Using dimensionality reduction techniques to parameterize and decompose the vertical turbulent flux of scalars

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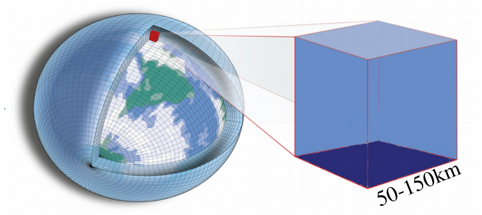
Vertical turbulent flux parameterization



Parameterization: processes smaller than grid size (not resolved) are approximated using resolved variables

Convective boundary layer:

$$\overline{w'\theta'} = \mathcal{F}(resolved\ variables;\ \overline{w},\ \overline{\theta},\ \overline{e}, ...)$$

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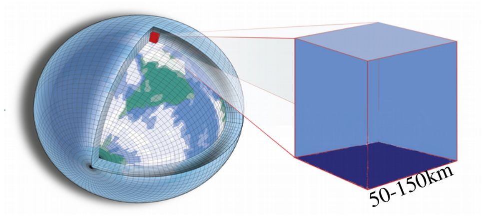
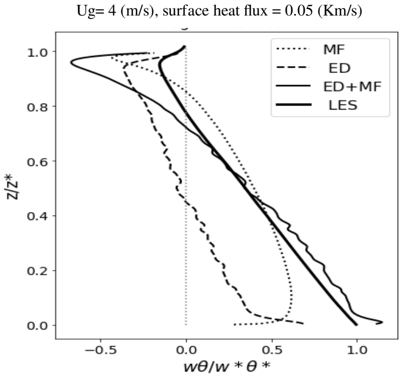


Parameterization: processes smaller than grid size (not resolved) are approximated using resolved variables

Convective boundary layer:

$$\overline{w'\theta'} = \mathcal{F}(resolved\ variables;\ \overline{w},\ \overline{\theta},\ \overline{e}, ...)$$

$$\overline{w'\theta'} \approx -K(z)\frac{\partial\overline{\theta}}{\partial z} + \mathcal{M}(z)(\theta_u - \overline{\theta})$$



MF: mass flux
ED: eddy diffusivity

- Overestimates the entrainment flux
- Does not generalize to the situations with strong wind
- Underlying assumptions may not hold (e.g., a_u << 1)

Objectives:

Developing a data-driven parameterization of vertical turbulent fluxes using reduced order representation of turbulent kinetic energy (TKE) and scalar profile that:

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Developing a data-driven parameterization of vertical turbulent fluxes using reduced order representation of turbulent kinetic energy (TKE) and scalar profile that:

- Generalizes across the turbulent regimes (weakly to strongly convective with various wind condition)
- Models the vertical turbulent fluxes of various scalars (e.g., heat, passive tracers)
- Decomposes the vertical turbulent fluxes to two main modes of variability

Strategies and assumptions

- All scalars are transported the same way by the flow

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- These two modes depend on the horizontal and vertical TKE respectively

$$\overline{w'x'} \approx \alpha f_1\left(\overline{X}, TKE_u\right) + \alpha f_2\left(\overline{X}, TKE_w\right)$$

Data

- High resolution LES* data (dry convective boundary layer)
- 6 simulations from weakly to strongly convective

- Horizontally coarse graining, computing mean variables and turbulent fluxes

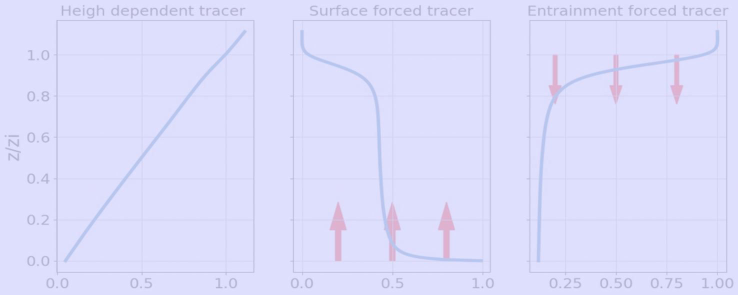
Simulations

name	Ug(m/s)	Q_0(Km/s)
16-03	16	0.03
16-06	16	0.06
8-03	8	0.03
4-05	4	0.05
4-1	4	0.1
2-1	2	0.1

strongly sheared → strongly convective

3 implemented tracers:

- height dependent
- surface forced scalar
- entrainment forced scalar



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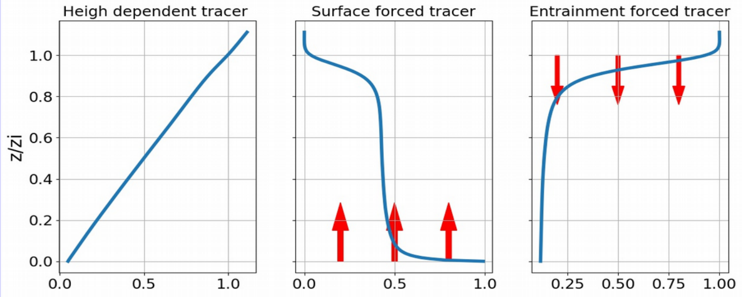
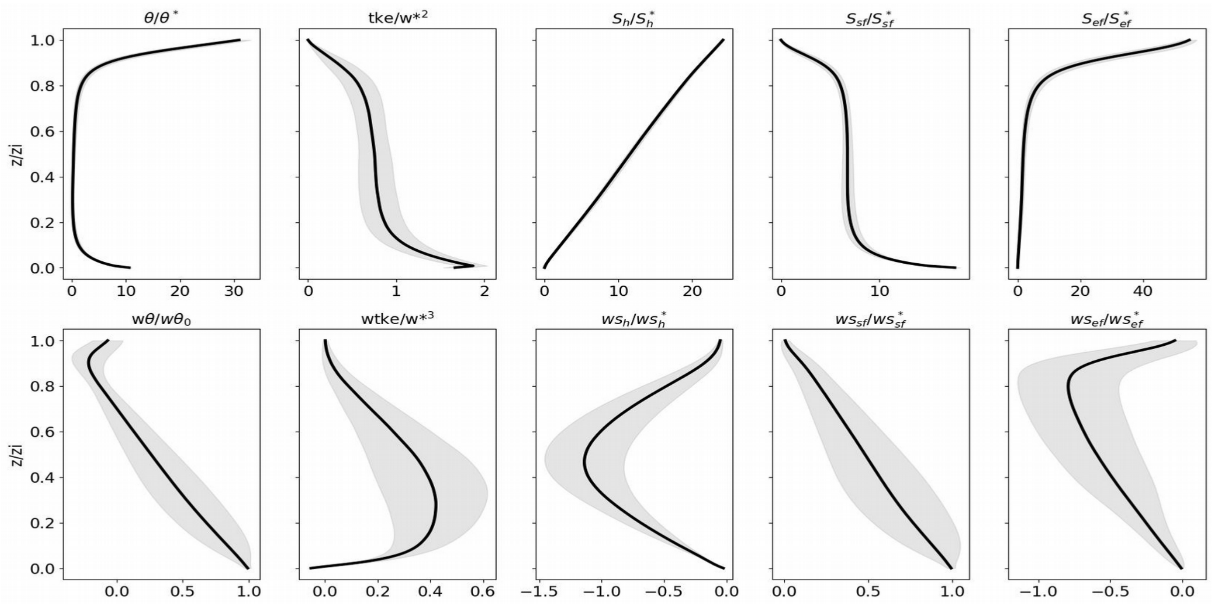


