



Parametrizing Turbulent Flow in The Planetary Boundary Layer











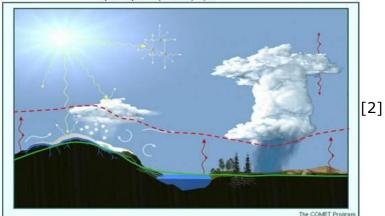
The Planetary Boundary Layer (PBL)

- Lowest layer of troposphere (~1 km)
 - Events are often too small to be resolved by climate models (~100km)
 - Directly affected by surface heating/cooling
 - Turbulent, well-mixed, unstable
 - Capped by a temperature "inversion"
- Vertical turbulent fluxes
 - Surface heat → buoyancy
 - Transport air and key quantities upward:
 - Pollution, heat, moisture, etc...



Depiction of various surfaces and PBL processes

--- Top of the planetary boundary layer

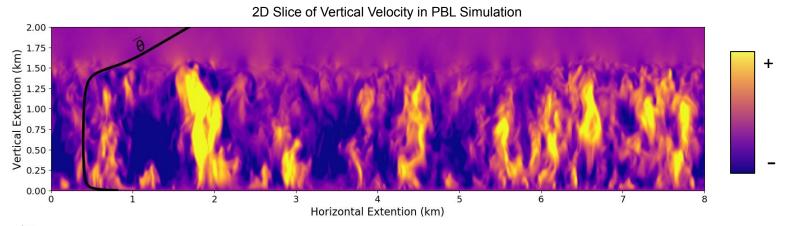






The Data

- Simulate PBL using Large Eddy Simulations (LES)
- Varying initial conditions: horizontal wind, surface heating, inversion strength
- Captures evolution of PBL at high resolution (24×24×6 m, 120 min)
- Coarse-grained and averaged down to vertical profile to remove noise
- Many variables and their higher order moments produced.







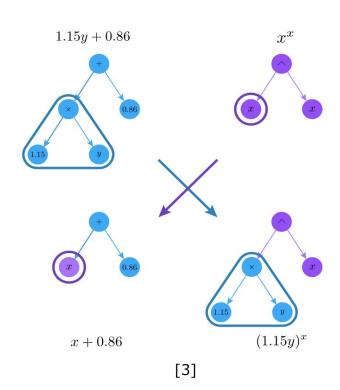




Symbolic Regression (SR)

A machine learning task which aims to discover human-interpretable equations.

- Genetic algorithm + optimization task
- Combines operators (+,-,×,÷), basic functions (sin, cos, inv), and coefficients.
- Inputs: response variable, potential predictor variable(s)
- Output: Equation relating predictors and response
- Inherently very random, not guaranteed to converge or find correct equation





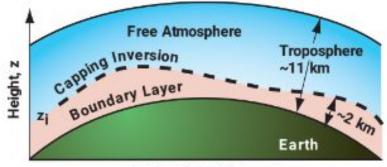






Eq 1: Entrainment Velocity

- How does the PBL grow over time?
- At the capping inversion:
 - Inertia of rising air overshoots to the free troposphere
 - This causes mixing at the PBL
- ullet Represented by $rac{dh}{dt}$ or w_e
 - \circ Large scale components in $\frac{dh}{dt}$ are not considered in our LES



Horizontal distance, x

[4]





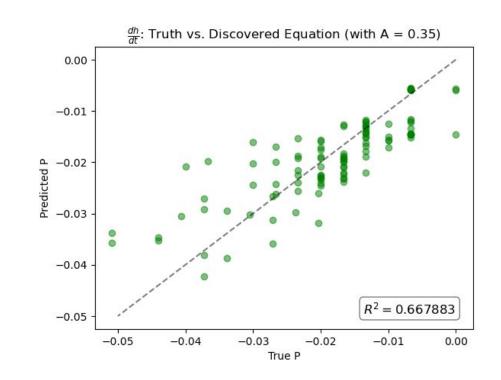
Eq 1: Discovering entrainment velocity

Current parameterization:

$$\frac{dh}{dt} = A \frac{\overline{w'b'}_{\text{sfc}}}{\frac{g}{\theta_0} \Delta \theta_{\rho}}$$

Discovered equation:

$$\frac{dh}{dt} = -10.751 \frac{\overline{w'b'}_{\text{sfc}}}{\Delta \theta_o} - 0.00076 U_g$$

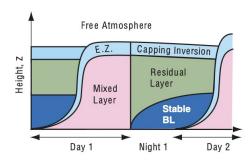


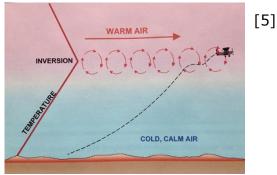




Eq 2: Inversion Layer Mass-Flux

- Calculation discrepancies
 - \circ Some textbooks [7] say: $h^- \frac{d heta_{ml}}{dt} = \overline{w heta_{h^-}} + \overline{w heta_{sfc}}$
 - \circ Where: $\overline{w heta_{h^-}}=w_e\Delta heta_
 ho$
- Looking for the mass flux in the inversion layer
 - Equation discovery struggles to adhere to physics & respect units









Eq 3: Heat Flux

We model the way the turbulent component of warm air vertically transports key quantities in the PBL ($\overline{w\theta}$)

First, the pressure redistribution term is found, as derived in [6]:

$$P = -\frac{1}{\rho_0} \overline{\theta} \frac{\mathrm{d}p}{\mathrm{d}z} = -C_1 \frac{\overline{w\theta}}{\tau_1} - C_2 \beta \overline{\theta}^2 + C_3 \sigma_w^2 \frac{\mathrm{d}\Theta}{\mathrm{d}z}$$

Then, the resulting coefficients C_1, C_2, C_3 are plugged into a parametrization for $\overline{w\theta}$ that is dependent on them.

