

CESM Working Group Meetings 2024

Computationally efficient method for predicting
evapotranspiration using a Gaussian Process Regression
Emulator

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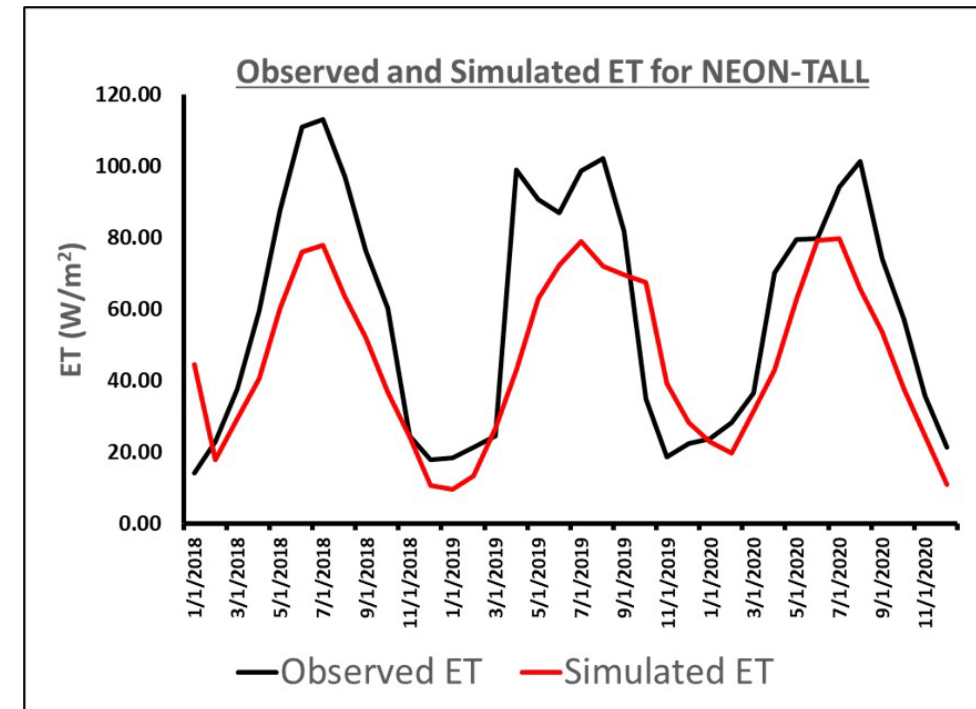
Background

- Process-based Land surface models (LSMs) are pivotal in understanding the changing climate system
- Understanding Evapotranspiration (ET)
 - ET is the linkage between carbon, water, and energy cycles.
 - Sixty-five percent of annual precipitation returns back to the atmosphere as ET



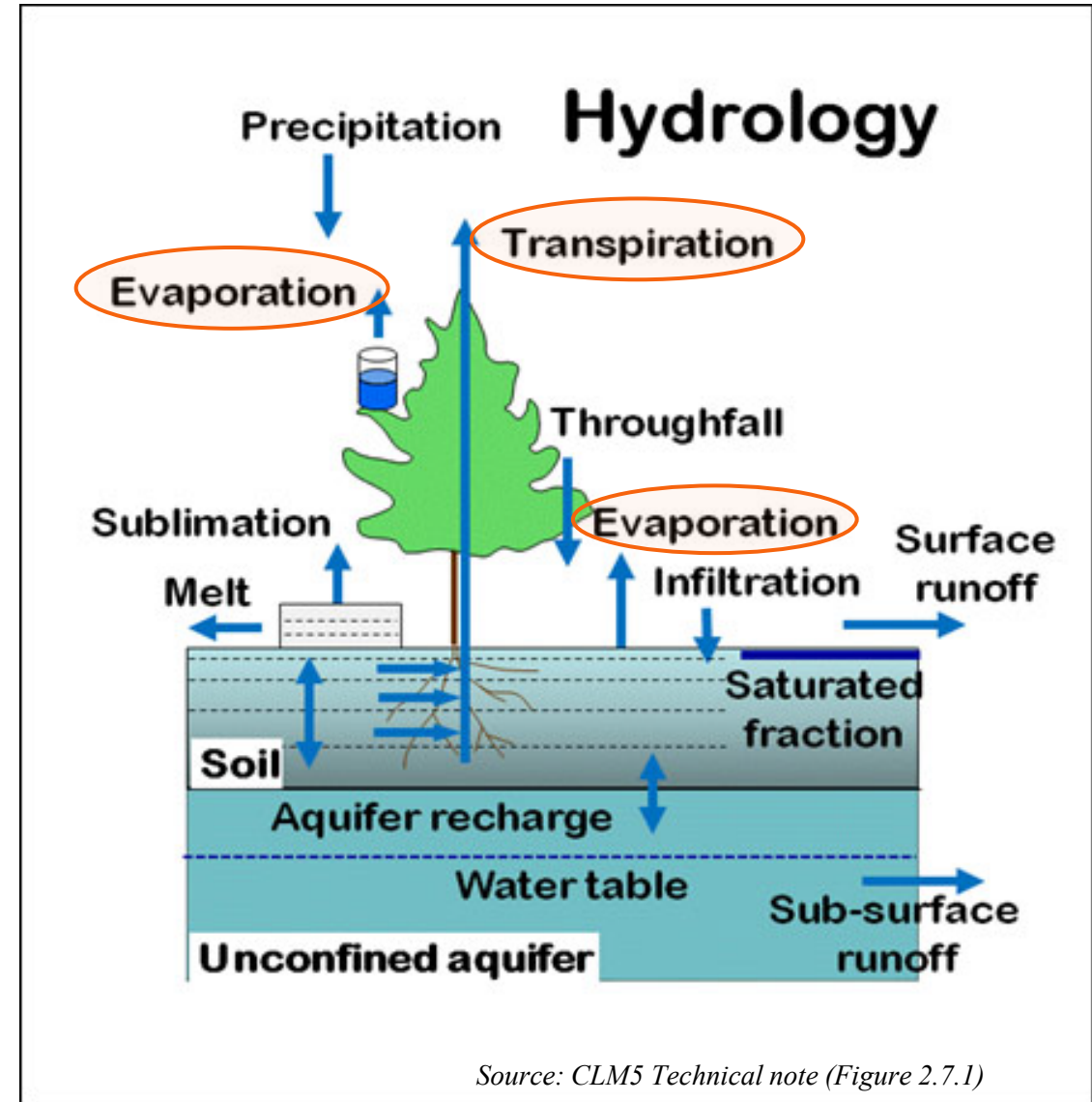
Motivation and Overview

- Current representations of land surface processes in LSMs exhibit uncertainties.
- Need for more accurate climate projections and understanding climate-carbon feedback.
- Better representation -> More details -> Increase computational demands.
- Robust and computationally efficient models (**emulators**) are essential for scalability and practicality.