Data

Inputs

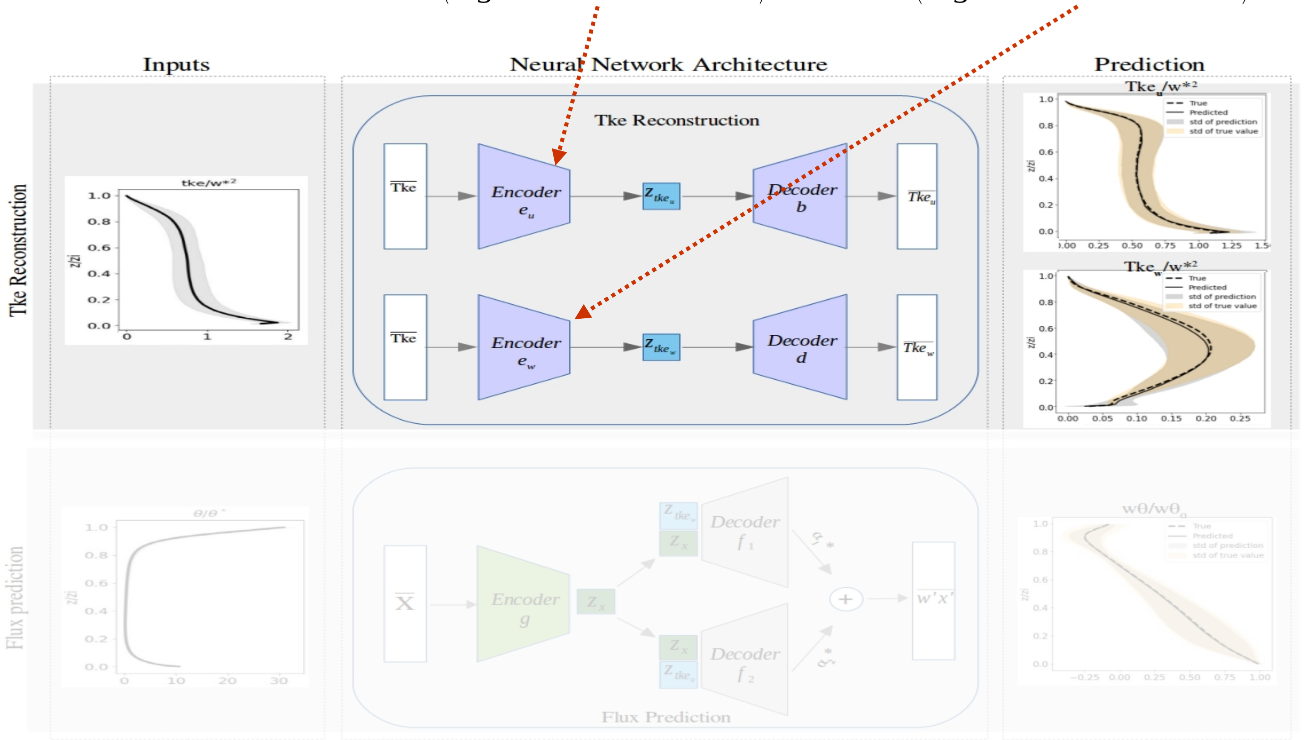
Outputs



A novel neural network is trained to parameterize the vertical turbulent fluxes of all 6 LES simulations and scalars together

Neural network architecture

$$w'x' = \alpha_1 f_1\left(e_g\left(\overline{X}\right), e_u\left(TKE\right)\right) + \alpha_2 f_2\left(e_g\left(\overline{X}\right), e_w\left(TKE\right)\right)$$



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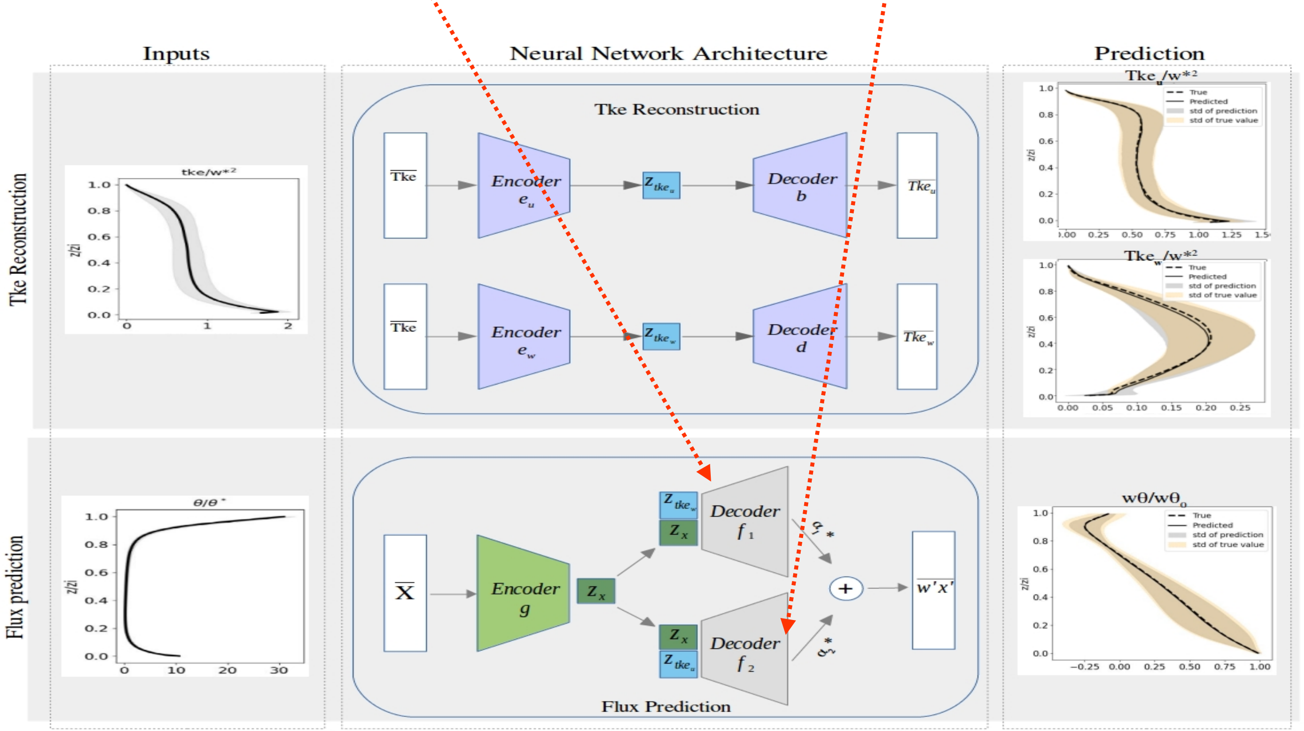

