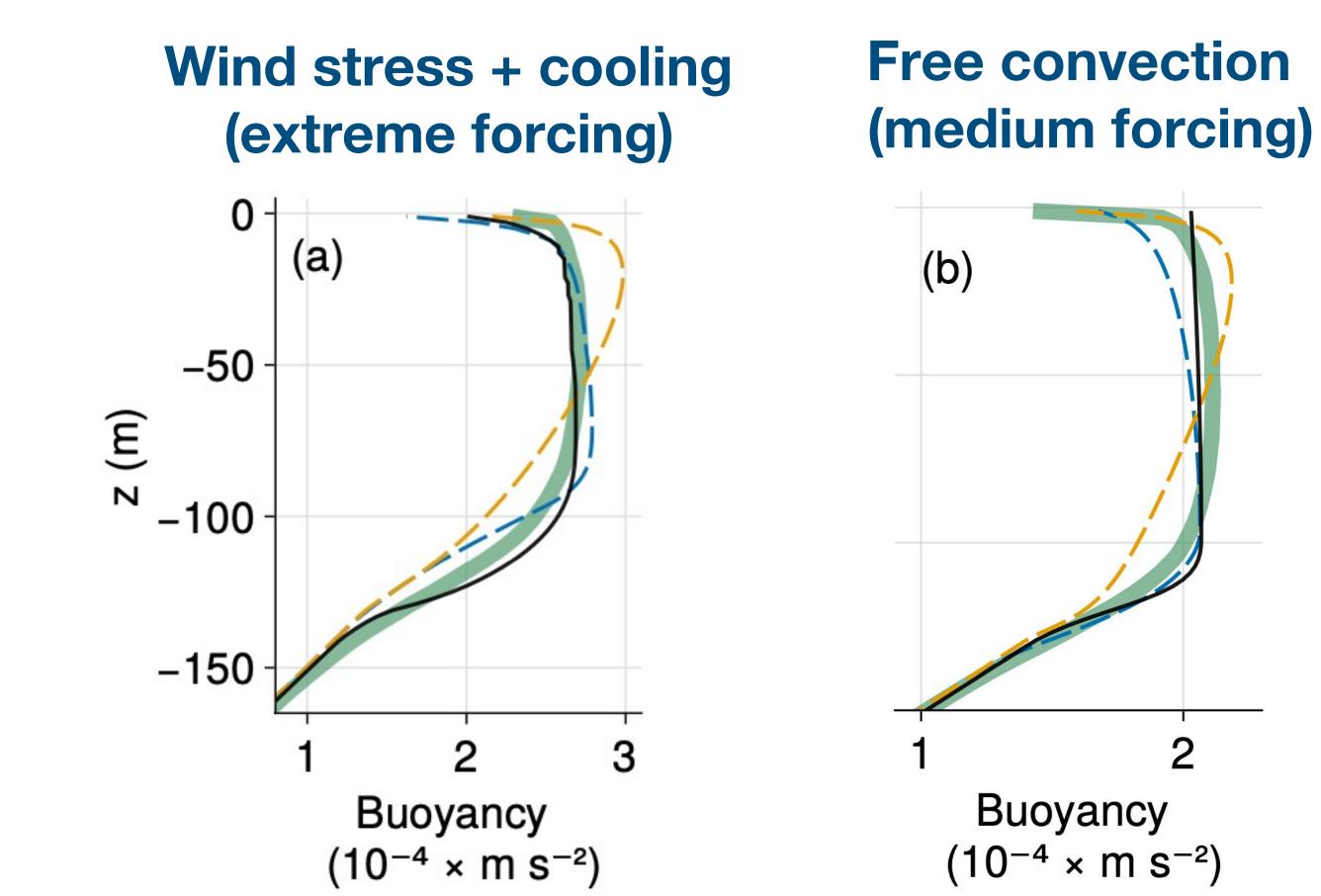
- Iteratively improve an ensemble of models
- 4m, and 2m vertical resolution