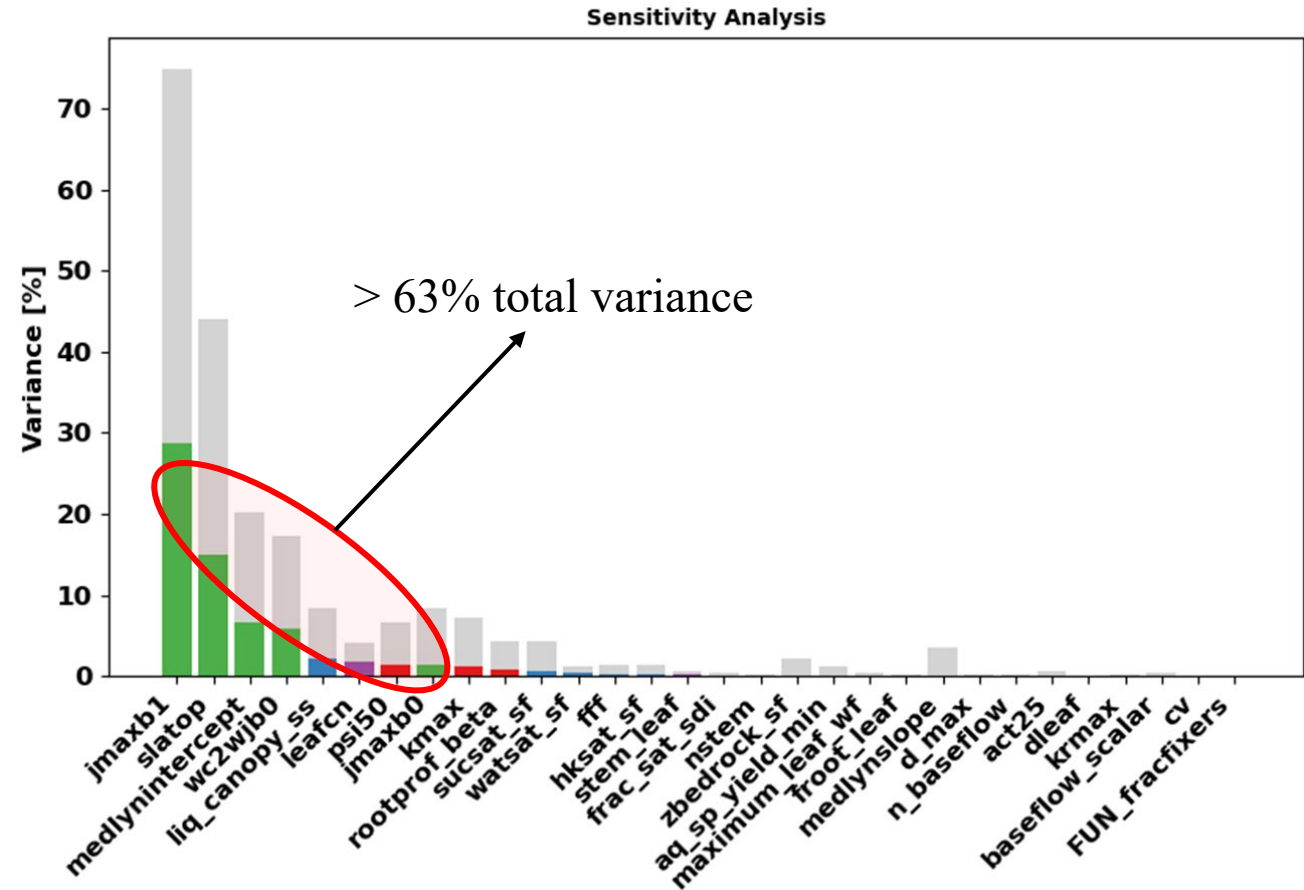
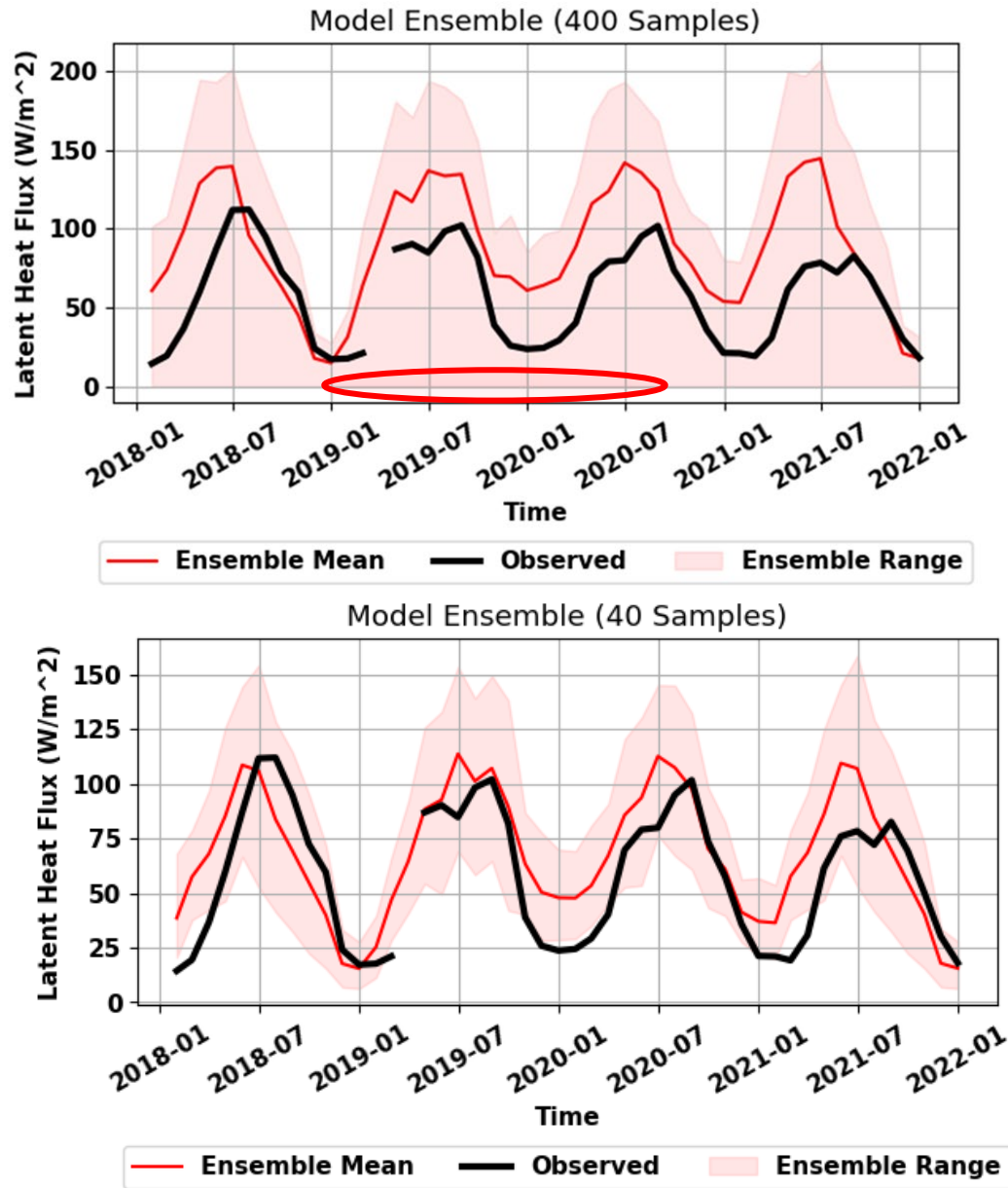


Computational challenge:

- LSMs strive for comprehensive representations of land surface processes.
- Increased complexity often leads to computational bottlenecks.



