Machine learning algorithms are often used as a 'black-box' to find the relationship from data. Choice of data affects quality of model, and presumably critical for physics discovery with data-driven methods. For rotating stratified turbulence, previous works have generally learned from divergence of eddy fluxes. Are there comparable or better choices?

Methods:

Mean quasi-geostrophic Potential Vorticity equation:

$$\frac{\partial \overline{q}}{\partial t} + \nabla\cdot(\overline{\mathbf{u}}\overline{q}) = -\nabla\cdot\overline{\mathbf{u}'q'} + \overline{Q}$$

Helmholtz decomposition:

$$\overline{\mathbf{u}'q'} = -\nabla\Psi^q_{\mathrm{eff}} + \hat{\mathbf{z}}\times\nabla\Phi^q_{\mathrm{eff}} + \mathbf{H}^q$$

Rotational fluxes can be large and obscure any underlying divergence.

For the divergence, could learn from
(1) itself $\nabla\cdot\overline{\mathbf{u}'q'}$
(2) $\overline{\mathbf{u}'q'}$
(3) Eddy Force Function, from

$$\nabla\cdot\overline{\mathbf{u}'q'} = -\nabla^2\Psi^q_{\mathrm{eff}}$$

(The Dirichlet boundary conditions Ψeff = 0 on the land boundaries)

Learning strategy:

f(x) = (y)
Same x (stream function, PV, etc.)
CNNs:
3 convolutional layers
1 fully-connected layer

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On the choice of training data for machine learning of geostrophic mesoscale turbulence

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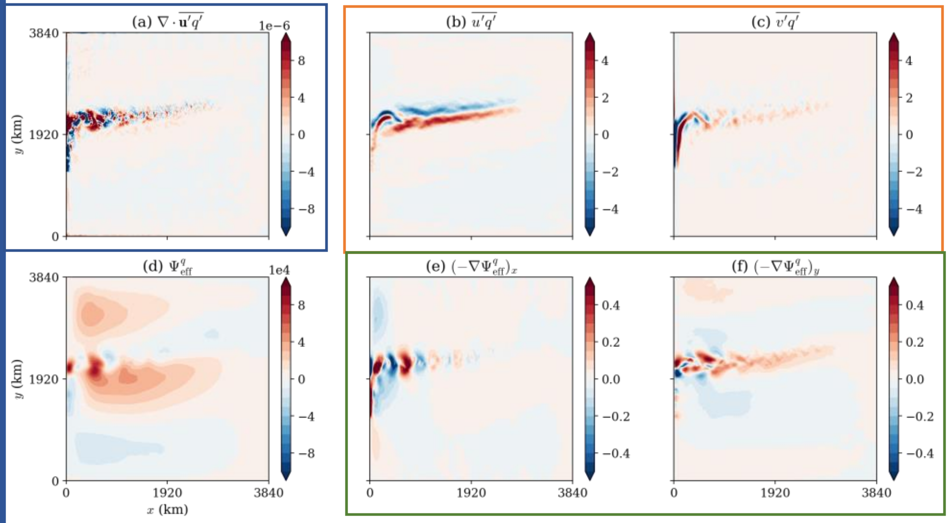
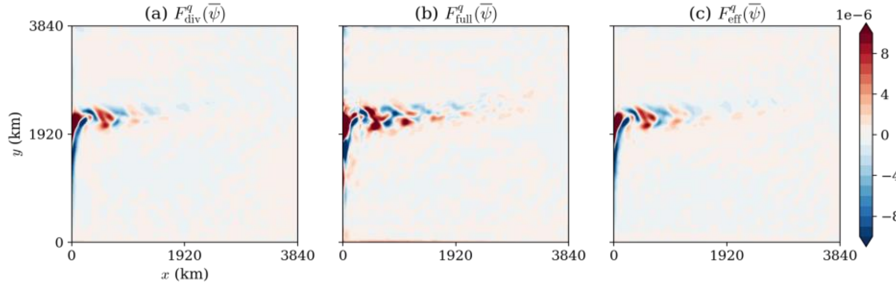
Choice of training data matters, and learning from the "Eddy Force Function" is comparable in quality as well as more robust than from the divergence of eddy fluxes

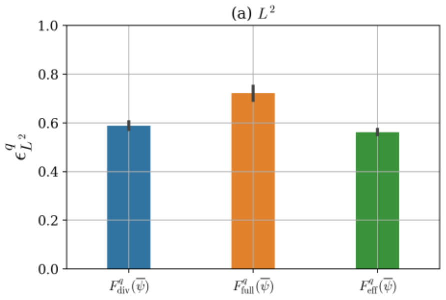
f(x) = (y) 3 pairs of learning data y



Main results:



Skill



Robustness