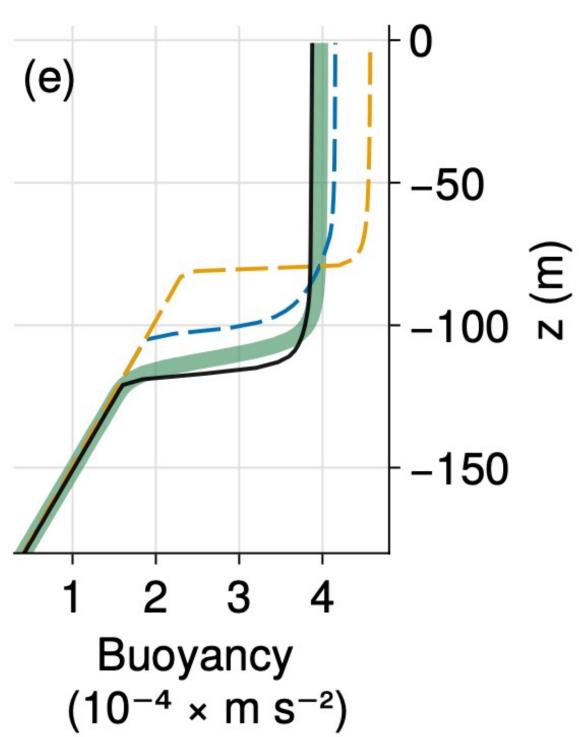


Realizing opportunity 1: more accurate models

Large eddy simulation --SMC-LT (Harcourt 2015) --KPP (Large et al. 1994) — CATKE



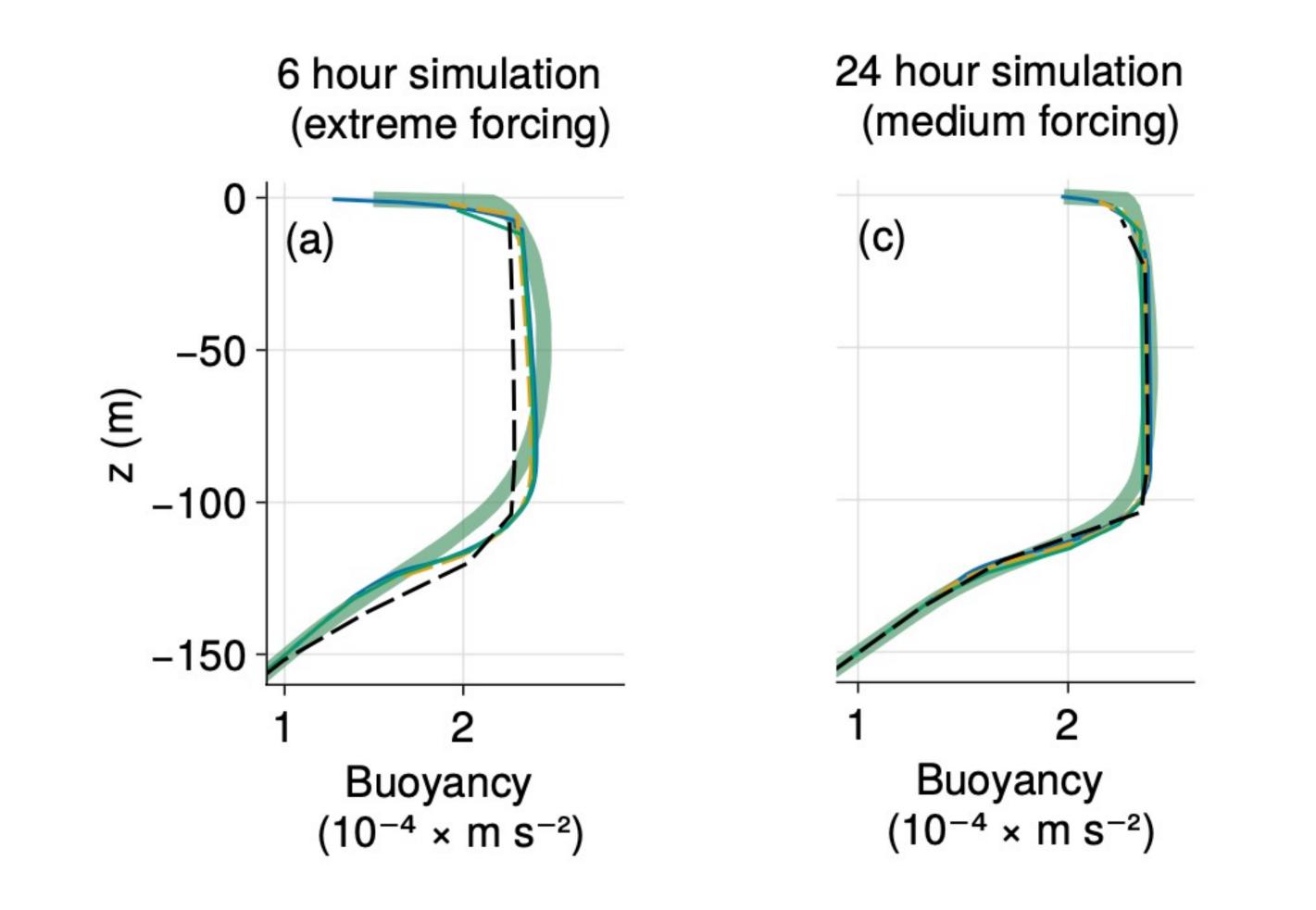
Wind stress only (weak forcing)