Data Availability



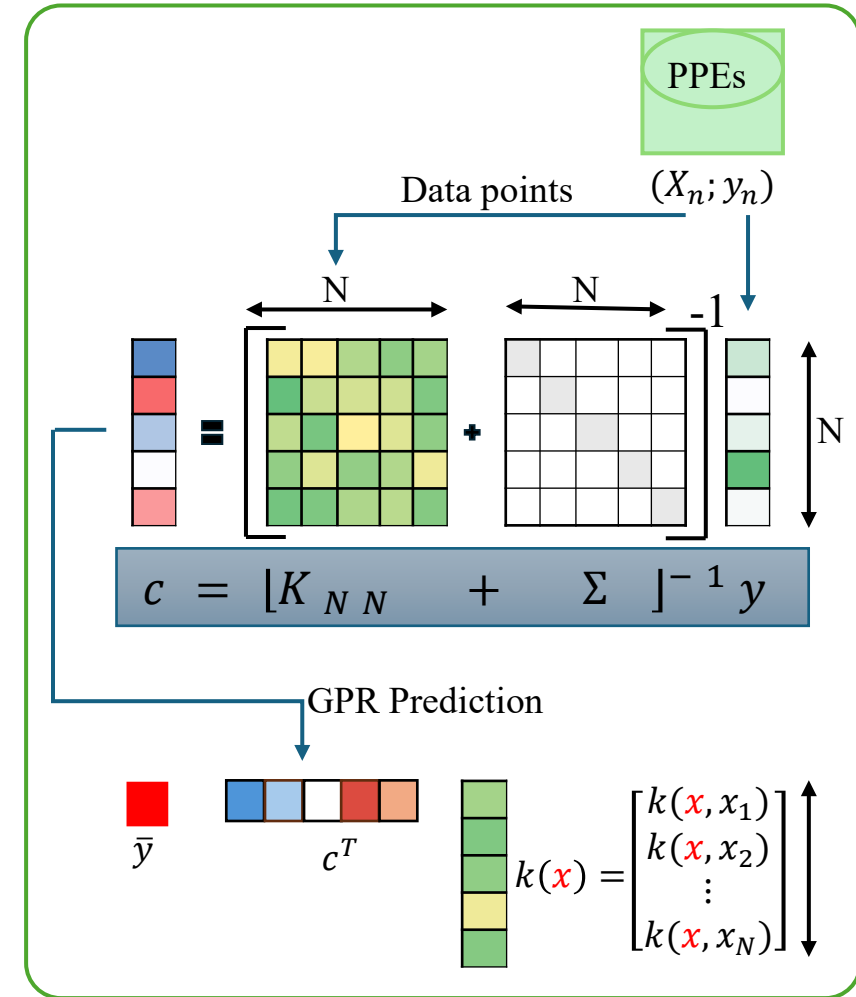
Gaussian Process Regression

- GP is defined by a mean function $m(x)$ and a covariance function $k(x, x')$
- Given a set of training data X and corresponding function values y , the GP defines a prior distribution over functions f such that:

$$f(X) \sim GP(m(X), k(X, X'))$$

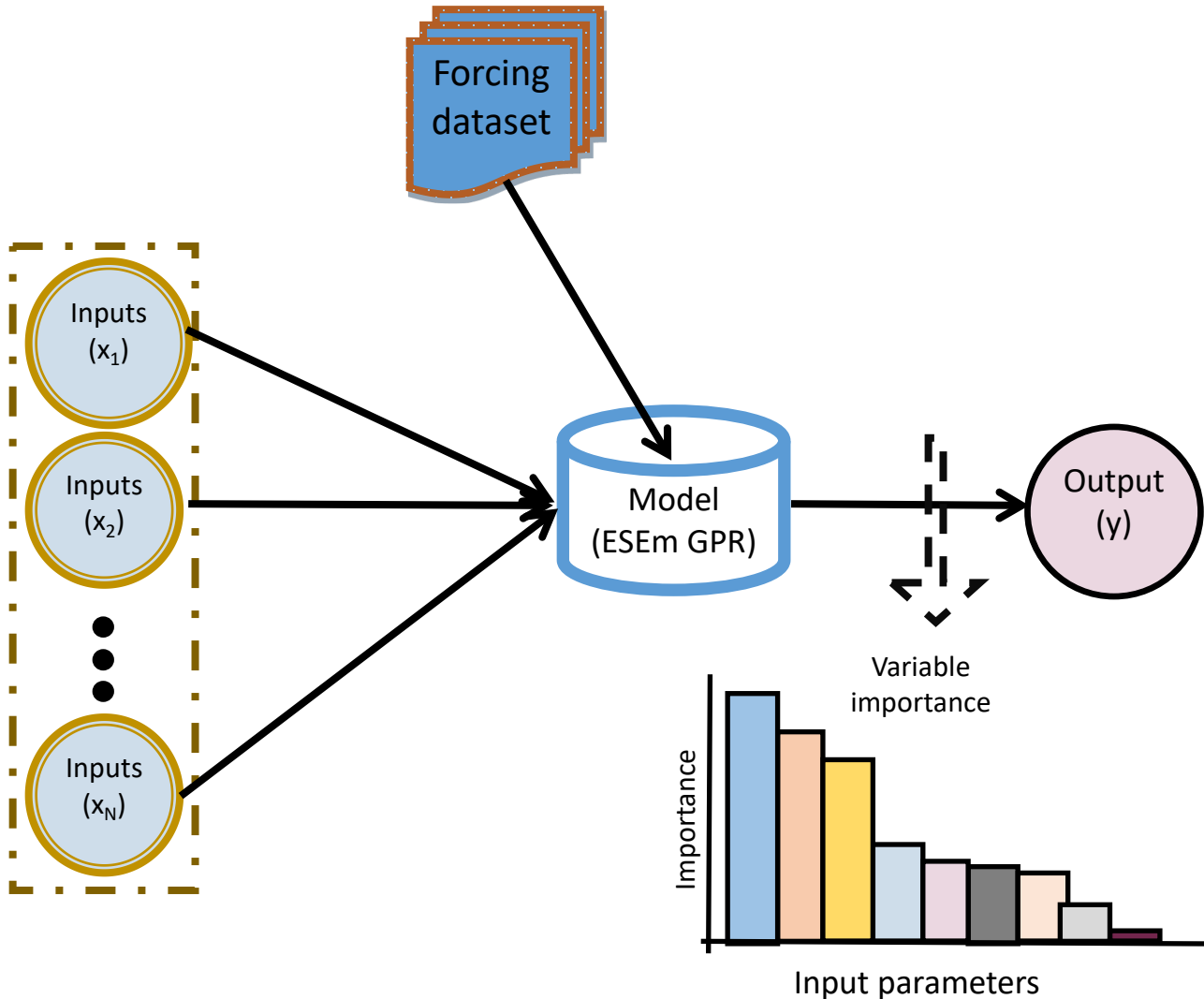
- The predictive distribution at point x_* given training data X and y is:

$$f_* | X, y, x_* \sim GP(m_* k_*)$$



Source: Adapted from Deringer et. al., 2021

Emulating Evapotranspiration



$$y_t(X_{\theta W}) \sim GP(\underbrace{m(X_{\theta W})}_{\text{Mean function}}, \underbrace{k(x, x')}_{\text{Covariance matrix}})$$

Forcing datasets (7 – variables)

Output (ET)

Perturbed parameters (7 – params)