Goals:

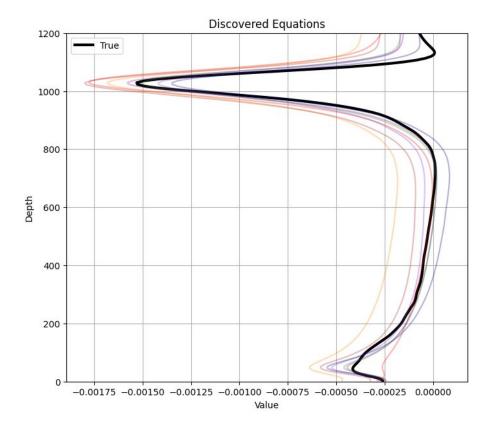
- 1. Verify the functional form for P, using the above predictors and response
- 2. If correct, compare discovered coefficients to theoretical/typical estimates
- 3. Plug coefficients in to test to see how well $\overline{w\theta}$ is parametrized.





Eq 3: Goals 1 & 2

 Rediscovery of eq for P is successful after lots of tuning: functional form appears correct

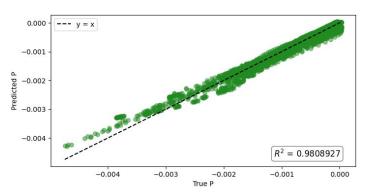


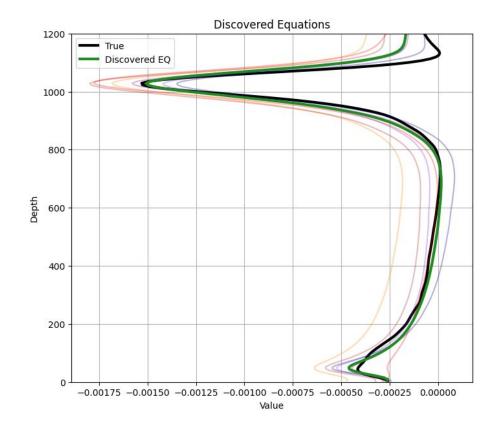




Eq 3: Goals 1 & 2

- Rediscovery of eq for P is successful after lots of tuning: functional form appears correct
- Final eq provides excellent fit.



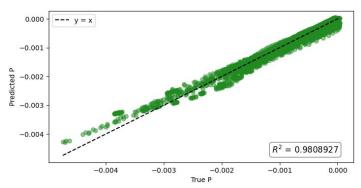


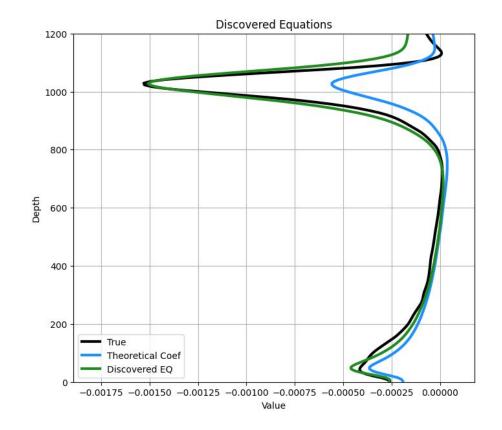




Eq 3: Goals 1 & 2

- Rediscovery of eq for P is successful after lots of tuning: functional form appears correct
- Final eq provides excellent fit.
- Coefficients differ strongly from theoretical/typical values





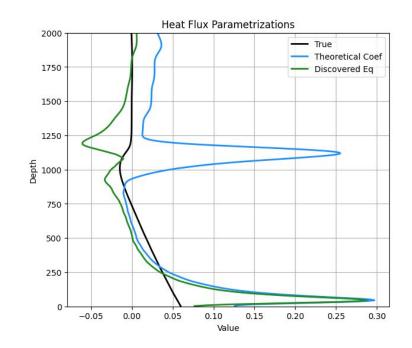




Eq 3: Goal 3

When coefficients are plugged back into $\overline{w\theta}$ parametrization, performance is bad..

- Discrepancy most likely from data issues, or extra dependency on large scale forcings.
- A second stage SR on the coefficients shows that C_1 may be dependent on U_g .
- This makes sense: horizontal wind likely speeds up mixing.







Conclusions

Our Contributions:

- Equation rediscovery: w_a, P
- Equation improvement: better coefficients & dependencies on large scale forcings
- Attention drawn to horizontal wind
- Github repo for reproducibility + future work

Future Directions:

- Include more simulations with varying initial conditions
- Refine the second stage SR for finding coefficient dependence on large scale forcings
- Building in physics/consideration of units
- One big limitation of equation discovery is reliance on local information, bring in non-locality (function space or inputs)





References

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