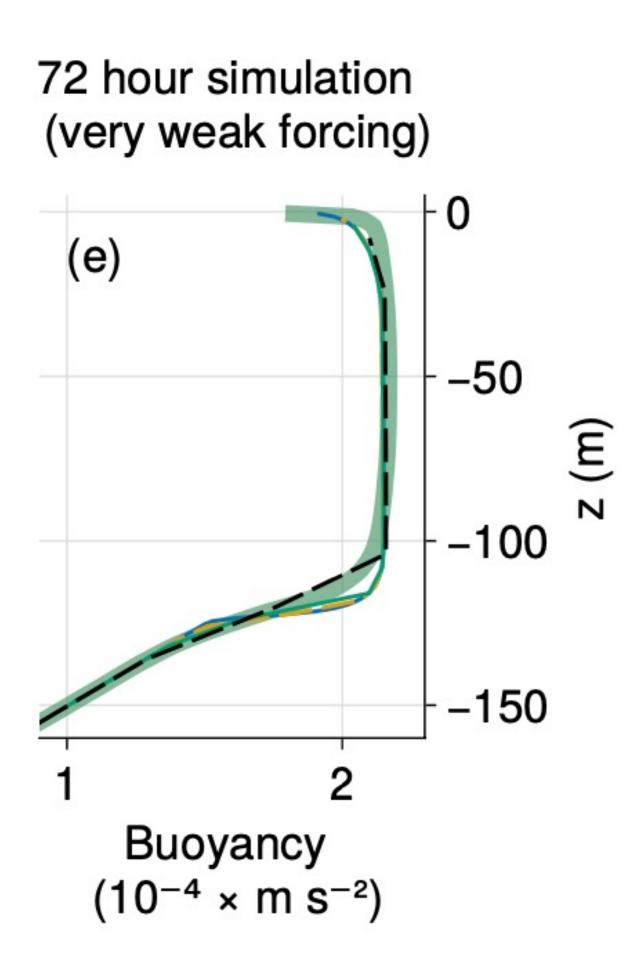




Realizing opportunity 2: flexible error design

Large eddy simulation $-\Delta z = 1$ meters $-\Delta z = 4$ meters $-\Delta z = 8$ meters $-\Delta z = -\Delta z = 16$ meters