ESEm Emulator Calibration

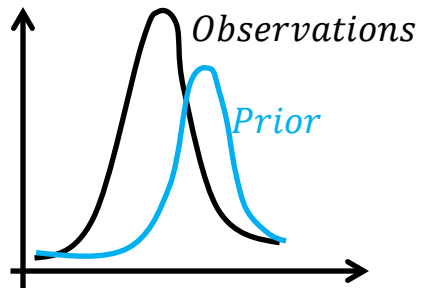
Bayes Theorem

$$p(\theta|Y^0) \propto p(Y^0|\theta)p(\theta)$$

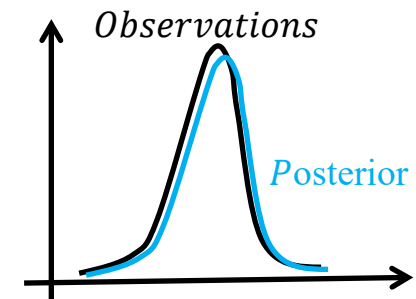
CLM5
Point-scale
simulations

Emulator

$$y_t(X_{\theta W}) \sim GP(m(X_{\theta W}), k(x, x'))$$



Sampling the posterior
distribution using
MCMC



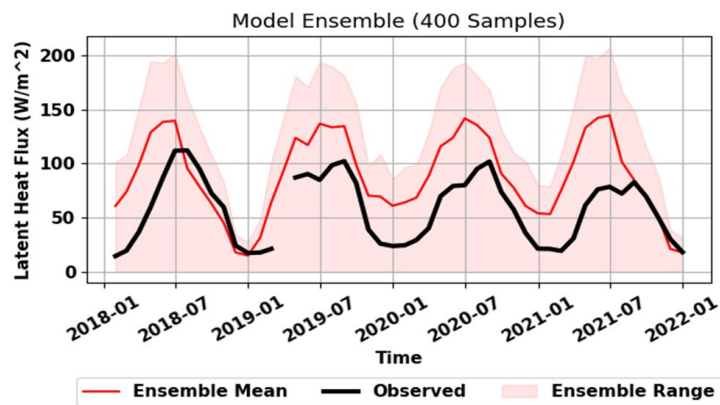
