Parametrization of dry convective boundary layer using machine learning

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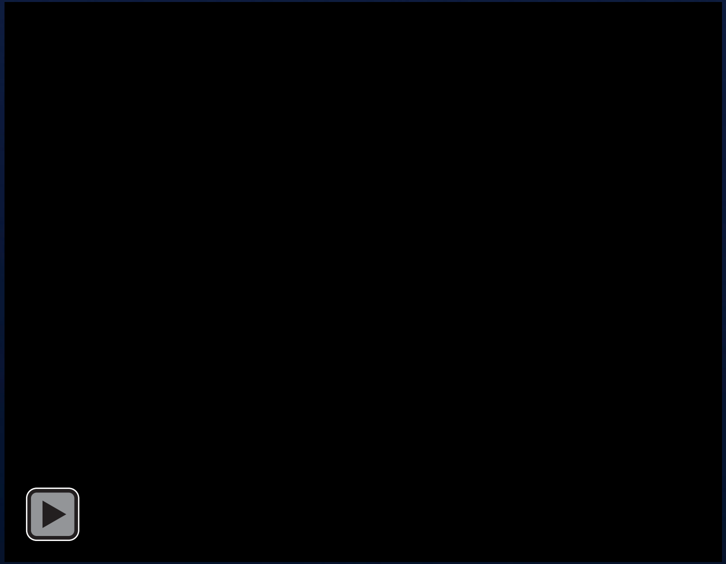


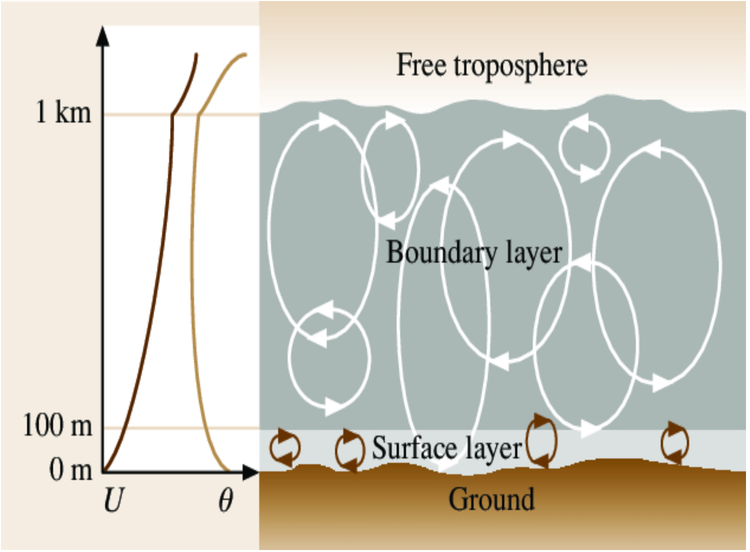
Outline:

- Introduction
- Network architecture and data
- Turbulent flux parameterization

Introduction:

The bottom layer of the atmosphere:

- Often turbulent and capped by statically stable air
- Small scale turbulent PBL processes as well as convective updraft an down drafts are important for mixing and vertical transport of energy and moisture
- But too small to resolve for km-scale models



$$\theta = \overline{\theta} + \theta'$$

$\overline{\theta}$: mean value, resolved

θ' : Turbulent, not resolved

Introduction:

Planetary boundary layer parametrization

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

Examples of PBL parametrization:

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

Eddy diffusion

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

Eddy diffusion mass flux
(no entrainment!)