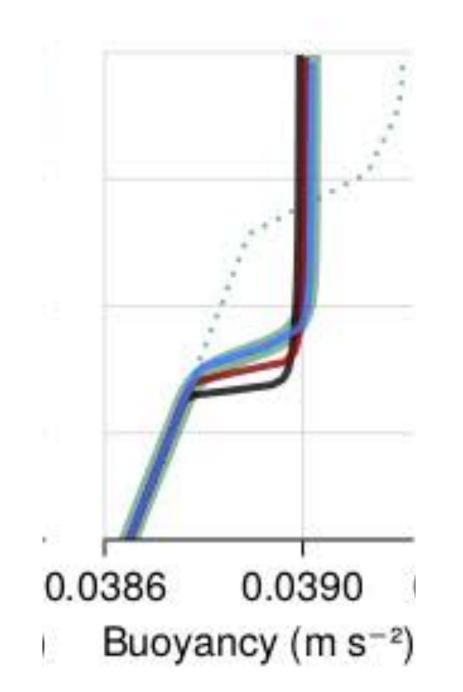
S

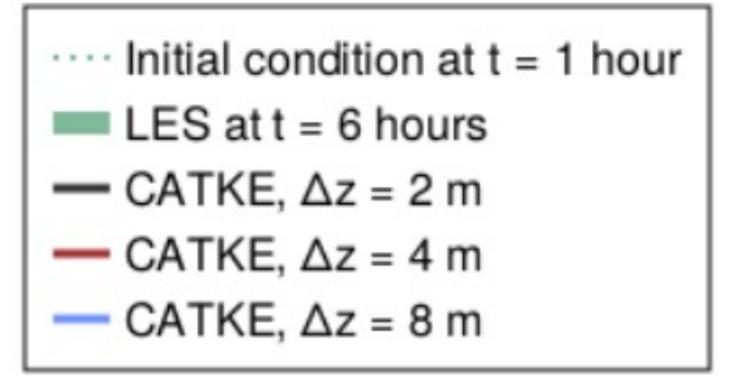
Realizing opportunity 3: accelerating model development

Evaluating three formulations of CATKE of increasing complexity

(7 parameters)

Strong wind no cooling



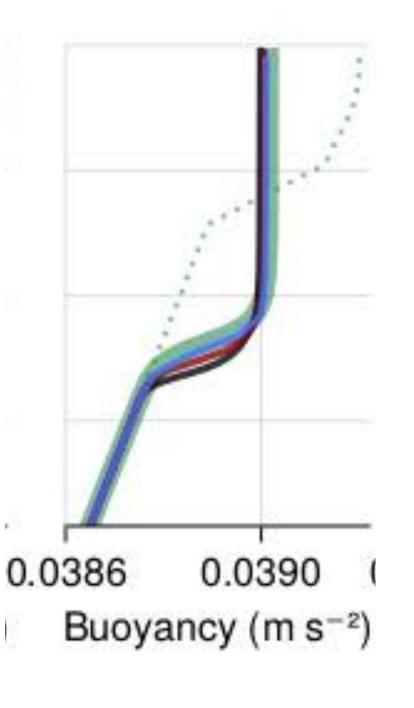


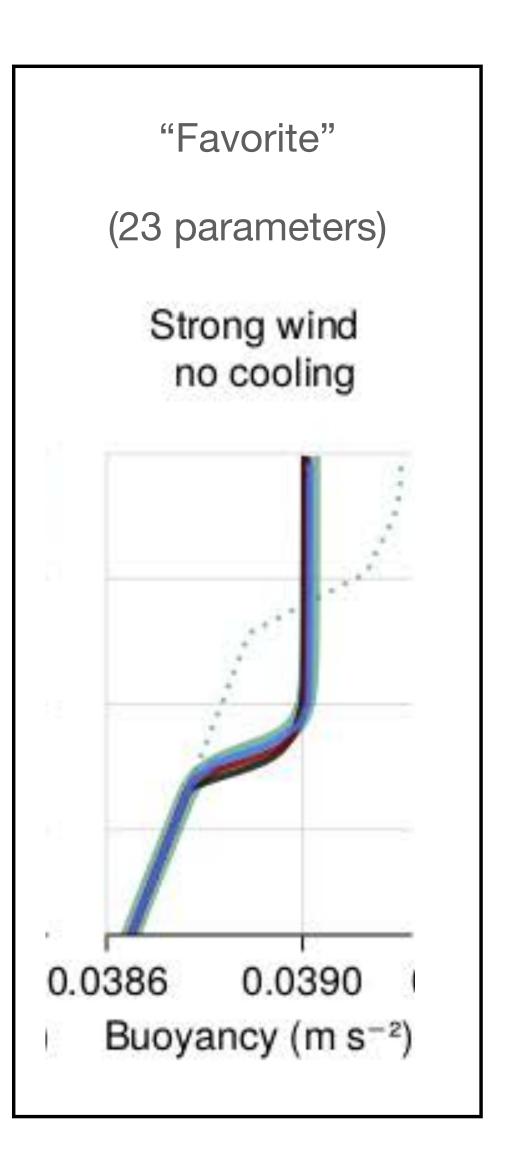
Minimalist

Variable Pr but no convective adjustment

(13 parameters)