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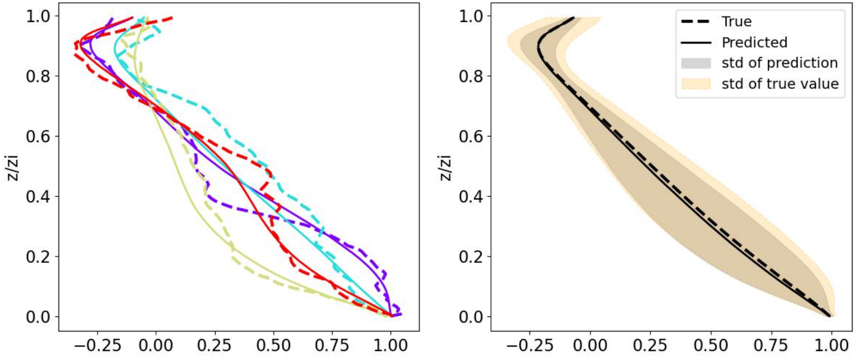
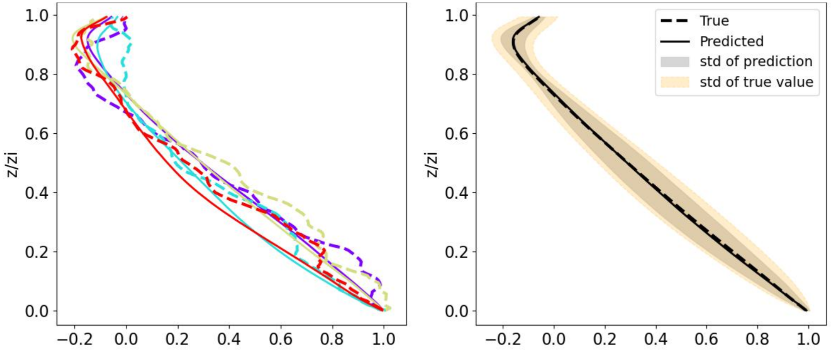
Heat flux prediction

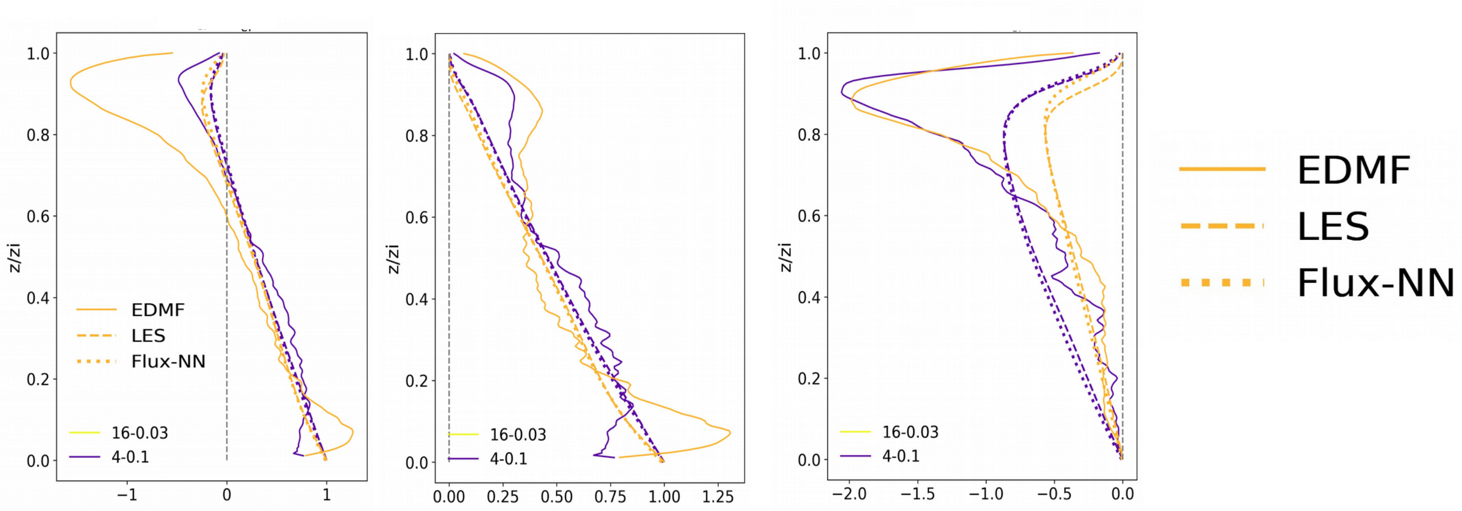
Strongly sheared
Ug = 16 m/s, surface heat flux = 0.03 (Km/s)



