Machine Learning Parameterization of the Offshore Surface Layer

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Motivation: Surface Layer Parameterization in NWP

Transfer of energy between the ocean surface and atmosphere is driven by radiation and convection.

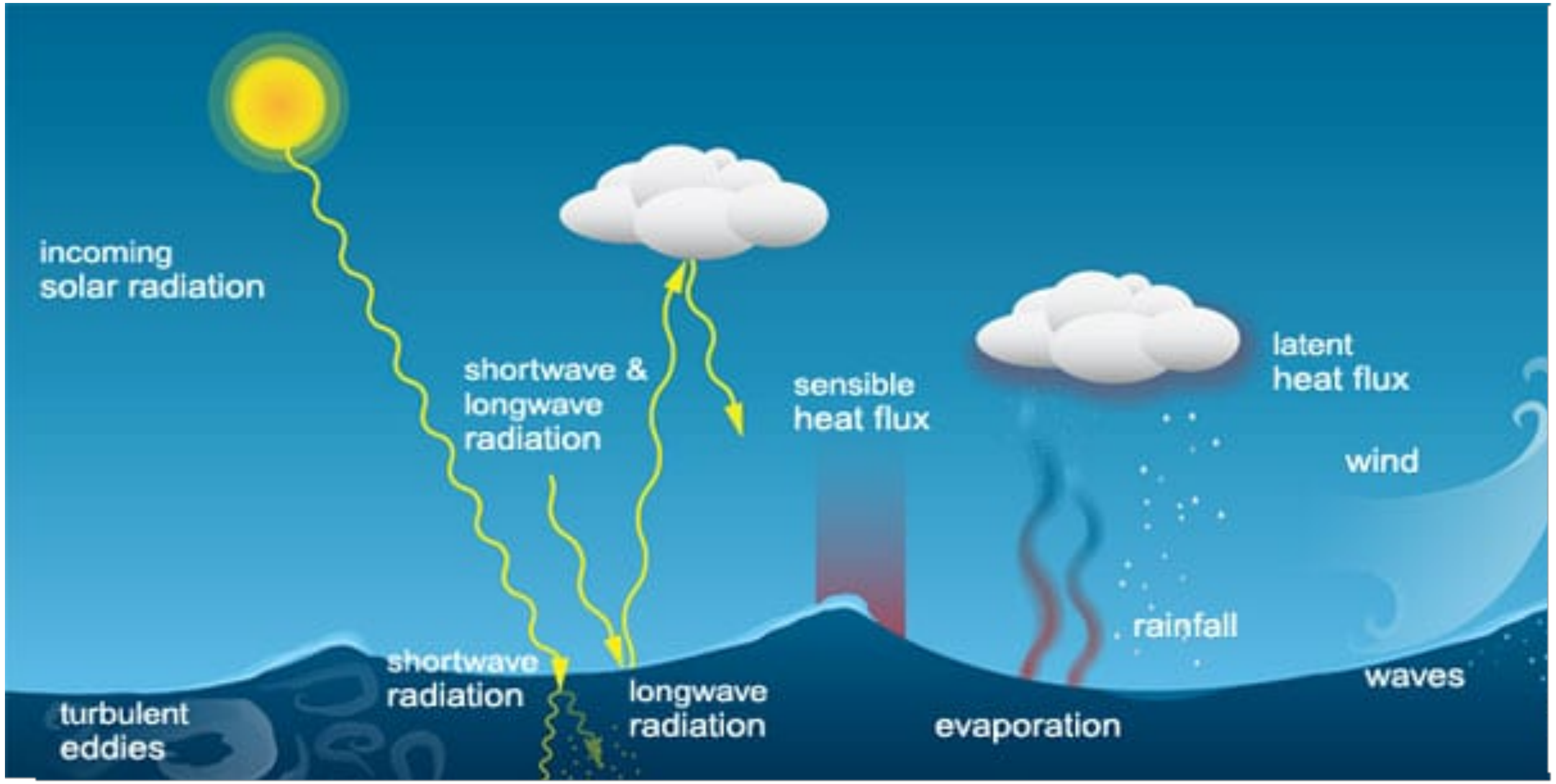


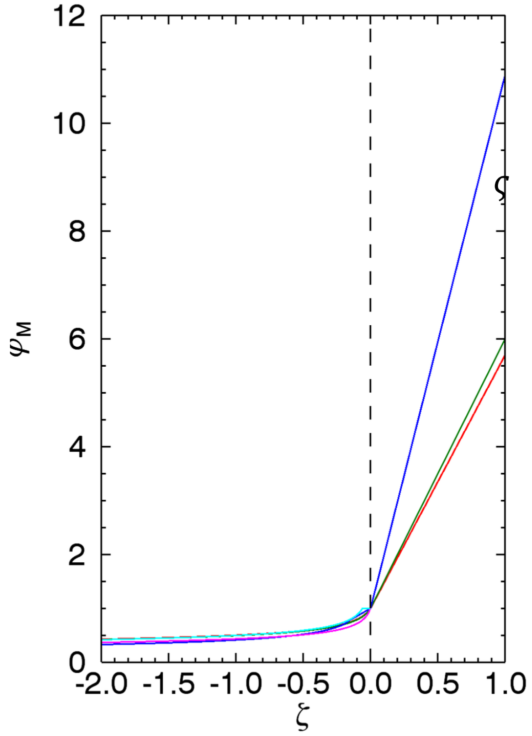
Image Credit:
Amy Caracappa-Qubeck, WHOI
https://www.whoi.edu/oceanus/feature/evaporation/