Strong wind no cooling



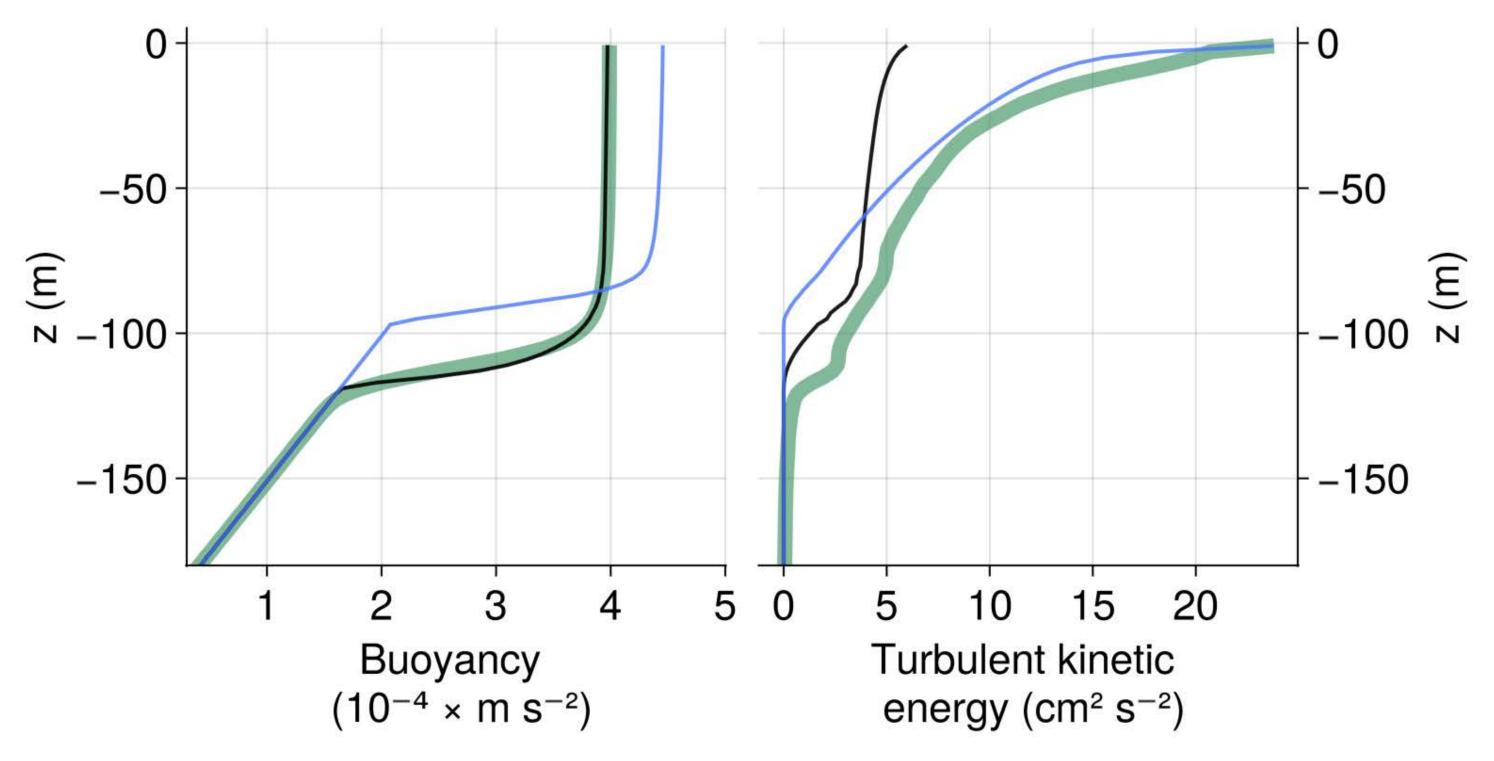


Pitfall: compensating error

Do we get the right answer for the wrong reasons?

