A calibrated **turbulent-kinetic-energy-based** parameterization **outperforms** a calibrated **K-profile parameterization** for stress-driven turbulence

CliMA CLIMATE MODELING ALLIANCE

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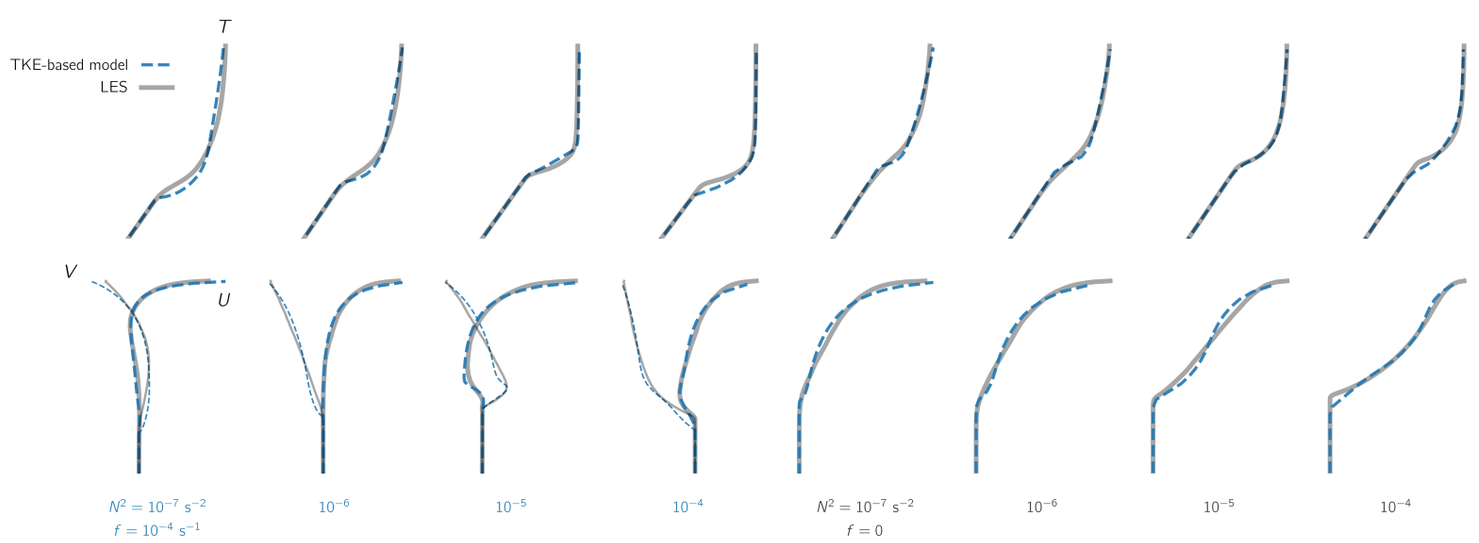
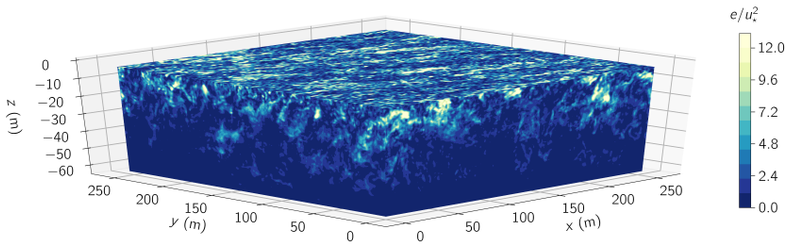


Oceananigans.jl

I. Large eddy simulations with open source Julia GPU software provide "data" for training parameterizations.



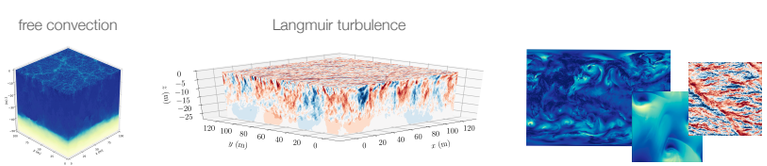
github.com/climate-machine/Oceananigans.jl

CliMa / LESbrary

I. This work is part of CliMa, a new Earth system model that synthesizes observations and high-fidelity simulations to hierarchically constrain parameterizations for climate prediction:

1. Constrain to physics
   Match parameterizations to high-res simulations
2. Constrain to global observations in present climate
   Refine parameterizations in global context

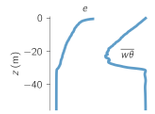
II. To accomplish 1, we plan to create a massive library of both idealized and realistic simulation data for training parameterizations called the **LESbrary**.