Strongly convective
Ug = 2 (m/s), surface heat flux = 0.1 (Km/s)



Flux prediction



Heat flux

Surface forced tracer flux

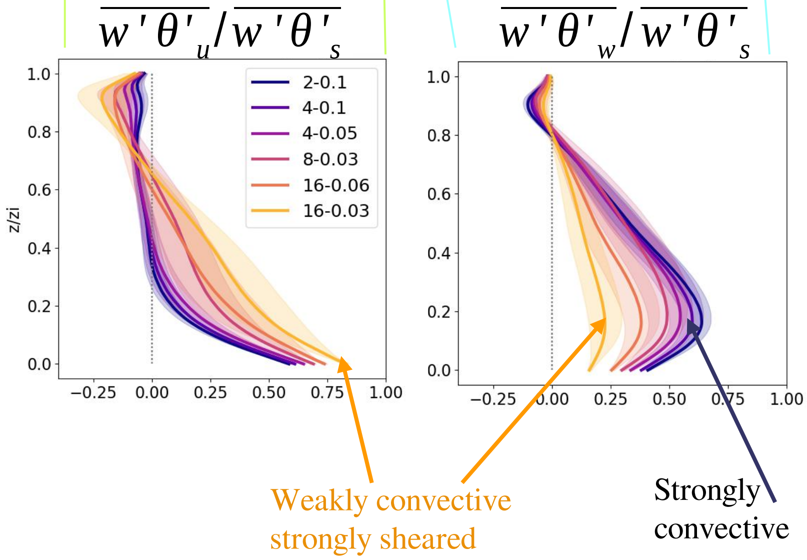
Entrainment forced tracer flux

Heat flux decomposition

$$\overline{w'\theta'} \approx \alpha_1 f_1\left(z_\theta, z_u\right) + \alpha_2 f_2\left(z_\theta, z_w\right)$$

Shear mode

Convective mode

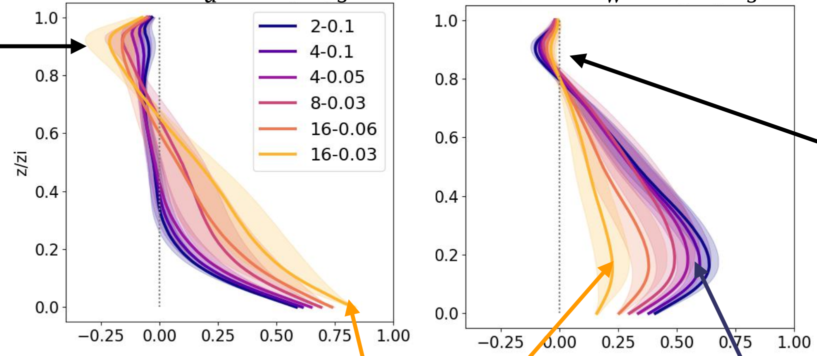


Heat flux decomposition

$$\overline{w'\theta'} \approx \alpha_1 f_1(z_\theta, z_u) + \alpha_2 f_2(z_\theta, z_w)$$

Shear mode | Convective mode

$\overline{w'\theta'}_u / \overline{w'\theta'}_s$ | $\overline{w'\theta'}_w / \overline{w'\theta'}_s$



Inversion layer flux Increases with wind shear

Inversion layer flux Increases with convective strength

Weakly convective strongly sheared

Strongly convective

How much of each mode can be explained by diffusion?

Projecting each mode on the gradient of its associated scalar → diffusive flux

$$\overline{w'x'}_u^{diff} \sim -K\frac{d\overline{X}}{dz}$$

$$\overline{w'x'}_w^{diff} \sim -K\frac{d\overline{X}}{dz}$$

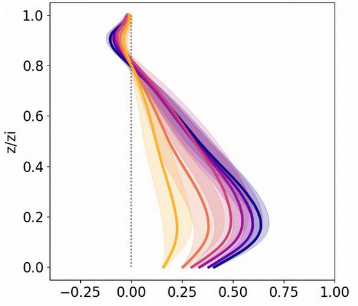
Constraint: K depends on flow

↓

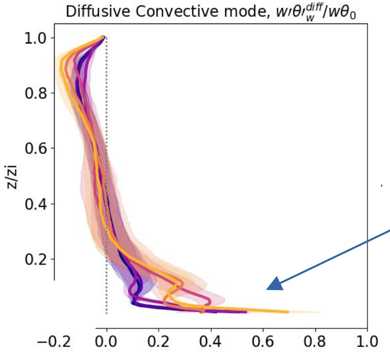
The same K for all flaxes of the same simulation

How much of each mode can be explained by diffusion?