Large eddy simulation $-CATKE - k-\epsilon$ (Umlauf and Buchard 2003)

48 hour simulation (weak forcing)



Solution

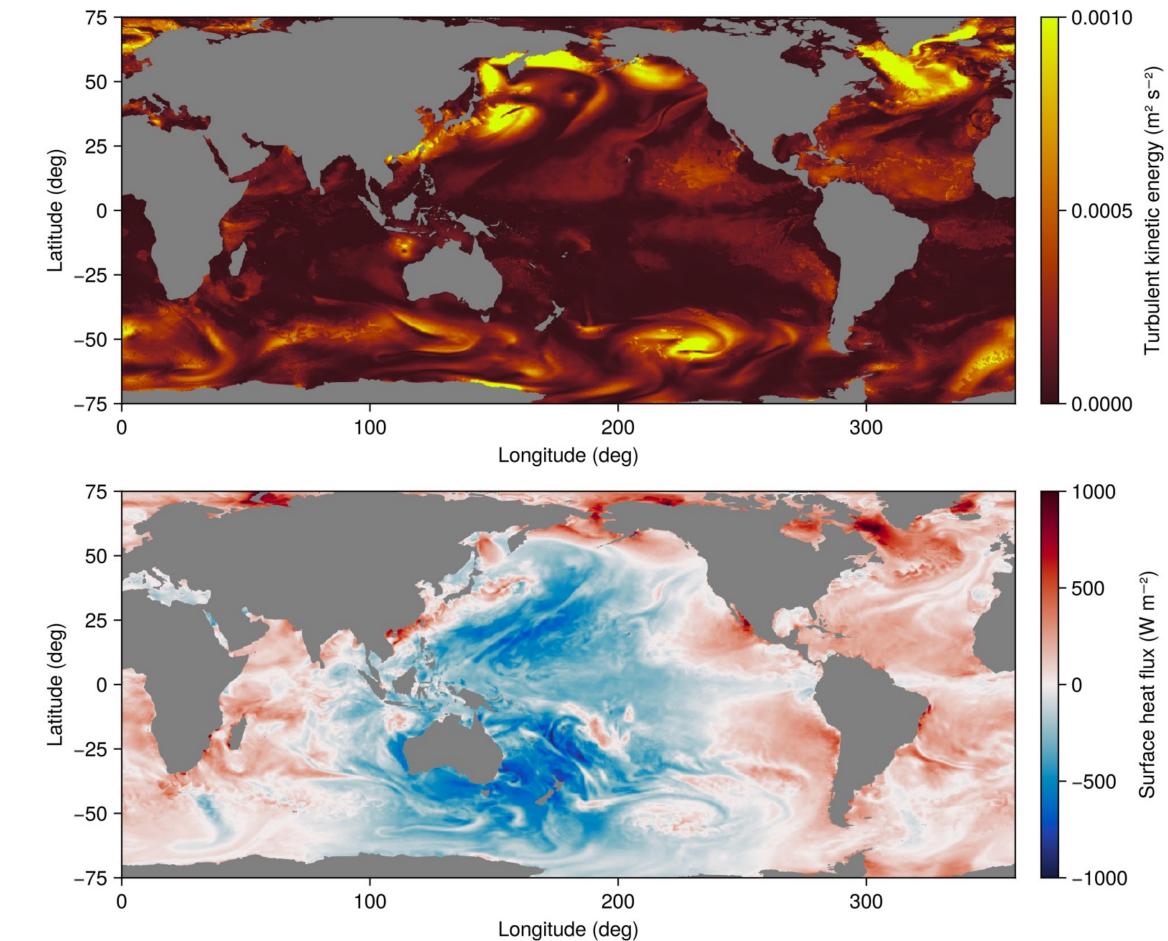
Reinterpret CATKE's "TKE" as a latent variable

Pitfalls in calibrating against observations (1)