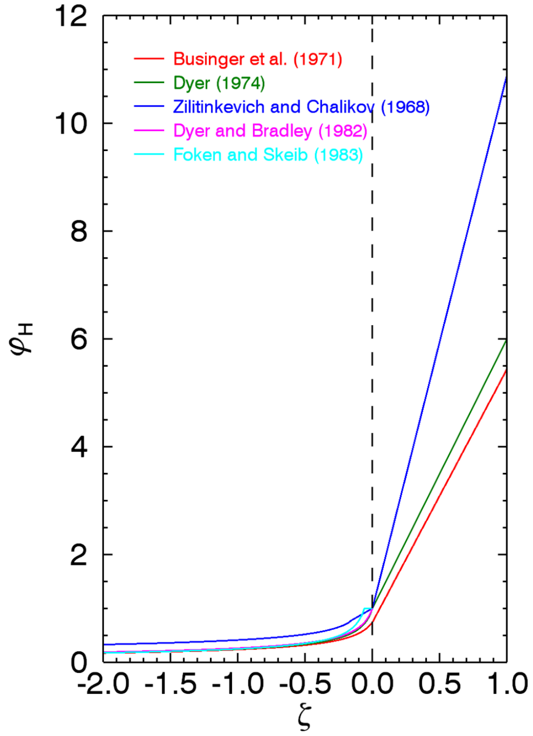
The turbulent fluxes of **momentum**, **sensible and latent heat** occur through unresolved eddies which **must be represented in numerical models through surface layer parameterizations**.

Motivation: Surface Layer Methods

Parameterizations of the Surface Layer use **Monin-Obukhov Similarity Theory** which depends on **empirically defined** stability functions ,$\boldsymbol{\varphi_M}$ ***and*** $\boldsymbol{\varphi_H}$, (for momentum and heat) for the estimation of surface fluxes.

φ_M





φ_H

x axis: Monin Obukhov Stability Parameter z/L where z is height and L is Monin Obukov Length

GOAL: Improve Surface Flux Estimates Using Machine Learning

- Used weather data and flux measurements from the FINO1 tower and buoys to train machine learning models to **estimate friction velocity $\boldsymbol{u_*}$** and **temperature scale $\boldsymbol{\theta_*}$ directly** (Avoiding explicit calculations using MO stability functions!)
- Compared results of Machine Learning estimates of u_* and θ_* to explicitly calculated values using MO Theory

Note: We did not predict moisture scale q* since the FINO1 dataset does not contain this information