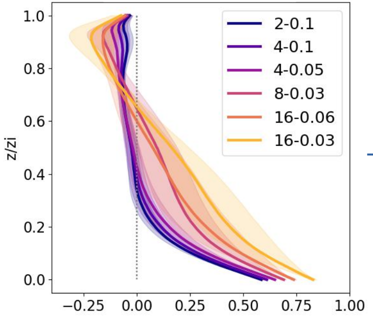
$\overline{w'\theta'}_w / \overline{w'\theta'}_s$



Diffusive part



$\overline{w'\theta'}_u / \overline{w'\theta'}_s$



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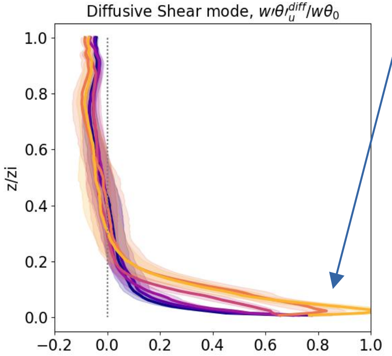
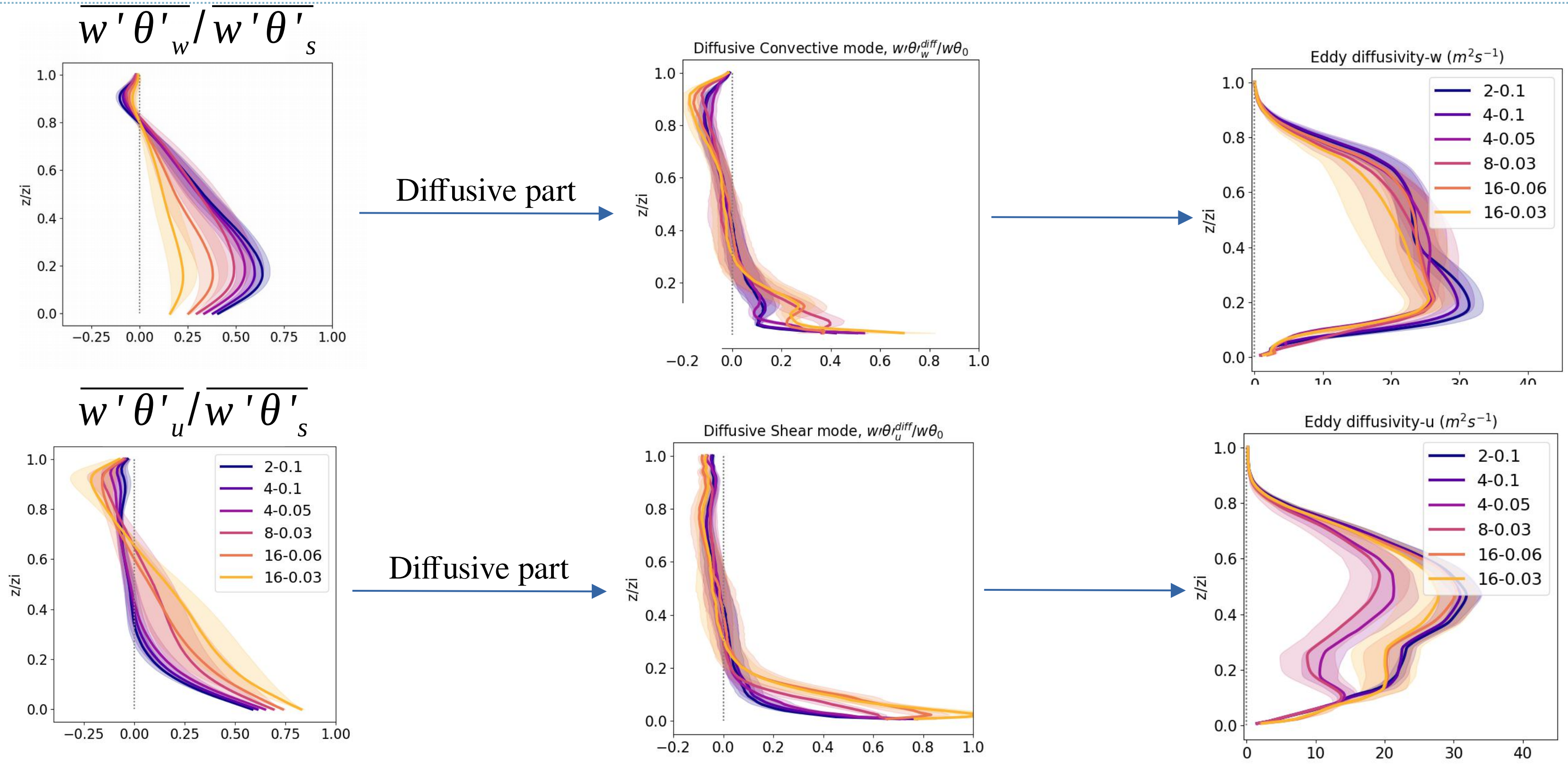