Re-calibrating CATKE together with surface flux parameterization

CATKE's turbulent kinetic energy

Surface heat flux



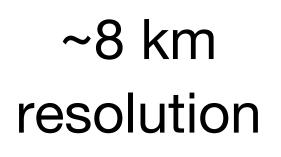
Solution

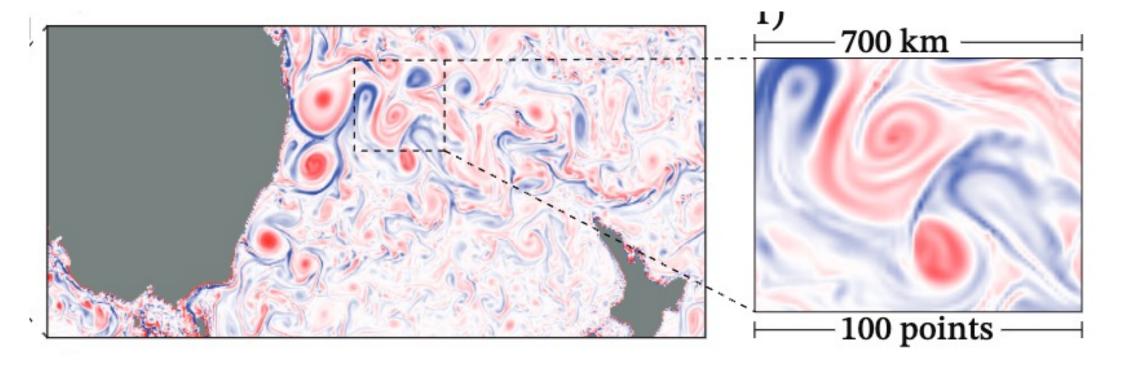
Need data on both mixed layer depth and SST



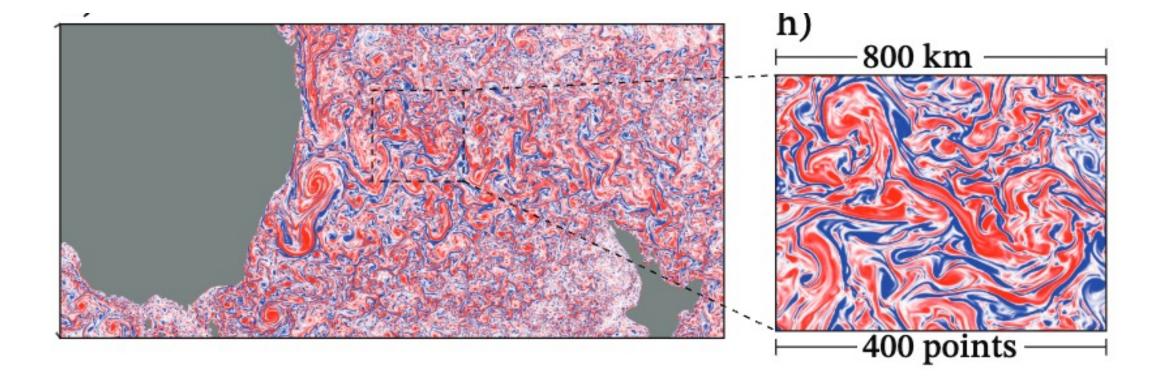
Pitfalls in calibrating against observations (2)