Observations



Emulator Designs

Mean

- Mean ET from CLM5
- Observations 400 x 7
- No forcing dataset used

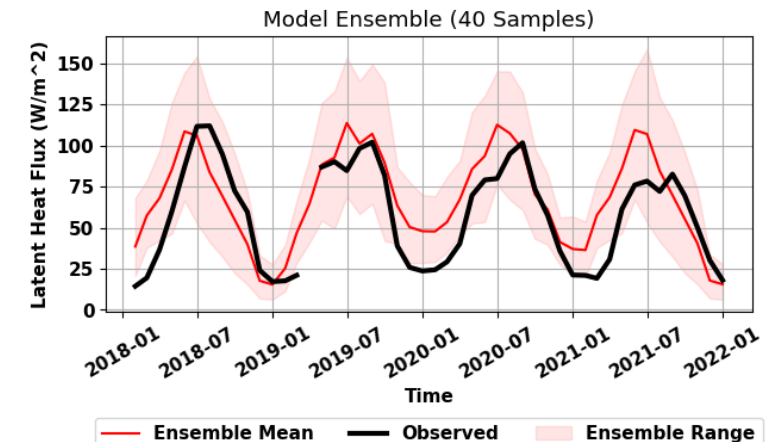


Metric

- Composite metric
- Observations 400 x 7
- No forcing dataset used

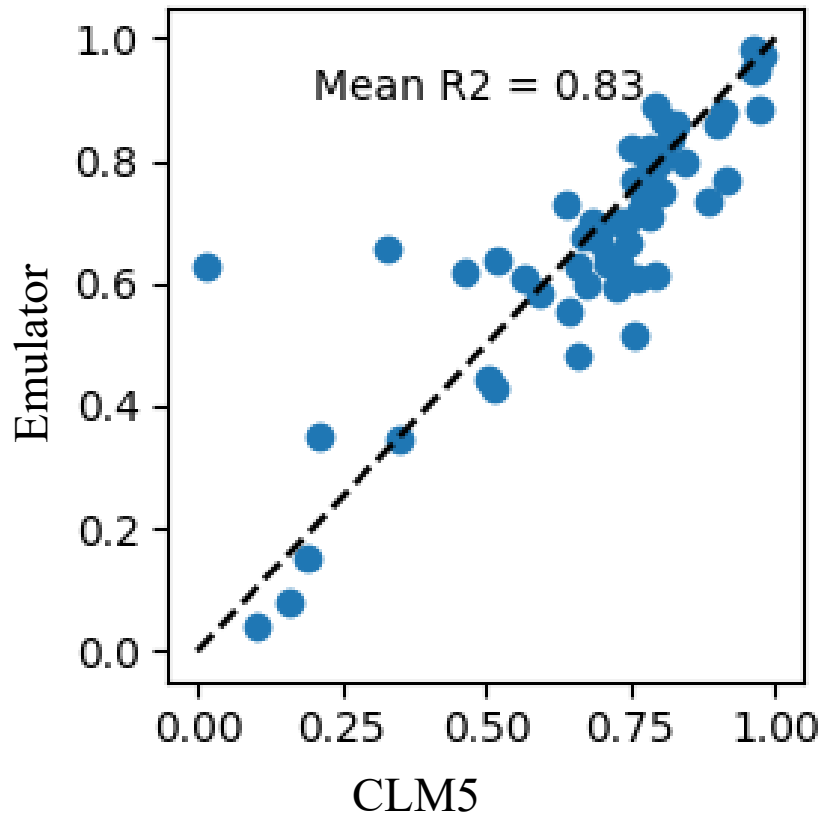
PPE Guided

- Monthly ET from CLM5
- Observations 1920 x 14
- Forcing dataset included