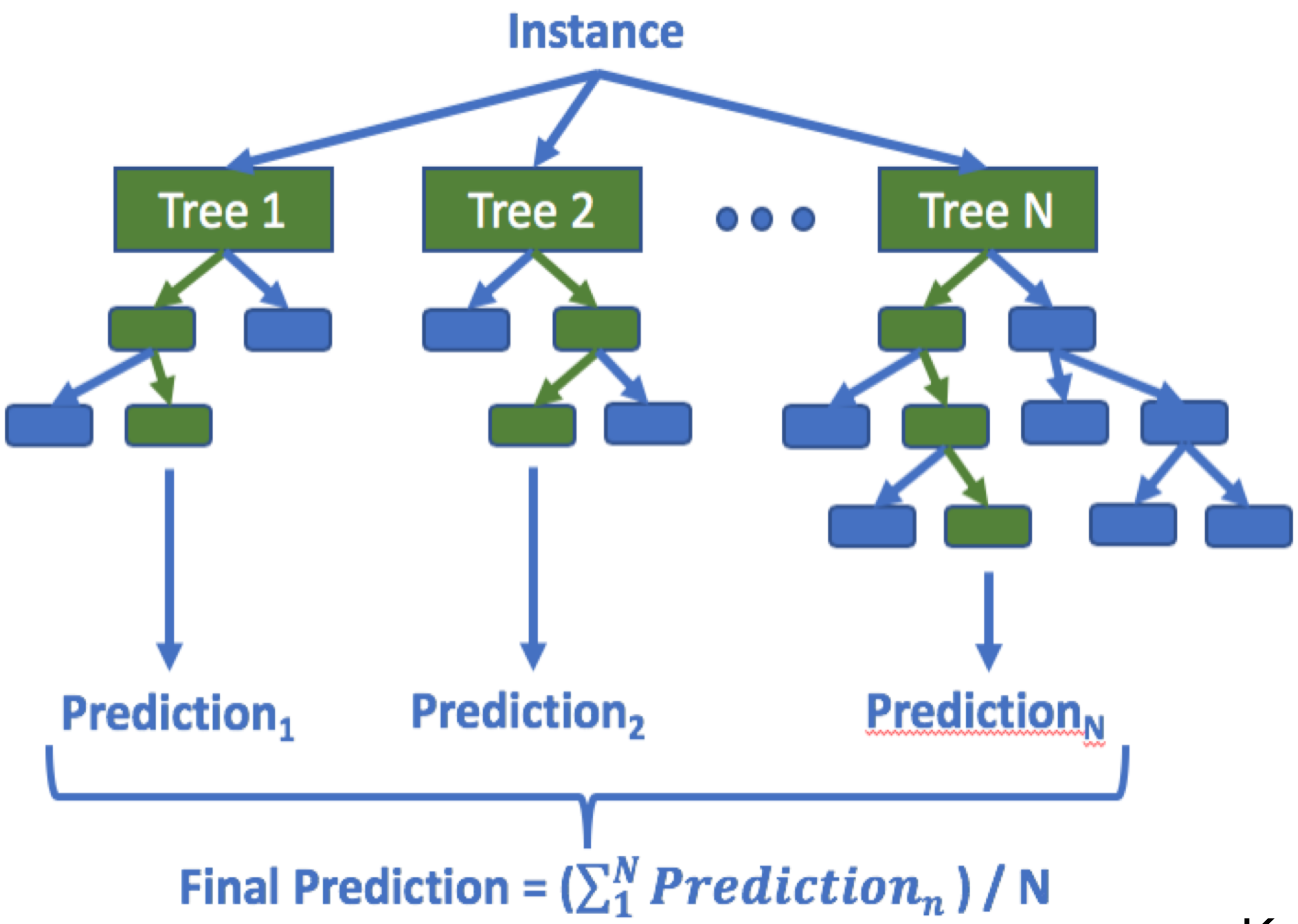
Machine Learning Model Input and Output

Input Variables	Heights
Sea Surface Temperature	0m
Wave Height	0m
Wave Direction	0m
Wave Period	0m
Potential Temperature	40m
Relative Humidity	40m
Wind Speed	40 m
Wind Dir	40m
Wind U, V	40m
GHI	30m
Bulk Richardson Number	40m
Potential Temperature Gradient	40m,60m
Wind Speed Gradient	40m,60m
Angle Between Wind/Wave Dir	40m/0m
Solar Zenith	0 m
Solar Azimuth	0m

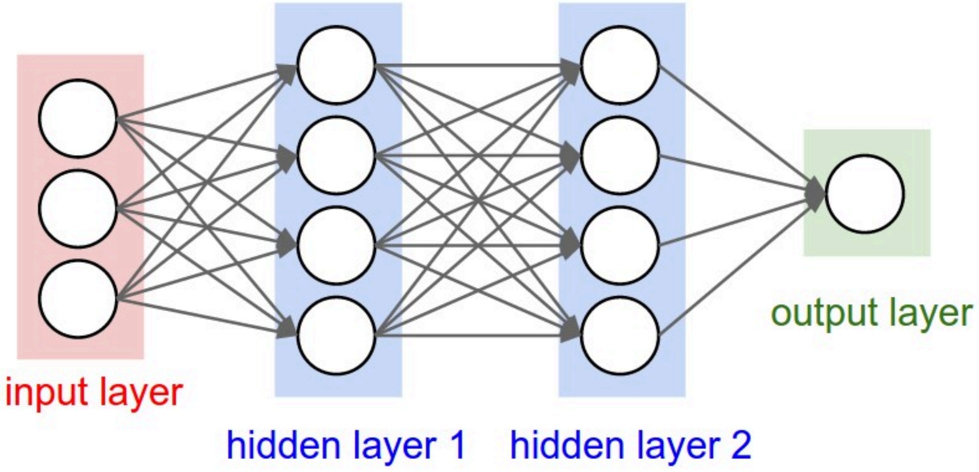
Predictands	Heights	Flux Calc for NWP
friction velocity u_*	40m	momentum flux $\tau = \rho u_*^2$
temperature scale θ_*	40m	sensible heat flux= $-\rho c_p \theta_* u_*$

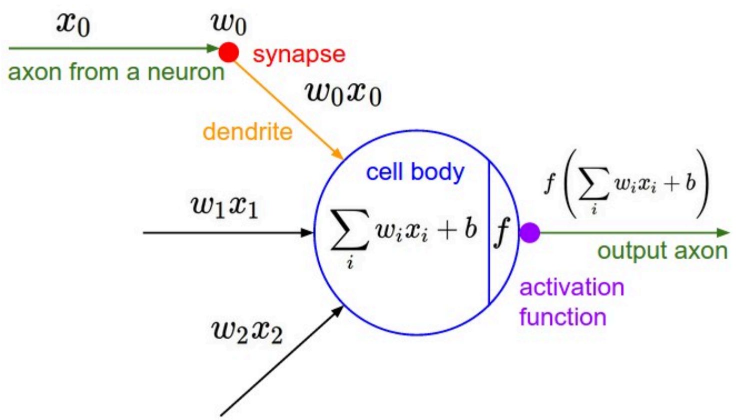
Notes: Dataset had 20 min temporal resolution, buoy data had to be interpolated to 20min intervals, we had only 6 months of complete data samples