Re-calibrating CATKE without submesoscale restratification





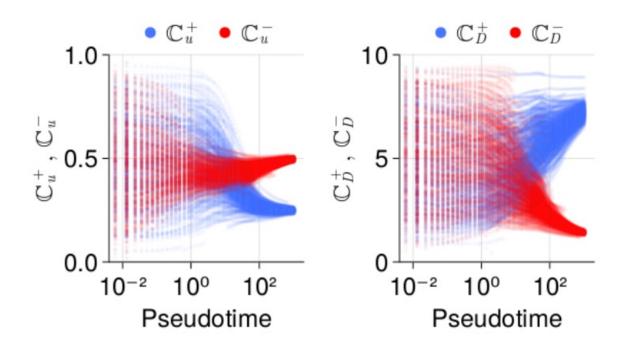
~2 km resolution



Fox-Kemper et al 2011 but see also Sinha and Callies 2023

Solution

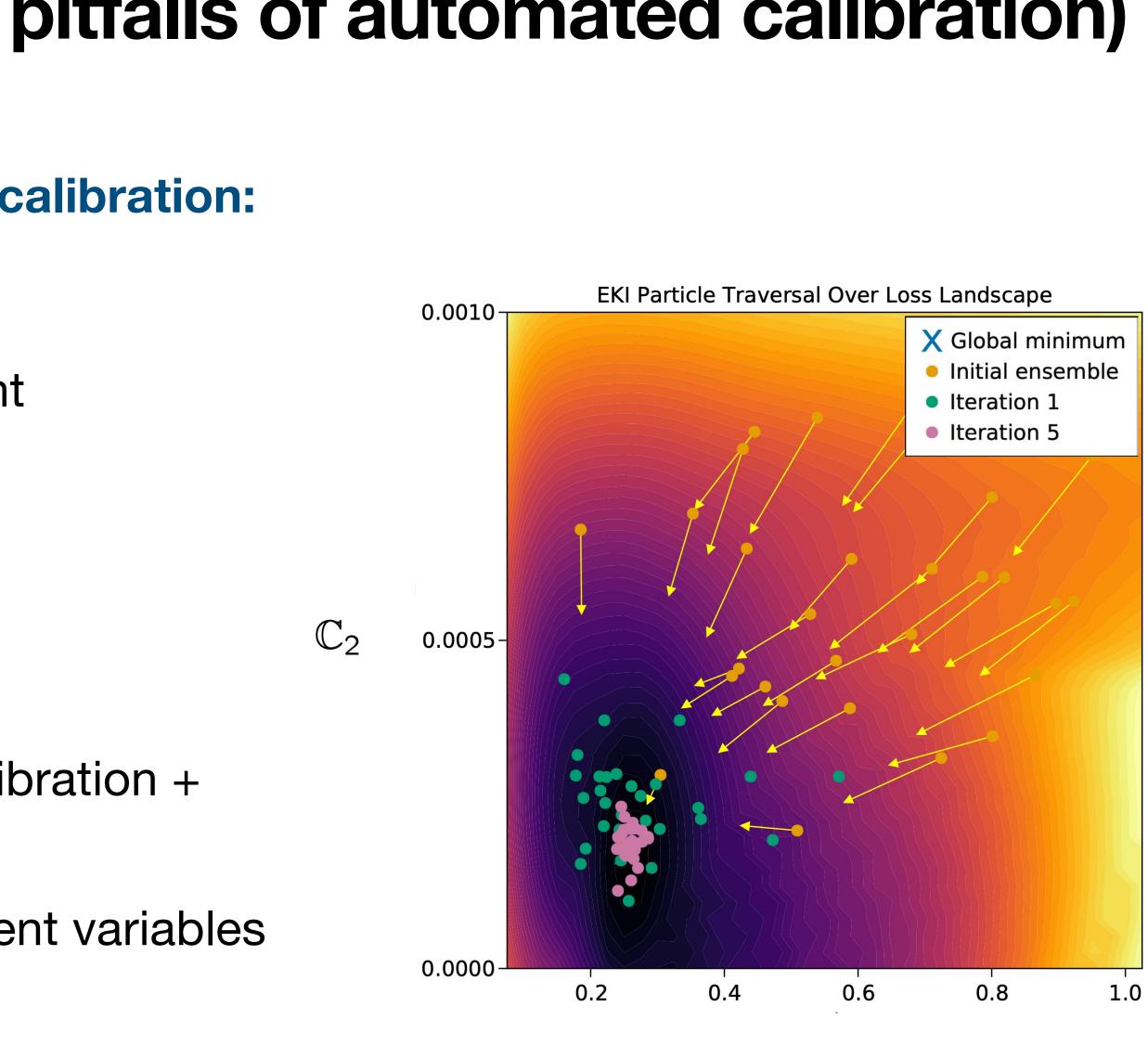
Use uncertainty quantification to constrain CATKE parameters a priori





Summary (opportunities and pitfalls of automated calibration)

- **Opportunities when using automated calibration:**
 - More accurate models
 - Faster parameterization development
 - Flexible error design
- **Pitfall: compensating error**
- But we have solutions:
 - A priori constraints via automated calibration + uncertainty quantification
 - Careful definition of observable vs latent variables
 - Use more data



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