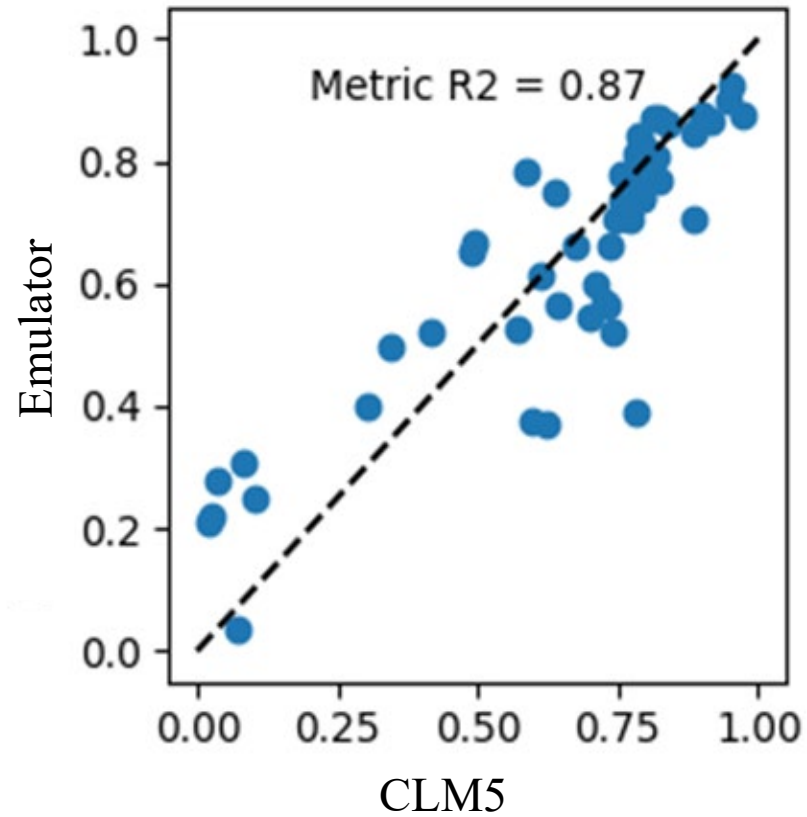


Emulator Performance

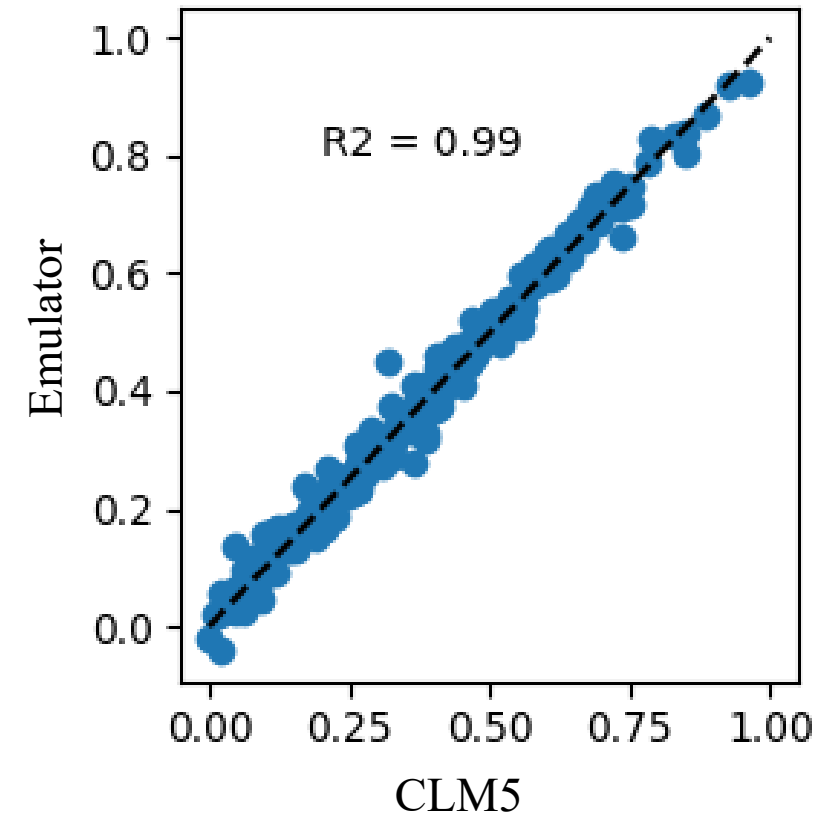
Mean



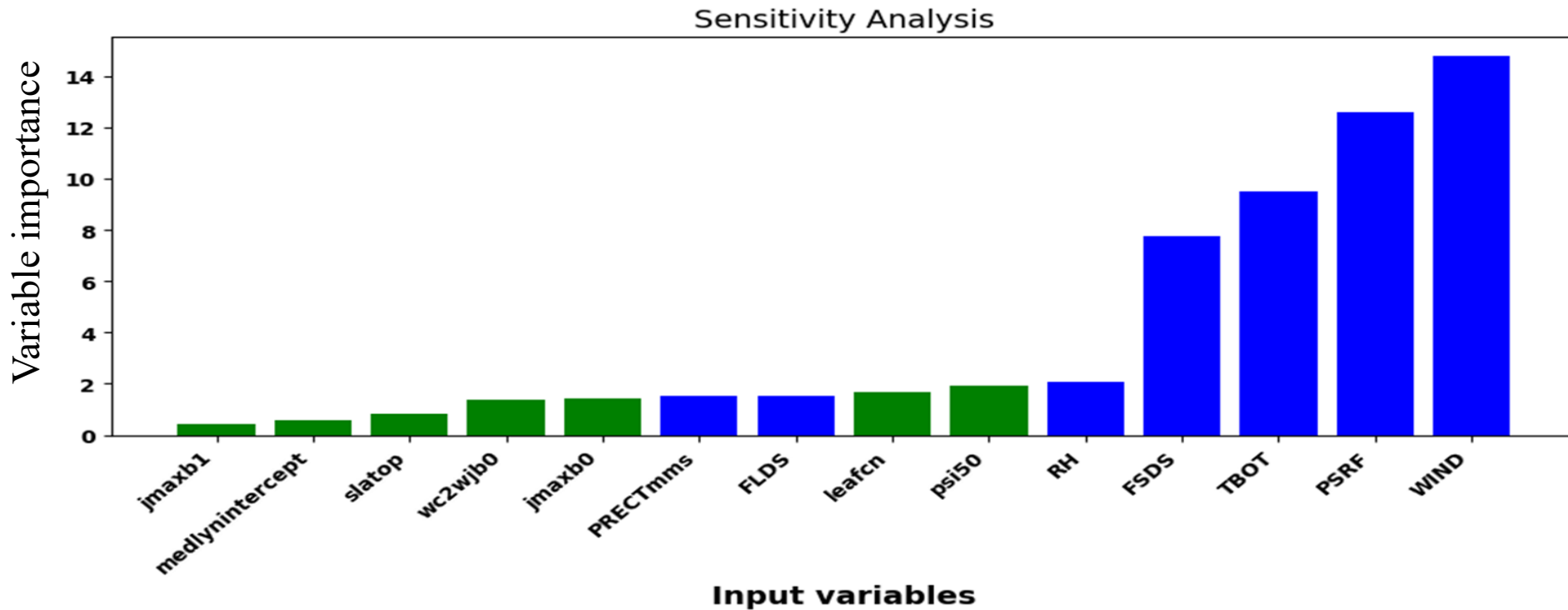
Metric



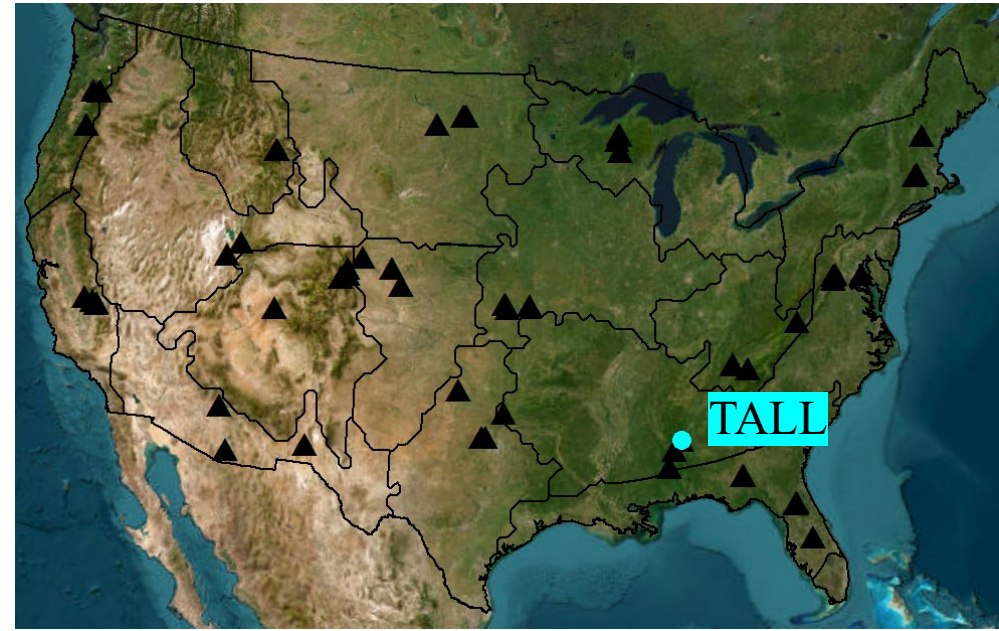
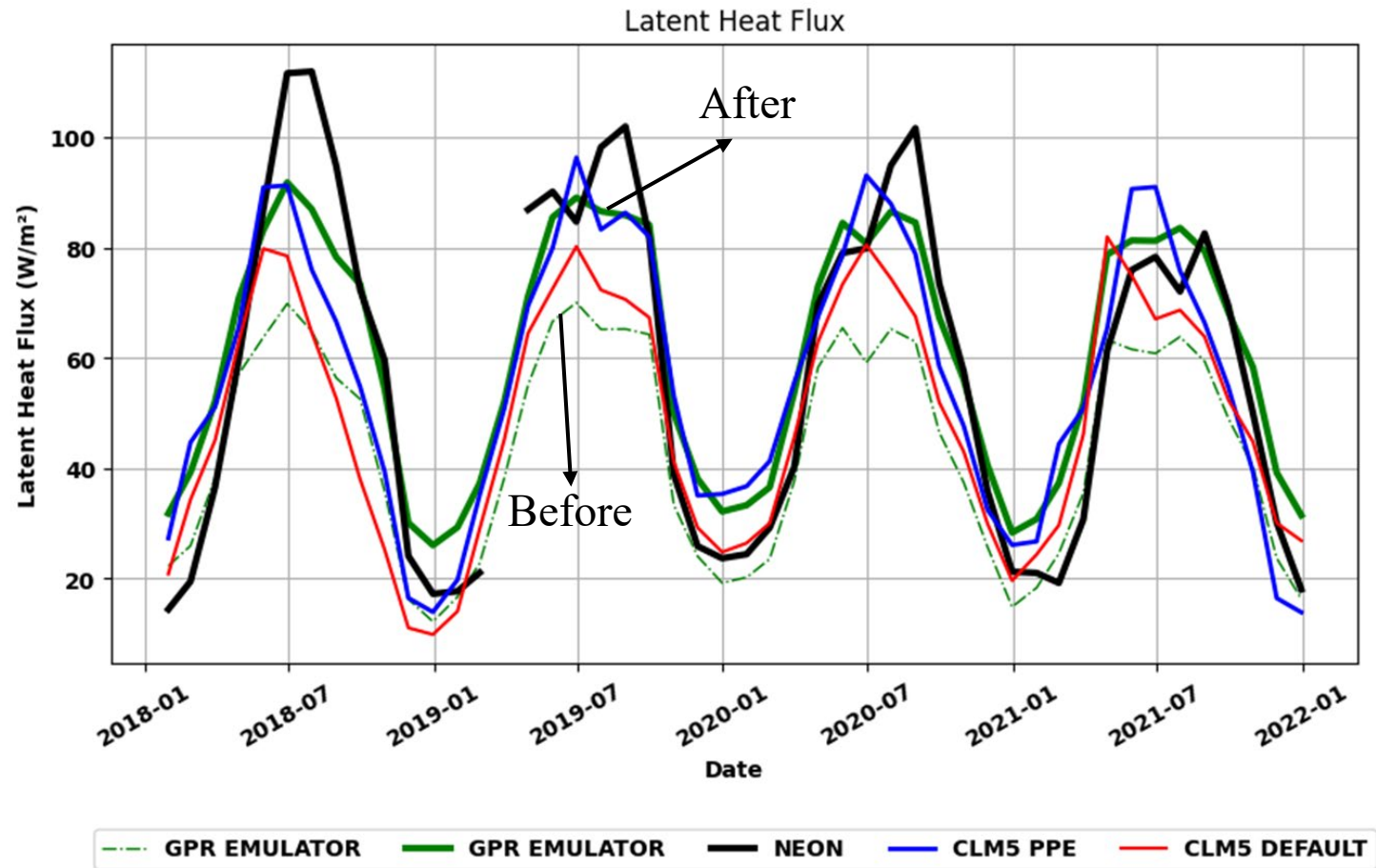
PPE Guided



Input variable importance

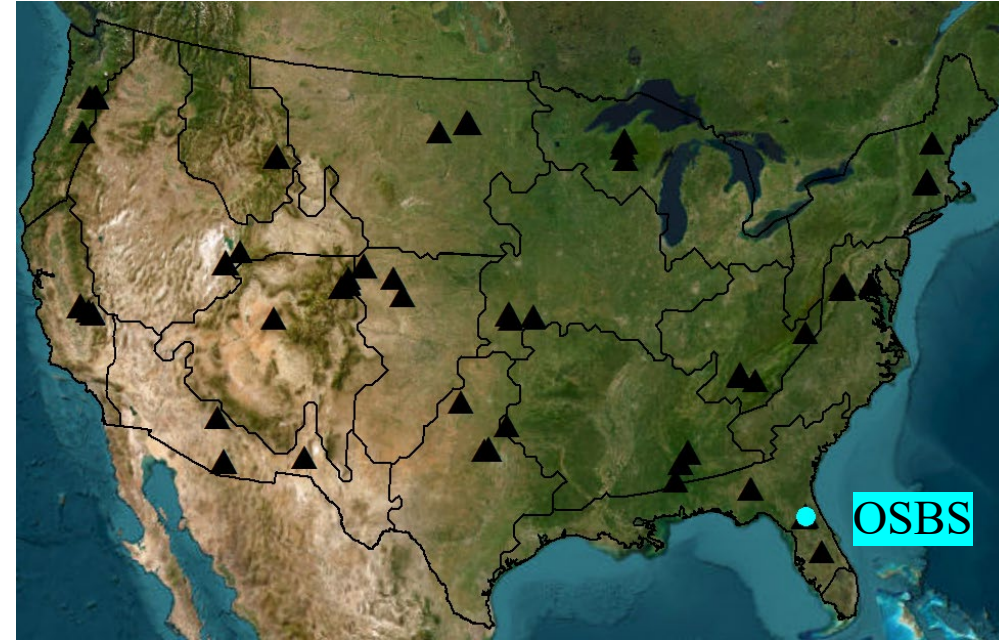
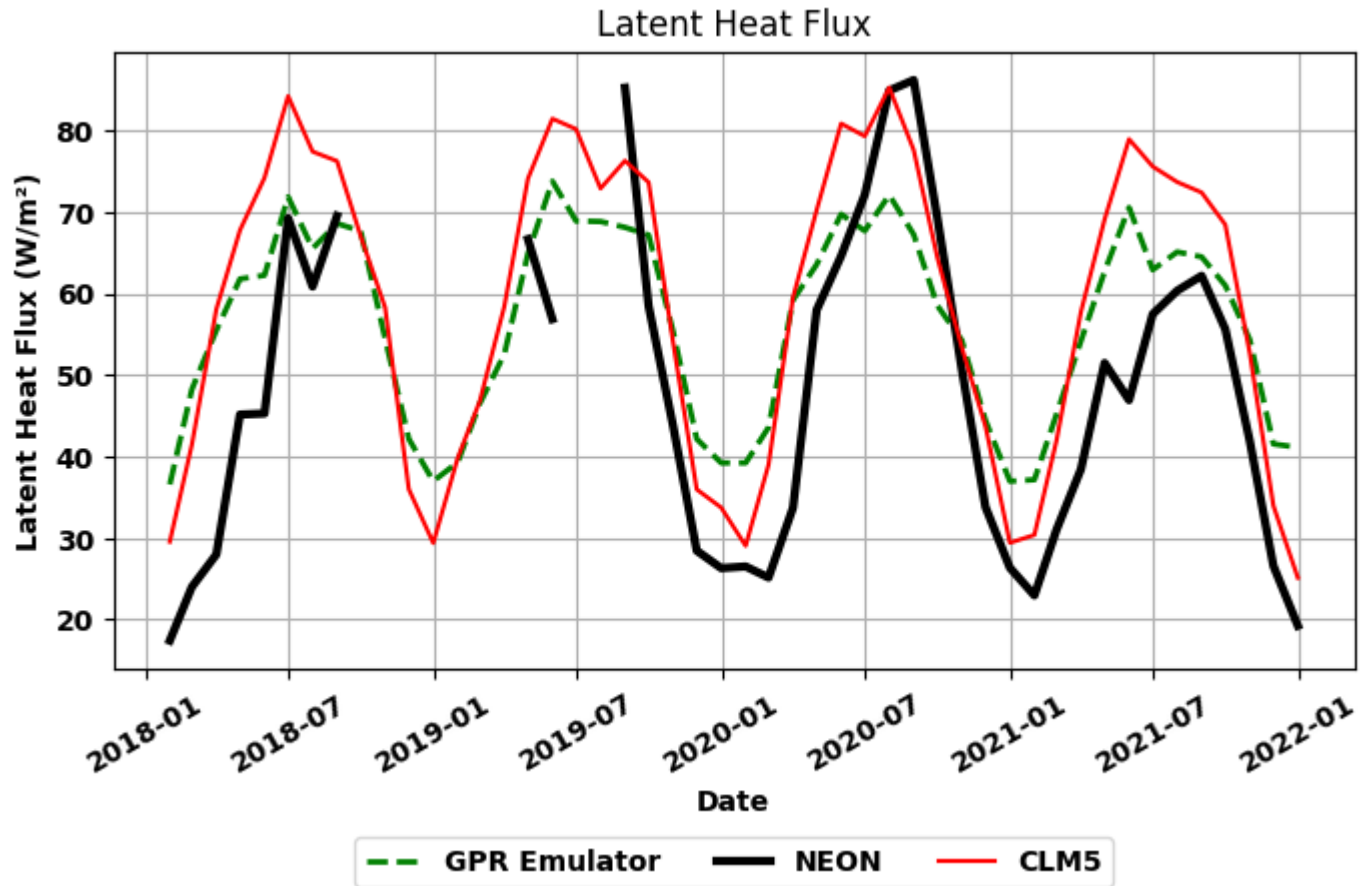