- The diffusive flux is important in the surface layer

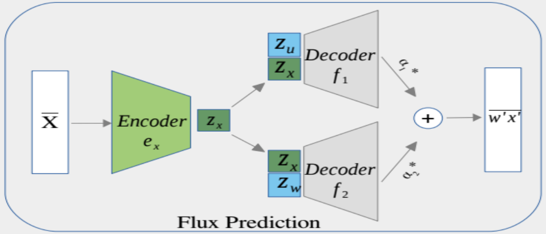
How much of each mode can be explained by diffusion?



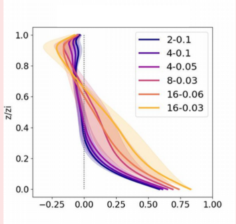
We develop a data driven parameterization of vertical turbulent flux of scalars in the convective boundary layer using low-dimensional representation of TKE and scalar profile

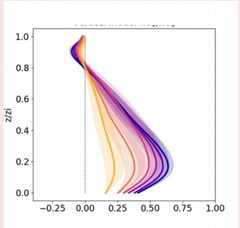
Our network:

- Generalize across turbulent regimes
- Models the vertical flux of various scalars
- Outperforms EDMF

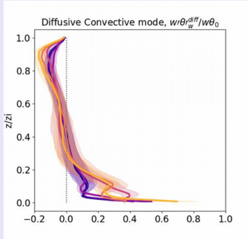


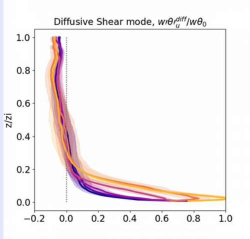
- Our network decomposes the total turbulent flux of any scalar into two main modes of variability associated with shear and convection





- By projecting shear and convective mode on the scalar gradient, we compute of the contribution of diffusion to each mode
- Diffusive flux is considerable only in the surface layer





Thank you!

Shamekh and Genitine, 2023 (submitted) ss6287@columbia.edu

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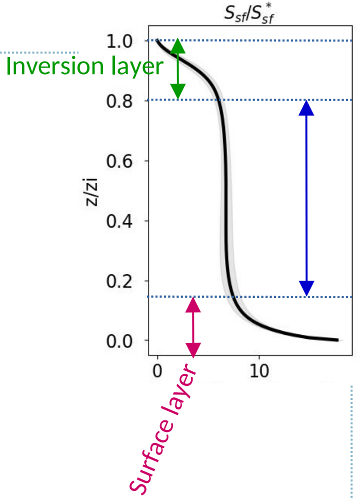
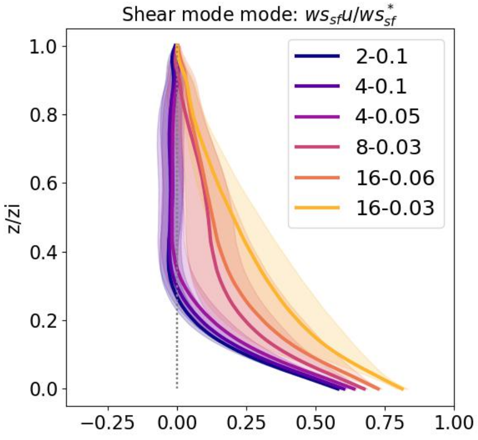
Flux decomposition : surface forced tracer flux

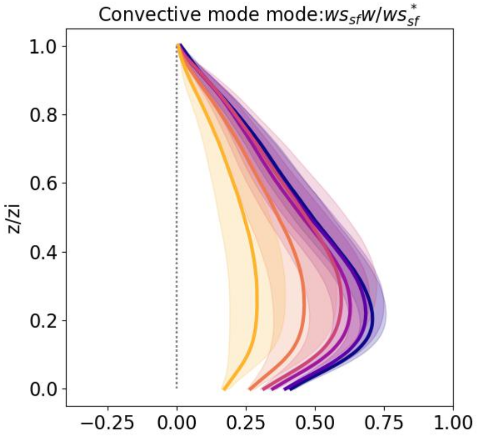
$$w's_{sf}' \approx \alpha_1 f_1\left(\overline{S_{sf}}, Tke_u\right) + \alpha_2 f_2\left(\overline{S_{sf}}, Tke_w\right)$$