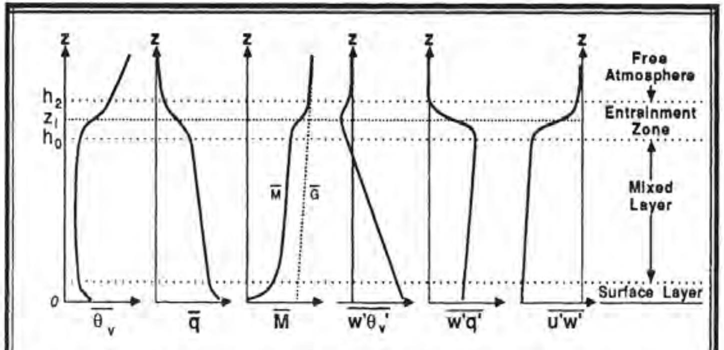
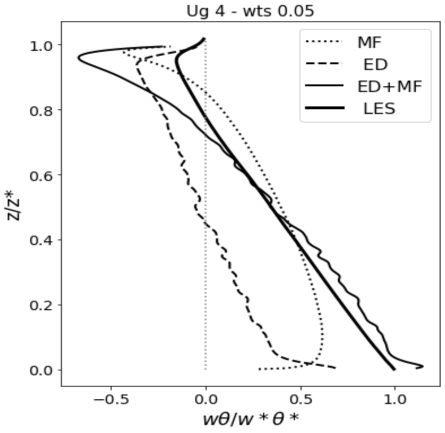


Fig. 11.1 Mean characteristics of layers within the convective boundary layer. (After Driedonks and Tennekes, 1984).

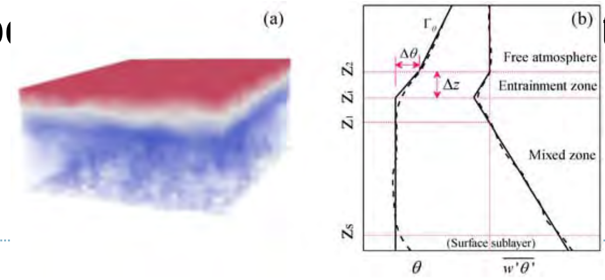
Stull
1988

Introduction:

- PBL models are substantial source of forecast inaccuracy in weather and climate models
- Critical in improving forecasts of high-impact weather phenomena such as organized severe thunderstorms



- Inaccurate prediction of standard approaches (e.g., ED, EDMF): To t.



Objectives:

Using machine learning to parameterize boundary layer turbulent fluxes

- Prediction of turbulent fluxes using machine learning
- Process base flux decomposition
- Gaining insight on turbulent fluxes from machine learning

Data:

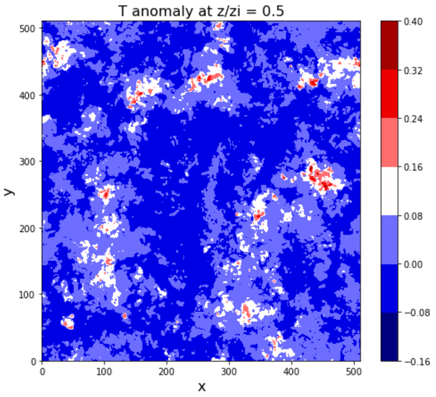
High resolution LES data (dry convective boundary layer)

Three simulation:

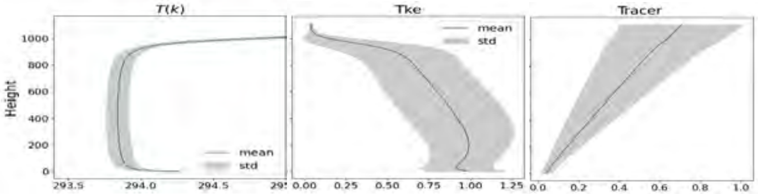
- Strongly convective (C),
- Sheared and convective (SC)
- Weakly convective and strongly sheared (S)

Horizontally: coarse graining, Computing mean variables and turbulent fluxes

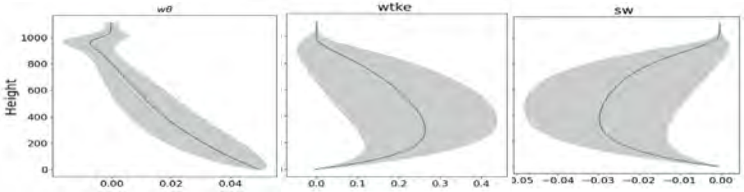
Vertically: interpolate 100 layers between the surface and top of the BL



Input:



Output:

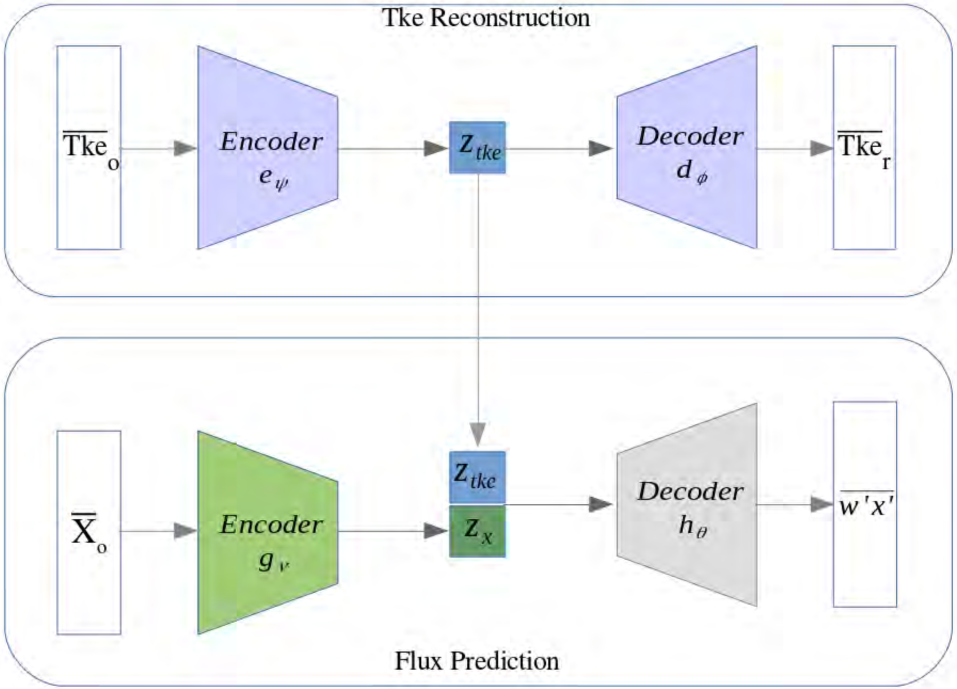


Neural Network:

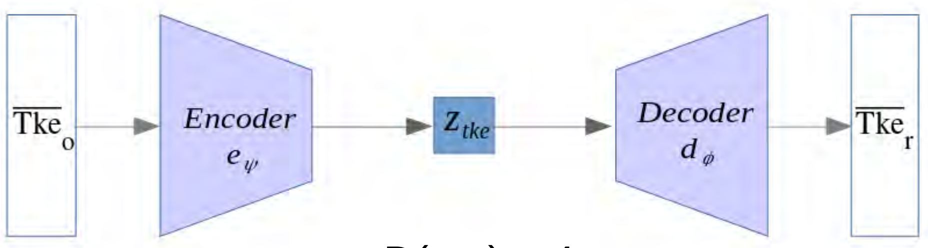
Two-part training:

- Reconstruction of tke → z_{tke}
- Prediction of turbulent fluxes using z_{tke} from step one

Neural Network architecture:



Neural Network: Tke reconstruction



$D(z_{tke}) = 4$

Loss : $\mathrm{MSE}(Tke_t, Tke_p)$

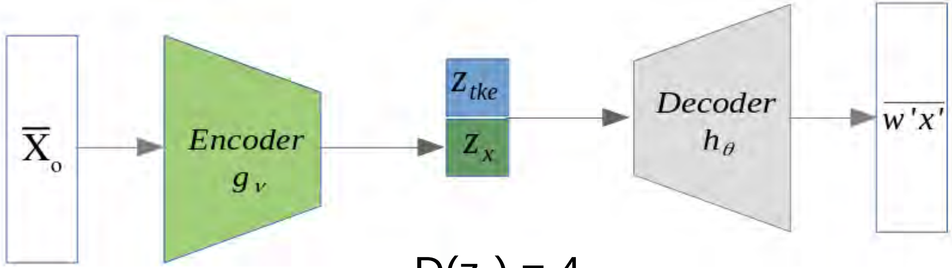
$- \beta_1 \, \mathrm{corr}(\mathrm{decoder}(z_{tkew}), tke_w)$