ML Algorithms: Random Forest and Neural Network



Key Hyperparameters: 100 trees, 1024 leaf nodes/tree



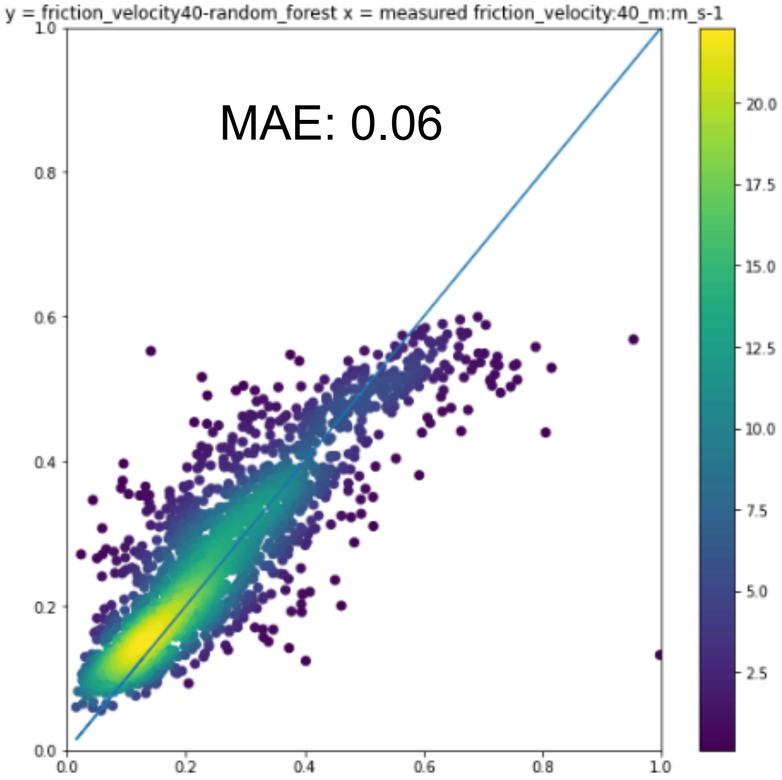


Key Hyperparameters: Dense network with 2-3 hidden layers,64 neurons, and tanh activation

Images from http://cs231n.github.io/convolutional-networks/

Results of Estimating of Friction Velocity: Scatter Plots

RandomForest



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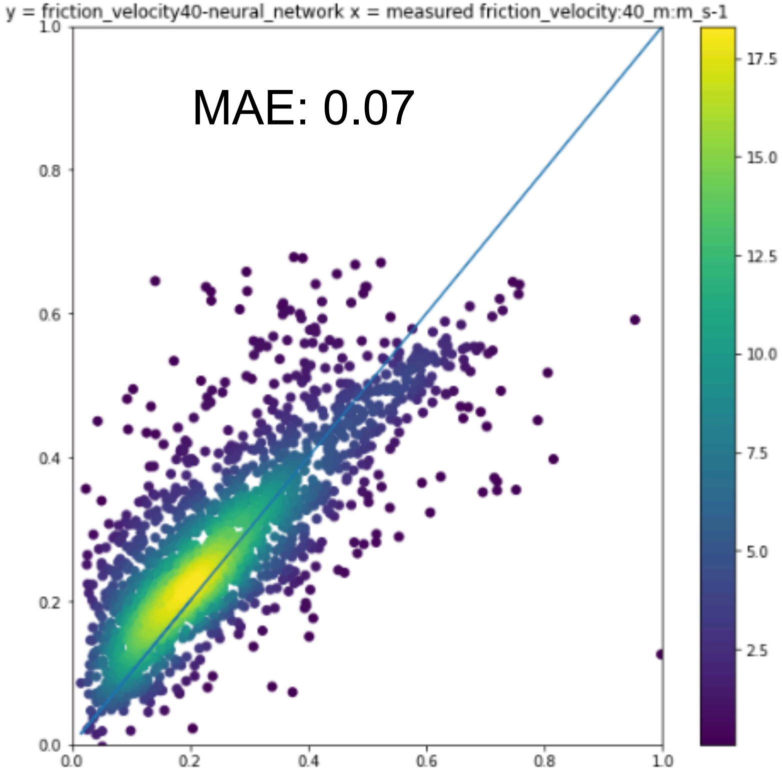
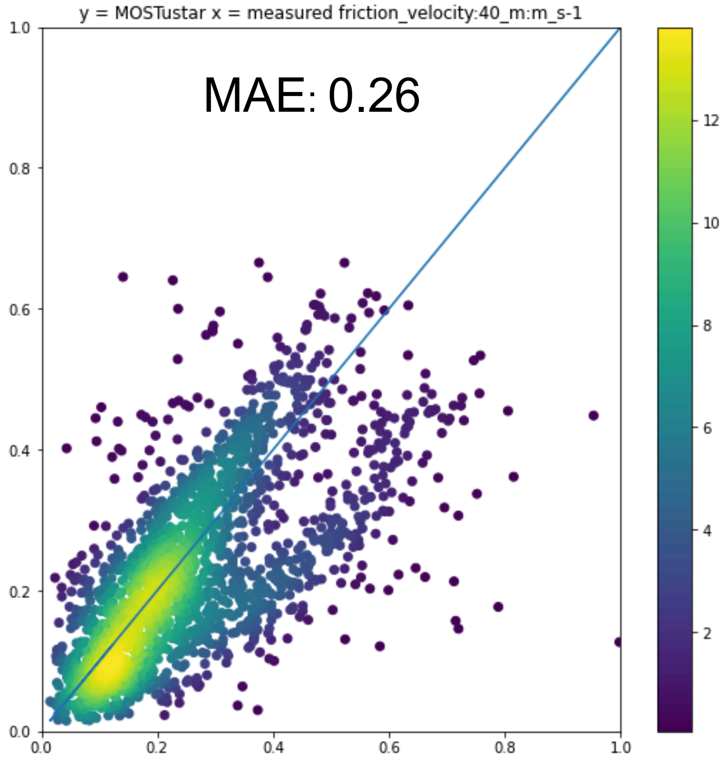