Shear mode

Convective mode

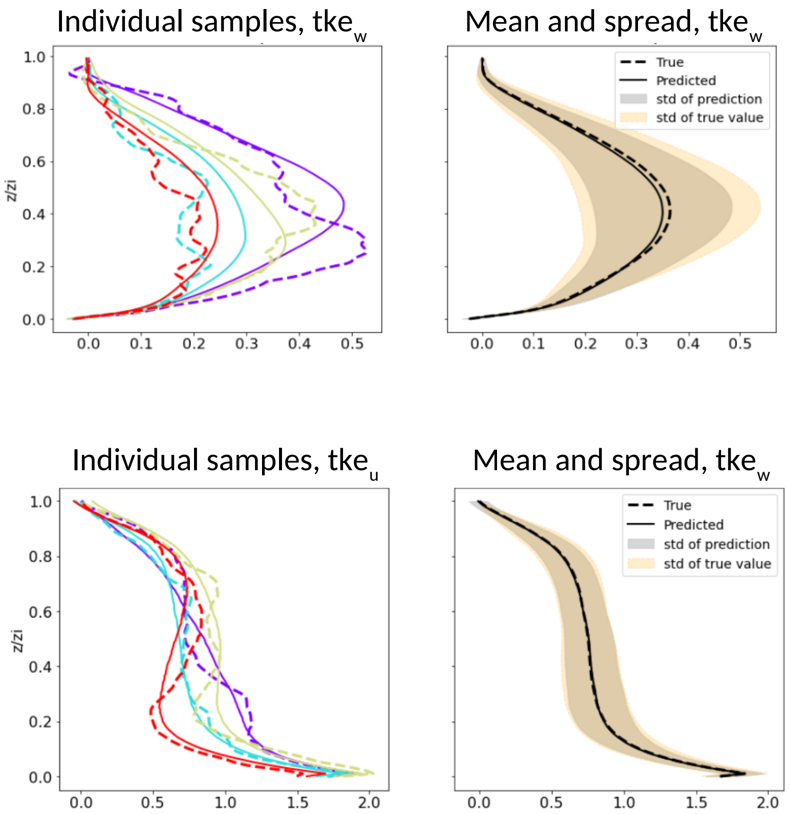






Results: modeling Tke_w and Tke_u

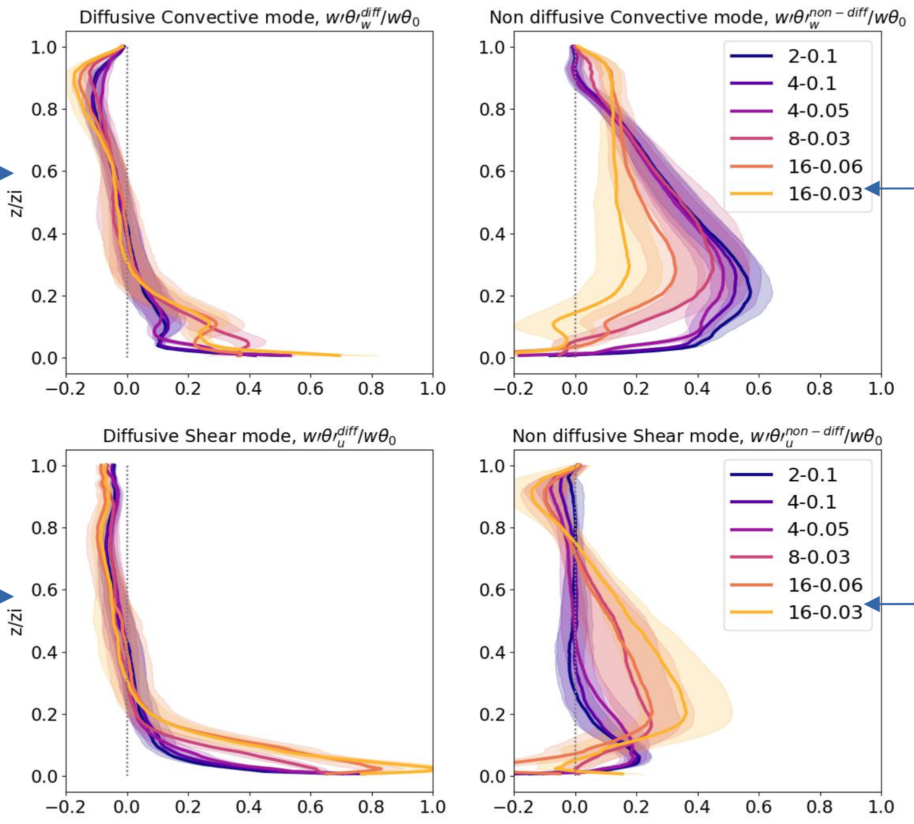
Dashed line: True profile
Line : prediction
Colors: randomly selected samples



How much of each mode can be explained by diffusion

Diffusive Convective mode

Diffusive Shear mode



Non-diffusive convective mode

Non-diffusive Shear mode