$- \beta_2 \, \mathrm{corr}(\mathrm{decoder}(z_{tkeu}), tke_u)$

Assumption:
z_{tke} can represents horizontal and vertical part of tke separately

Enforced using constraints in the loss function

Neural Network: Flux prediction



$D(z_x) = 4$

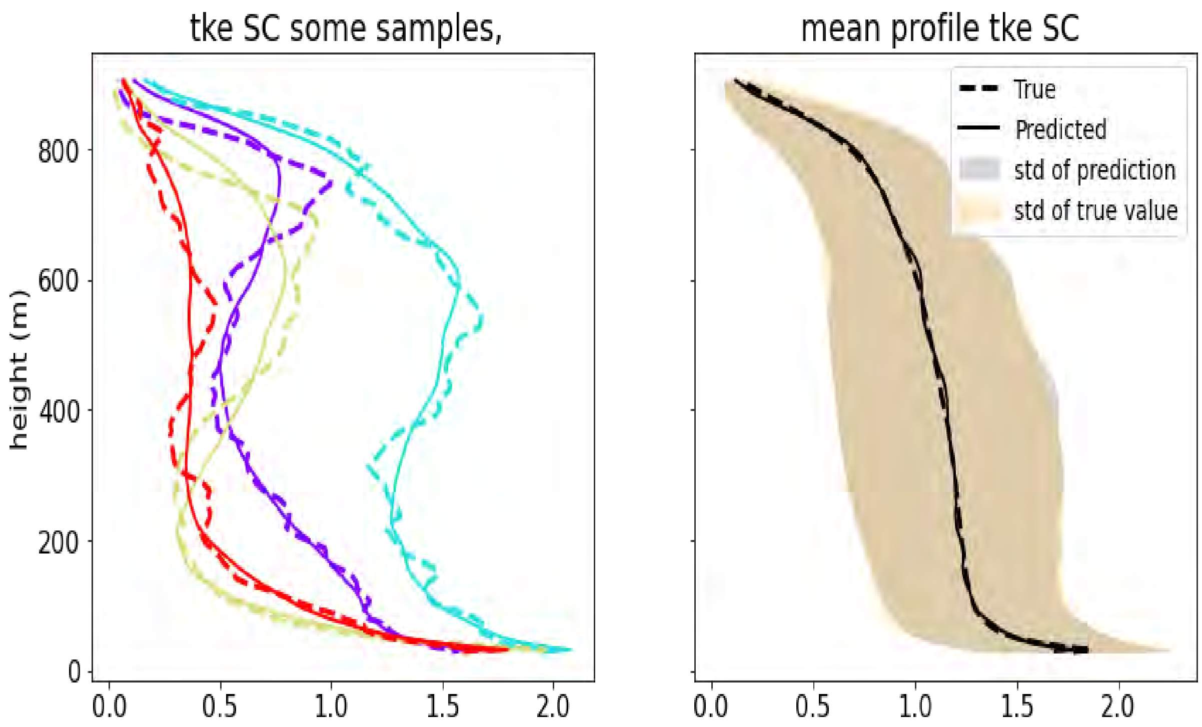
$X \in [T, Tracer, TKE]$

Assumption:
All scalars are transported the same way by flow

$z_T = g_v(T)$
$z_S = g_v(S)$
$z_E = g_v(Tke)$

Each scalar has its own latent space but the mapping is the same

Overall results: Tke reconstruction

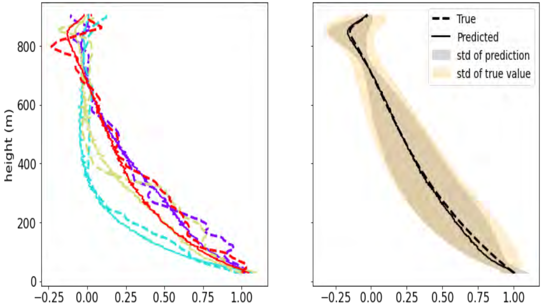


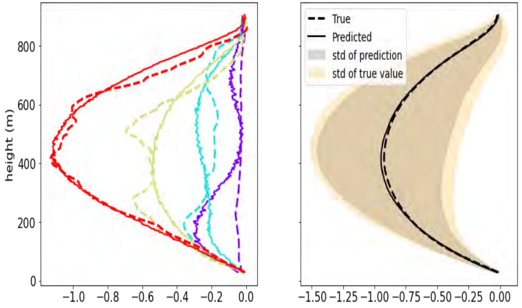
Overall results: Flux prediction