Monin Obukhov

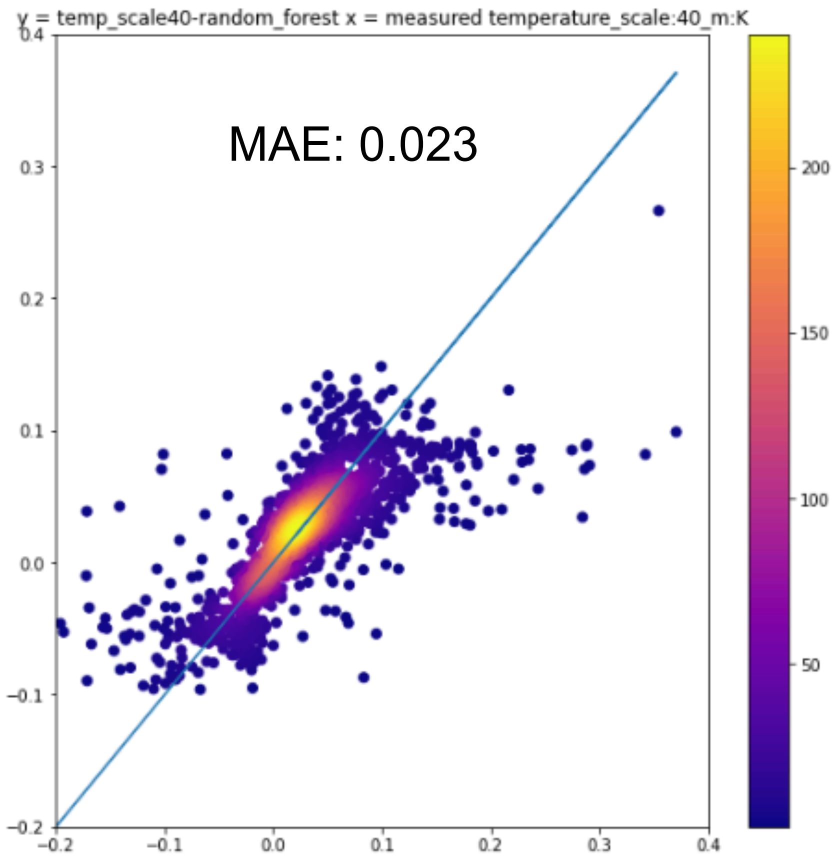


X-axis: Observed u_*

Y-axis: Predicted or Calculated (MOST) u_*

Results of Estimating Temperature Scale: Scatter Plots

RandomForest



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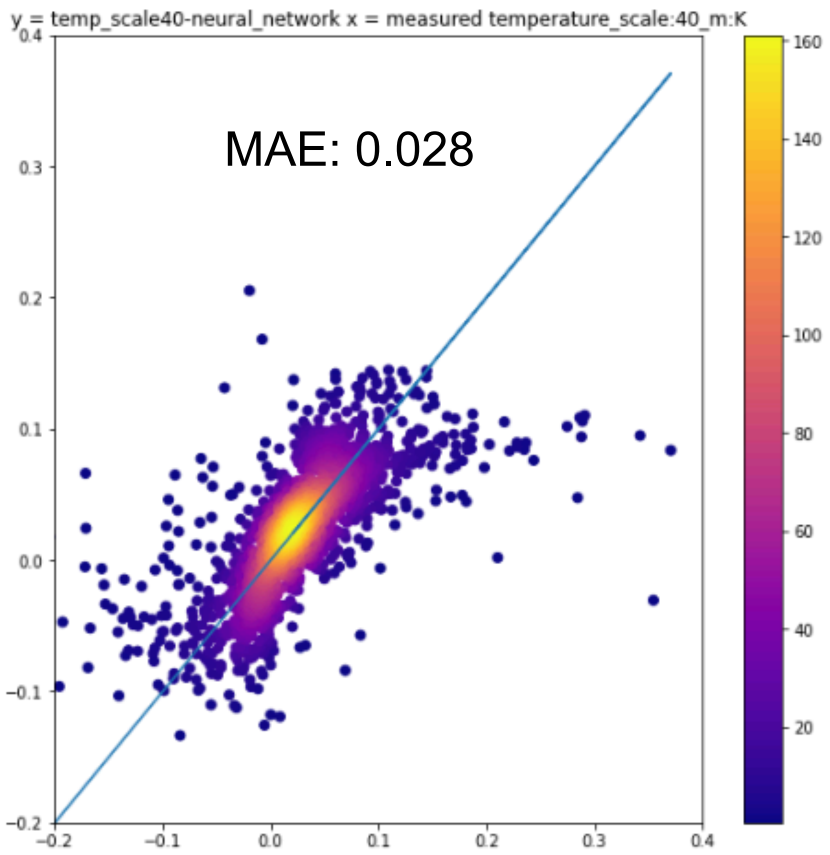
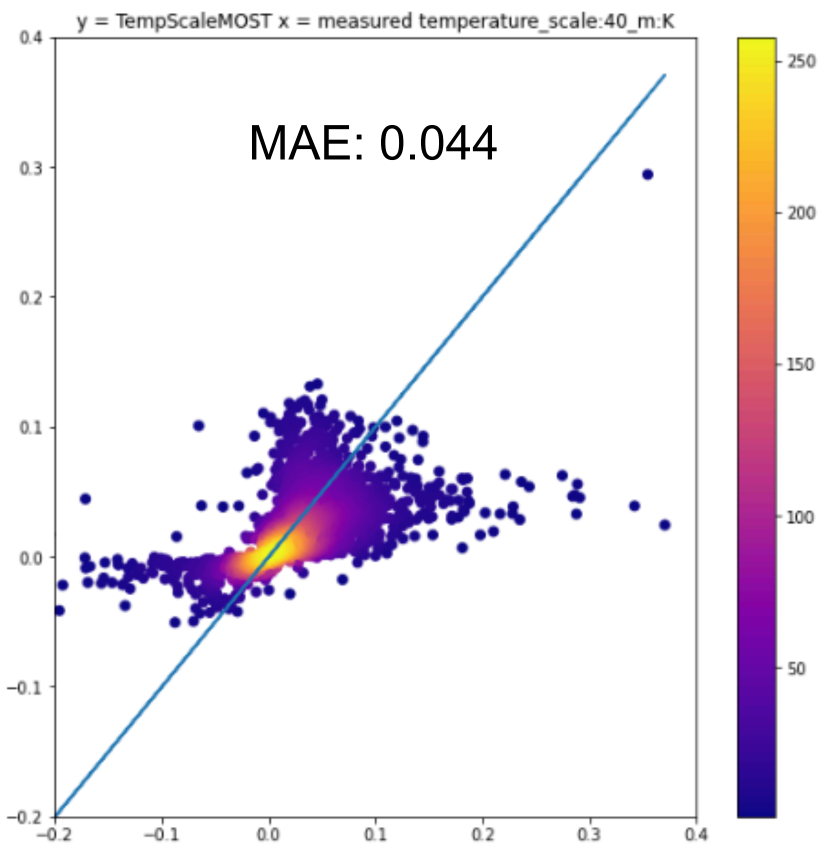


Monin Obukhov



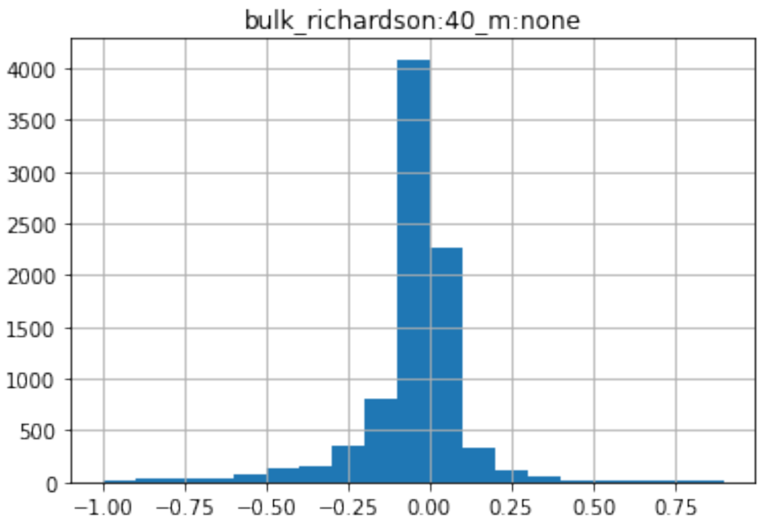
X-axis: Observed θ_* Y-axis: Predicted or Calculated (MOST) θ_*

Permutation Predictor Importance by Stability Regime

- Test data samples were separated by stability regime as determined by the Bulk Richardson Number
- Permutation Importance was determined for each predictor
  - Predictor variables in the test dataset are permuted one at a time, then the model is applied to the test data with the scrambled predictor and and the change in prediction error is recorded