Calibration improves emulator model performance



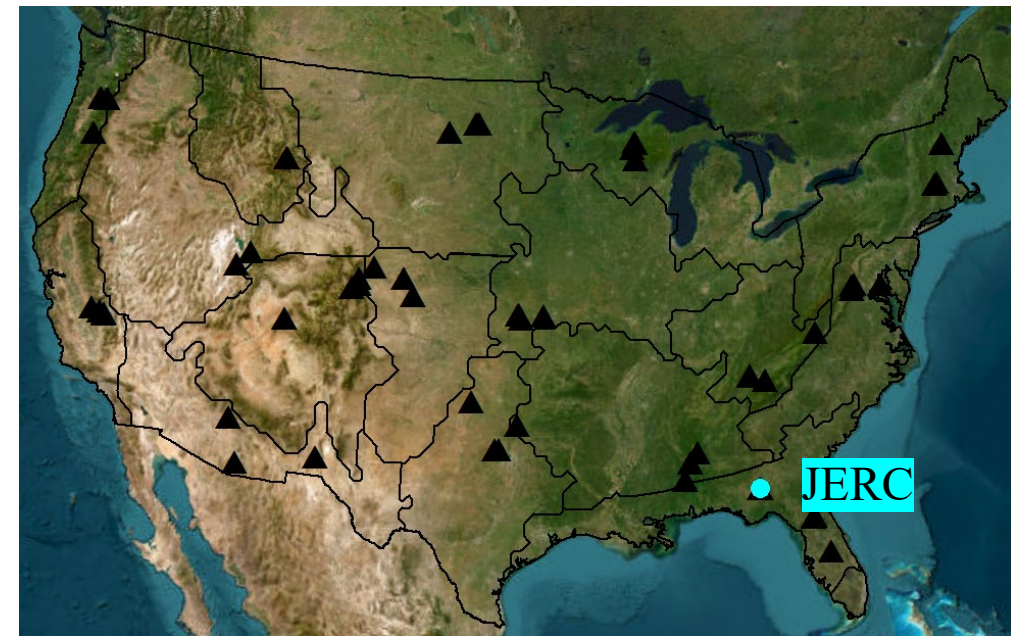
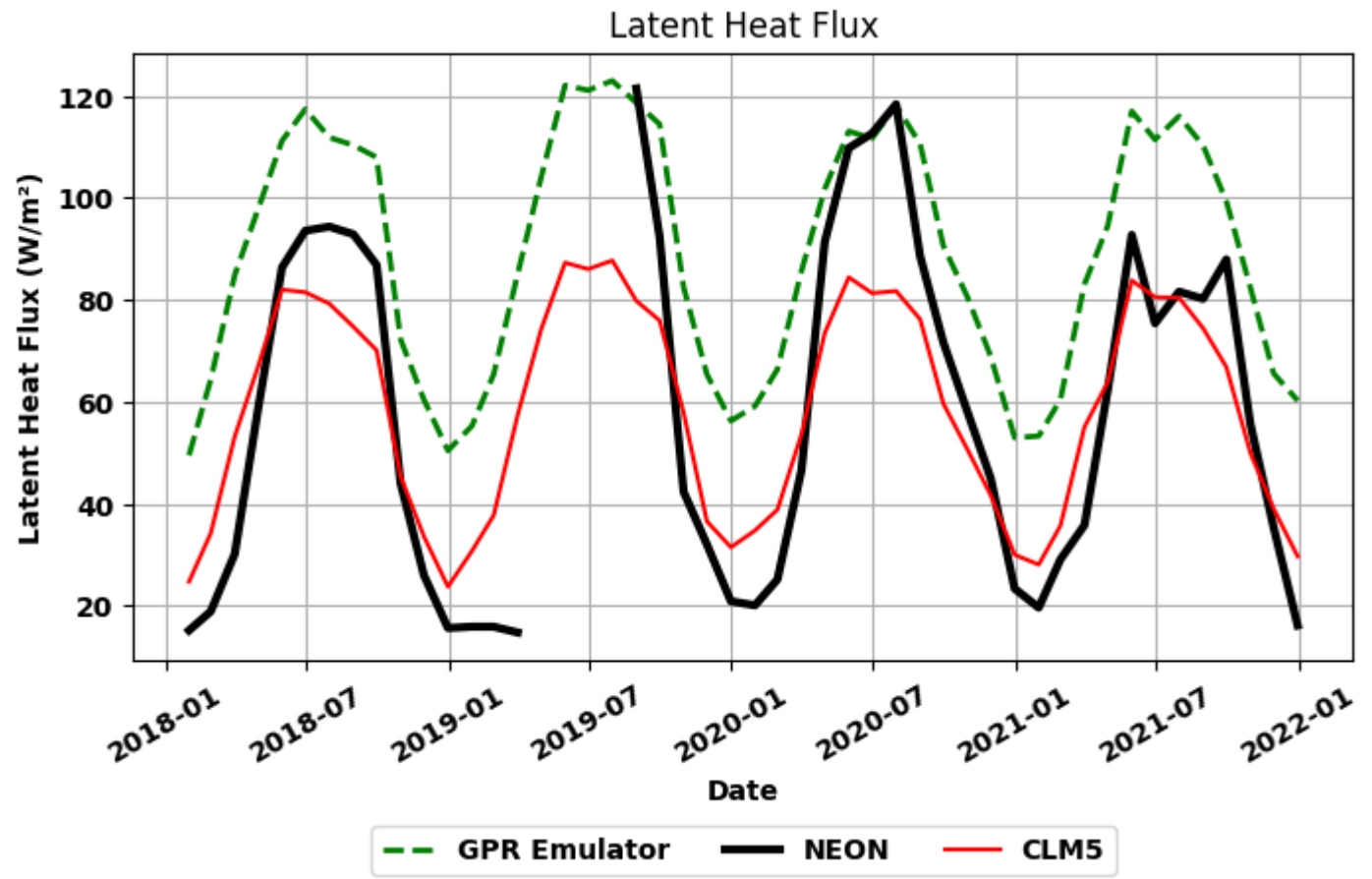
	RMSE	MBE	R^2
Default	26	-8.5	0.59
PPE	17.95	-2.28	0.74
Emulator	19	5.6	0.81

The TALL calibrated emulator was applied to other NEON sites with similar characteristics.