Parameterization

I. We use a down-gradient assumption and eddy diffusivity to model horizontally-averaged turbulent fluxes of momentum, tracers, and turbulent kinetic energy.

$$\overline{w\phi} \approx -\underbrace{\mathbb{C}_\phi^K \, \ell \sqrt{e} \, \partial_z \Phi}_{\stackrel{\text{def}}{=} K_\phi}$$



$$\Phi \stackrel{\text{def}}{=} \Phi_{\text{TKE}}(z,t)$$

$$\bar{\phi} \stackrel{\text{def}}{=} \frac{1}{A}\int \phi_{\text{LES}} \, \mathrm{d}A$$

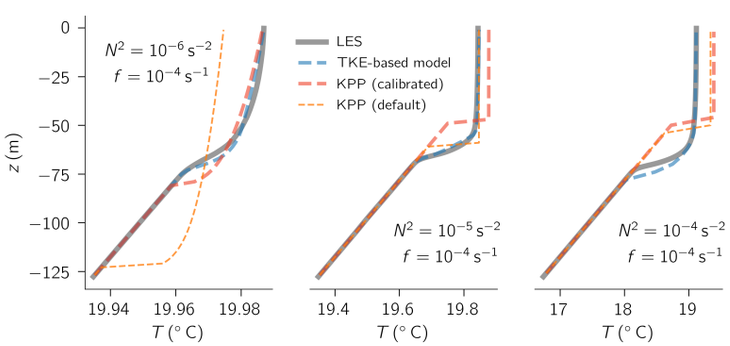
II. Eddy diffusivities are proportional to a mixing length and the turbulent velocity, the square root of turbulent kinetic energy.

$$\partial_t e = (\partial_z K_e \partial_z)\, e + K_u |\partial_z \boldsymbol{U}|^2 - K_c \partial_z B - \mathbb{C}^D \frac{e^{3/2}}{\ell}$$

transport | production | buoyancy flux | dissipation

$$\ell = \max(\Delta z, \tilde{\ell}) \qquad \tilde{\ell} = \min\left(\mathbb{C}_w^\ell z, \mathbb{C}_b^\ell \frac{\sqrt{e}}{N}\right) \qquad N \stackrel{\text{def}}{=} \sqrt{\max(0, \partial_z B)}$$

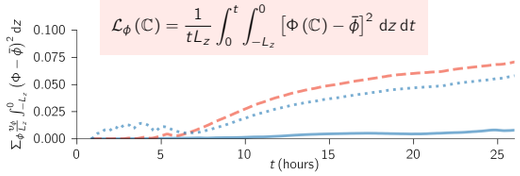
III. The calibrated TKE-based model predicts stress-driven boundary layer profiles better than a calibrated K-profile parameterization. In stress-driven turbulence, the TKE-based model has 7 free parameters and KPP has 3 free parameters.

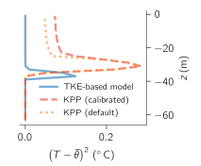


Calibration

I. Loss functions measure discrepancy between parameterized and LES profiles. We use weighted sums of field-specific loss functions to coalesce multi-field and multi-case loss functions.

$$\mathcal{L}_\phi(\mathbb{C}) = \frac{1}{tL_z}\int_0^t \int_{-L_z}^0 \left[\Phi(\mathbb{C}) - \bar{\phi}\right]^2 \mathrm{d}z\,\mathrm{d}t$$



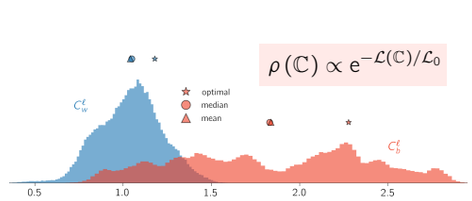


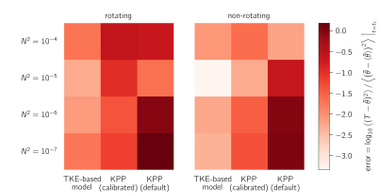
$$\mathcal{L}_{\text{case}}(\mathbb{C}) = \sum_{\bar{\phi} \in (\bar{u}, \bar{v}, \bar{\theta}, \bar{e})} \upsilon_\phi \mathcal{L}_\phi(\mathbb{C})$$

$$\mathcal{L}_{\text{batch}}(\mathbb{C}) = \sum_{\text{cases}} \upsilon_{\text{case}} \mathcal{L}_{\text{case}}(\mathbb{C})$$

II. We use a Markov Chain, Monte Carlo method to sample parameter PDFs and to calibrate the TKE-based parameterization to four rotating LESs and four non-rotating LESs with varying initial stratification.

$$\rho(\mathbb{C}) \propto \mathrm{e}^{-\mathcal{L}(\mathbb{C})/\mathcal{L}_0}$$





III. A hierarchy of mini-batched calibrations illustrate the dependence of optimal parameters on batch size and the role of batch size in calibration.