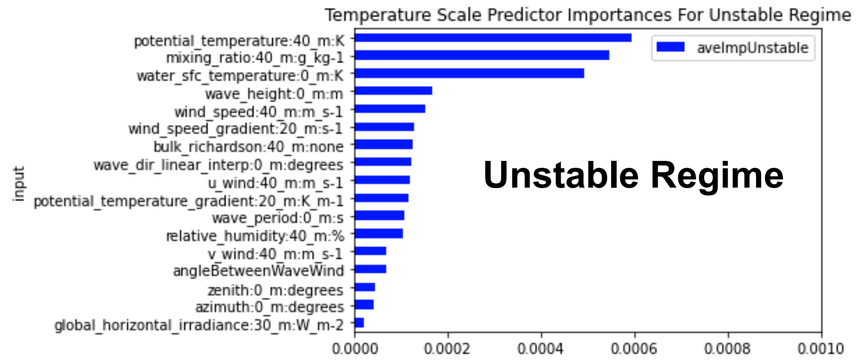
  - The **larger the error increase** when randomly permuted, **the more important the variable** is

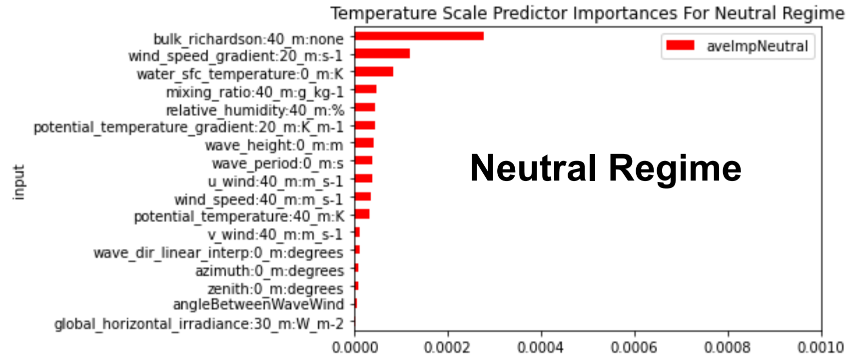
Bulk Richardson's number distribution

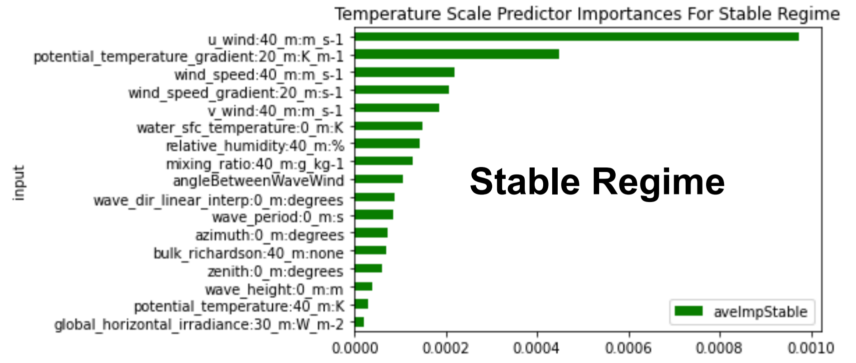


Regime Category Sizes
Unstable (bulk Ri < .02): 4308
Neutral (bulk Ri in[-.02,02]): 1851
Stable (bulk Ri > .02): 2647