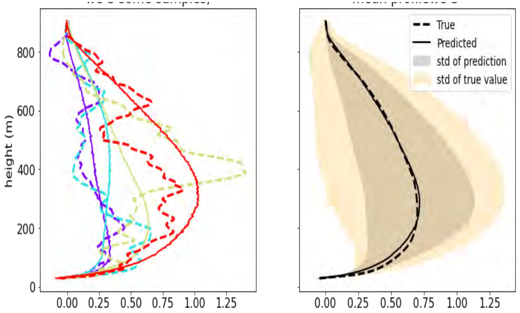
Heat flux

Tracer flux

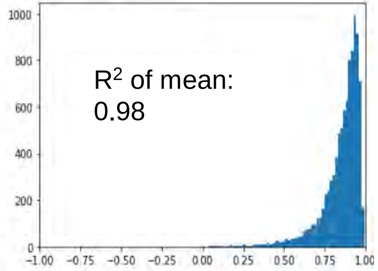
Tke flux

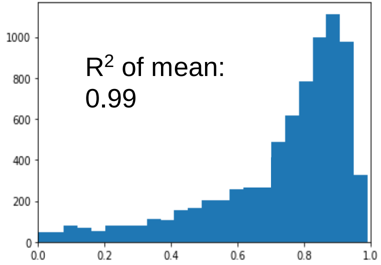


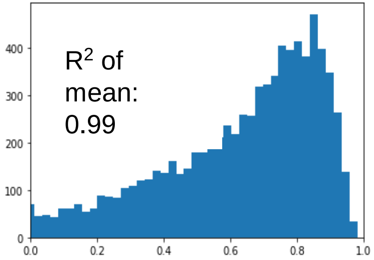




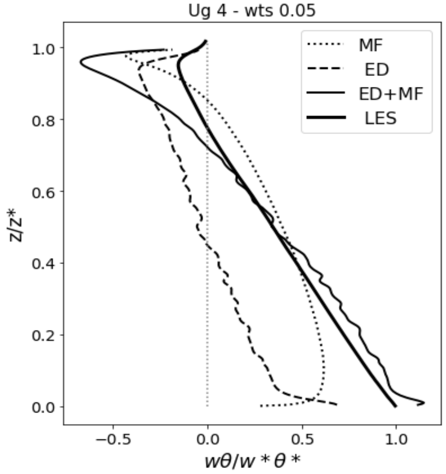
Distribution of R^2



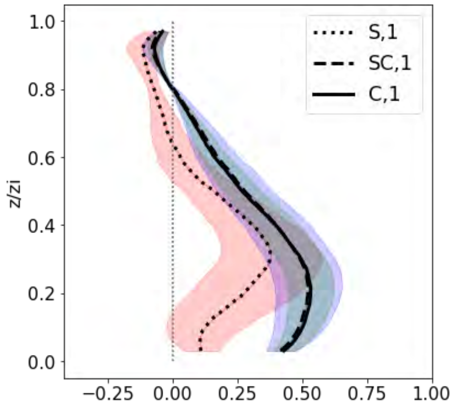




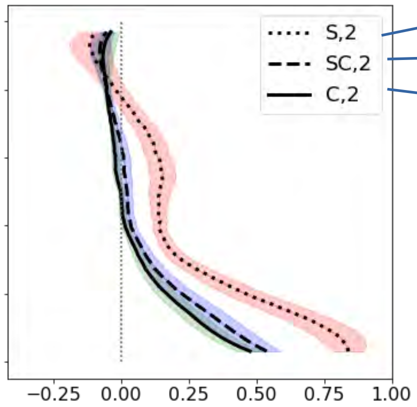
Flux decomposition: Heat flux



Convective mode



Shear mode



Sheared

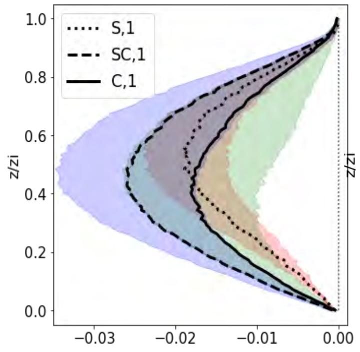
Sheared and convective

Very convective

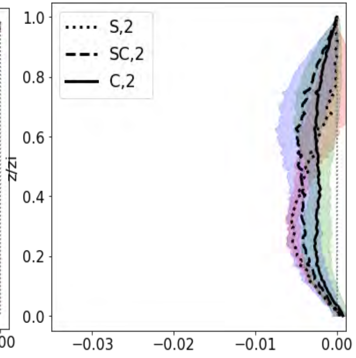
Flux decomposition: Tracer and Tke

Tracer

Convective mode

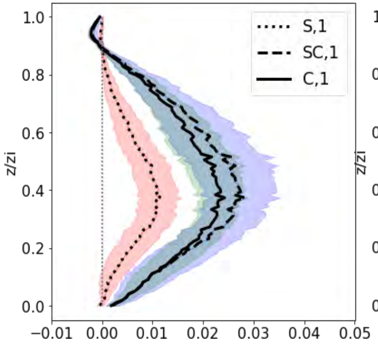