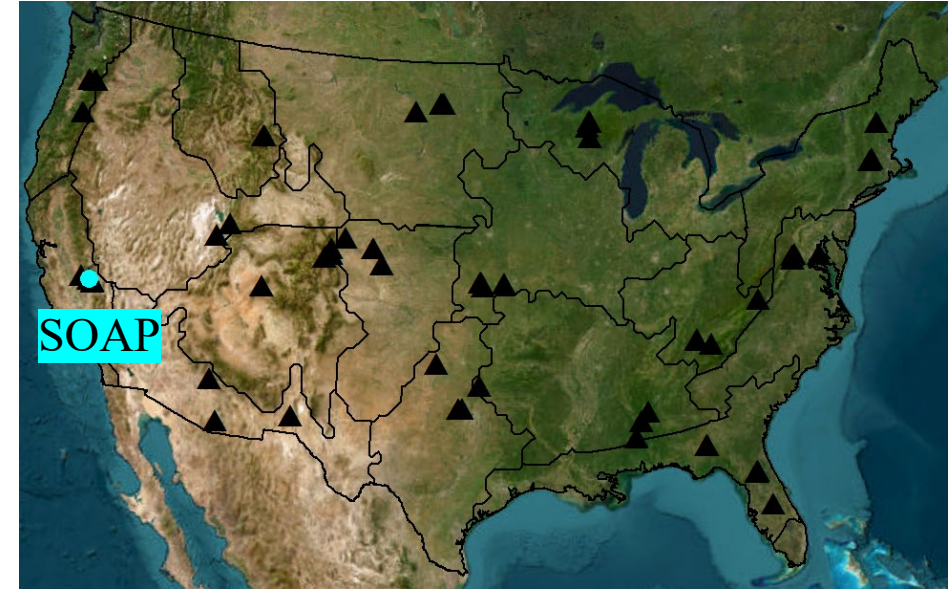
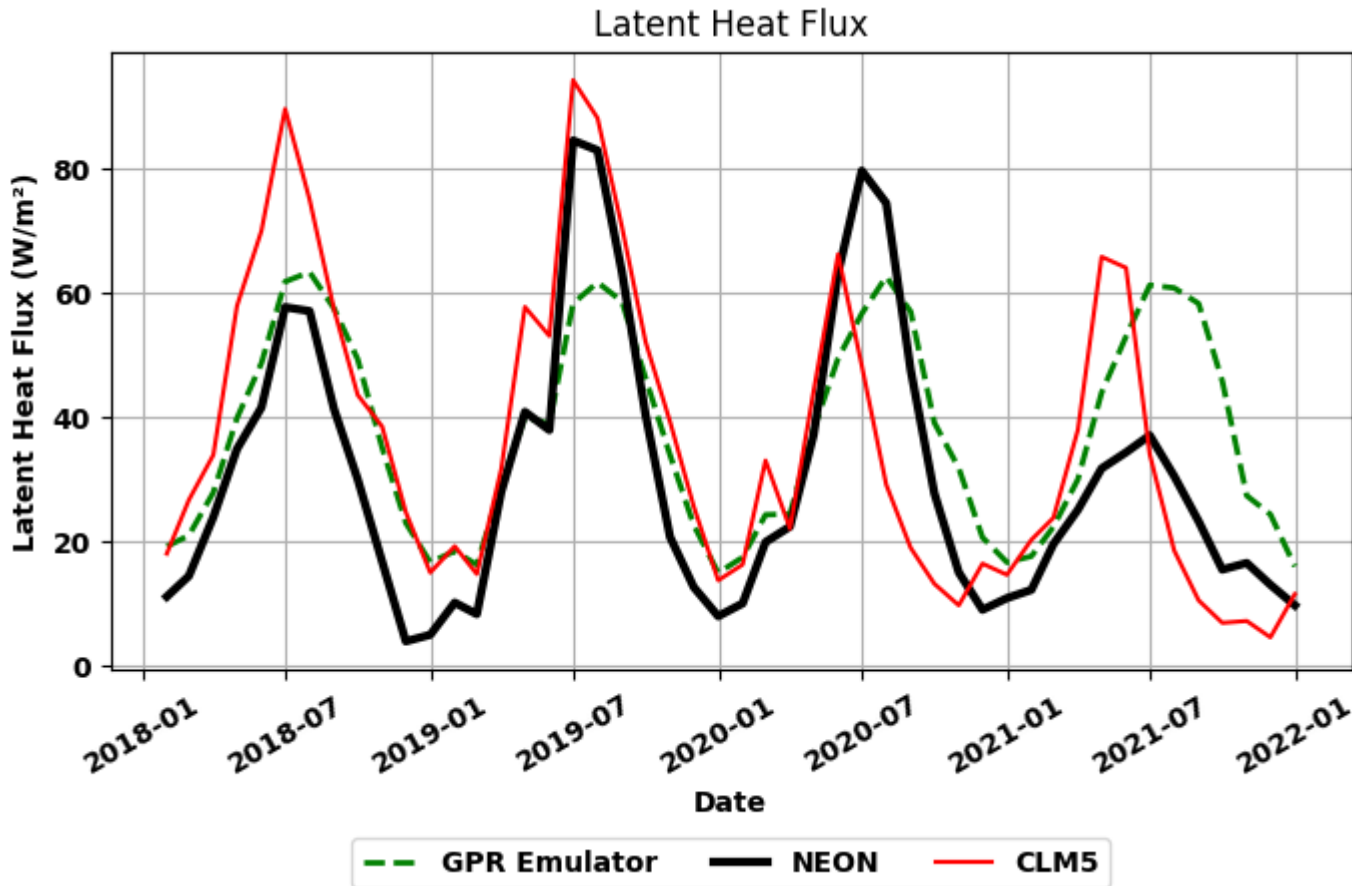
	RMSE	MBE	R^2
Default	20	12	0.58
Emulator	18	11	0.67

The TALL calibrated emulator was applied to other NEON sites with similar characteristics.



	RMSE	MBE	R ²
Default	24	-1.5	0.68
Emulator	34	28	0.80

The TALL calibrated emulator was applied to other NEON sites with similar characteristics.



	RMSE	MBE	R ²
Default	17	7.1	0.51
Emulator	20	5	0.61

Computation Cost: Comparing CLM-NEON run versus emulator

- CLM-NEON (point scale simulations - ~9 minutes
- CLM-NEON With initialization ~ 5.5 hrs. for 200 years
- Emulator - ~ 2 seconds

Summary

- Emulator - fast prediction, parameter tuning, and sensitivity analysis
- Emulating CLM5 ET highlights the adaptability of the approach for various land surface model processes
- Emulator provides more flexibility – parameter sensitivity