Permutation Predictor Importance of RF by Stability Regime



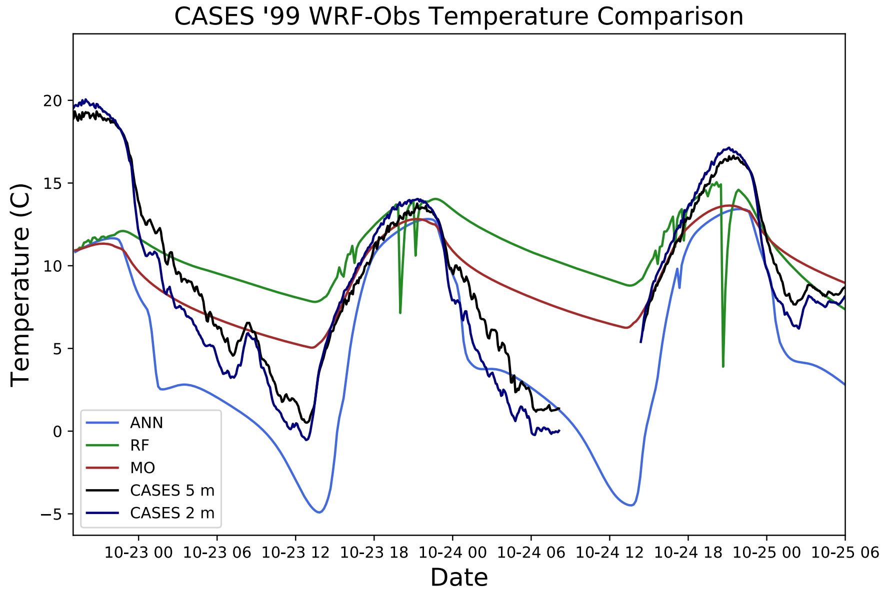




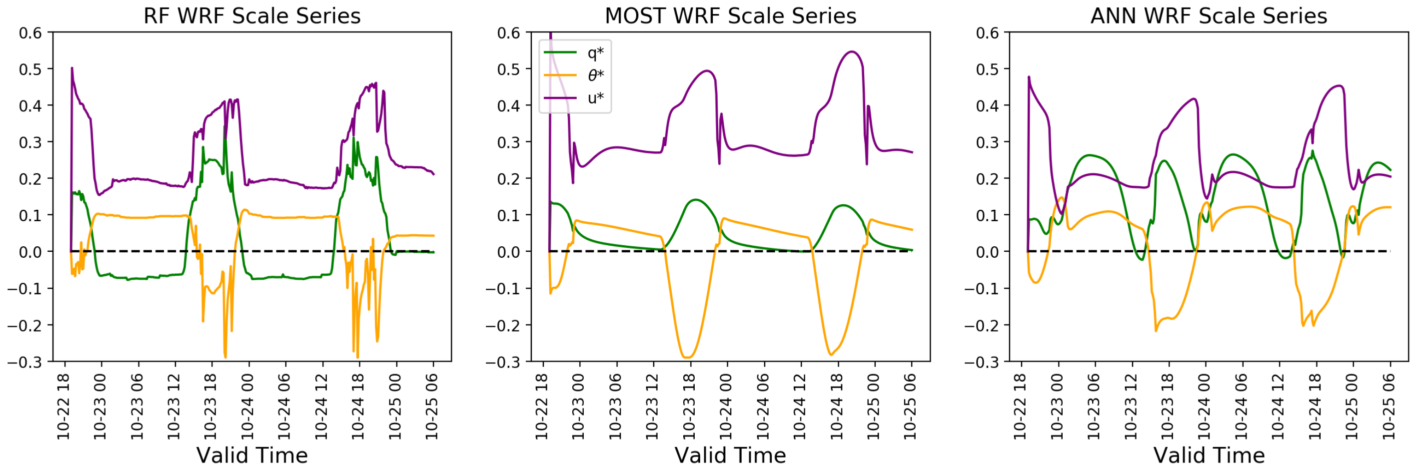
Temperature Scale:

- Predictor importance spread over larger subset of predictors for all regimes
- Top predictors in stable regime are dominated by wind variables
- Potential Temp top predictor for unstable regime, one of lowest for the stable regime
- Wave variables: height and direction are important, wave period shows greater importance for temp scale models.
- GHI at the low end of importance for all regimes in offshore models

Machine Learning with the NWP Model



- Surface Layer ML models have been incorporated within WRF for onshore surface layer case
- Wrote Fortran inference engines for random forest and dense neural networks
- Neural network produces smoother predictions than random forest and has more cooling at night, potentially due to larger moisture flux



Ongoing Challenges

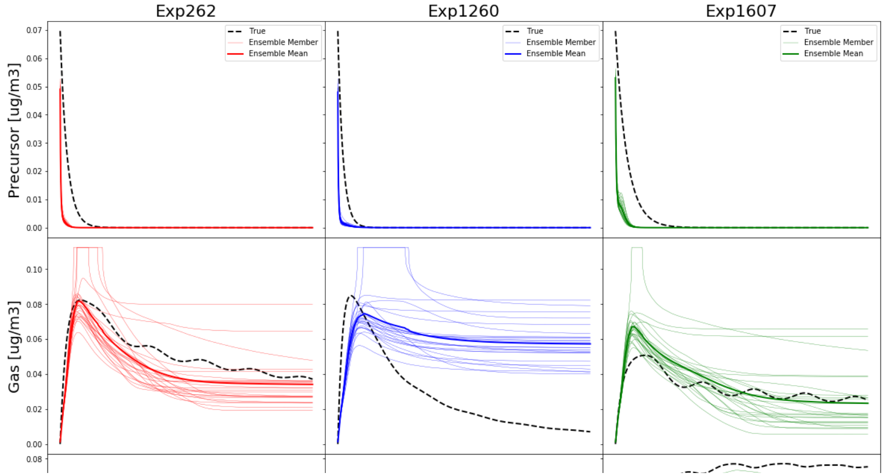
Bridging Python ML Frameworks with Fortran and C Simulations

- ML frameworks like Tensorflow can be called through poorly documented C API
- Cannot accept Fortran or CUDA arrays directly
- Need to build with same compiler as simulation, which can be daunting for Tensorflow
- Potential overhead issues going from simulation to framework

Offline vs Online Performance of ML Emulators

- ML emulators often fail to perform as well within simulations as offline
- Error growth and feedbacks can cause instabilities and damping effects
- Time memory in ML is helpful but may not be feasible in full 3D sims.

Ensemble Runs - Dodecane (single timestep DNN)



Dual Expertise and Training

- Successful implementation of ML in NWP requires experience in both areas
- Takes months/years of experience to understand how to build these components from scratch
- Need more documentation and training on both sides to engage a larger community