Shear mode

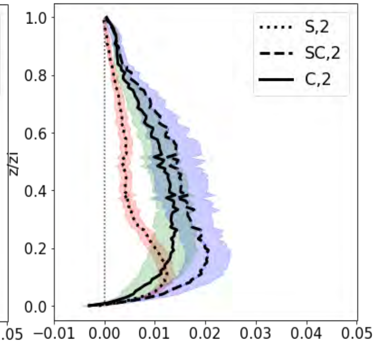


TKE

Convective mode



Shear mode

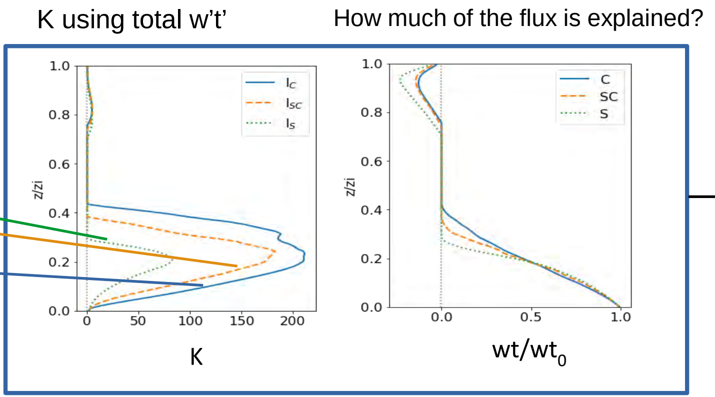


Projection on gradient:

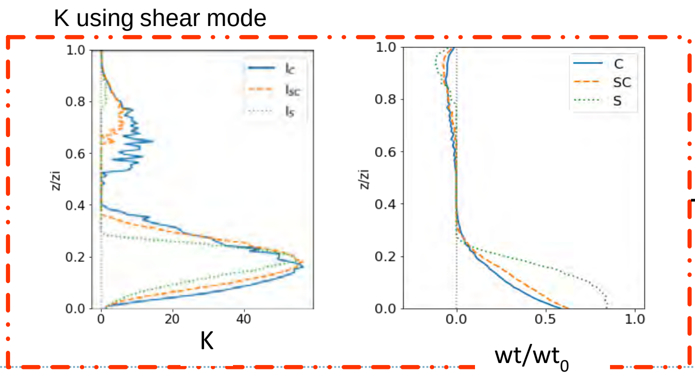
Sheared

Sheared and convective

convective



Using total flux



Using second mode from decomposition

Summary:

Machine learning allows:

- Accurate prediction of turbulent fluxes across regimes (outperforms standard EDMF approach) & with low dimension
- Better understanding of physics

But

- Physics guided approach is necessary for flux separation
- Two modes explain the total flux: shear related mode and convective related mode