

# Scaling up: Can point scale calibration using NEON data improve coupled carbon-water cycle in CLM at a regional scale?

**LAND MODEL / BIOGEOCHEMISTRY WORKING GROUP MEETING**  
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AUBURN UNIVERSITY

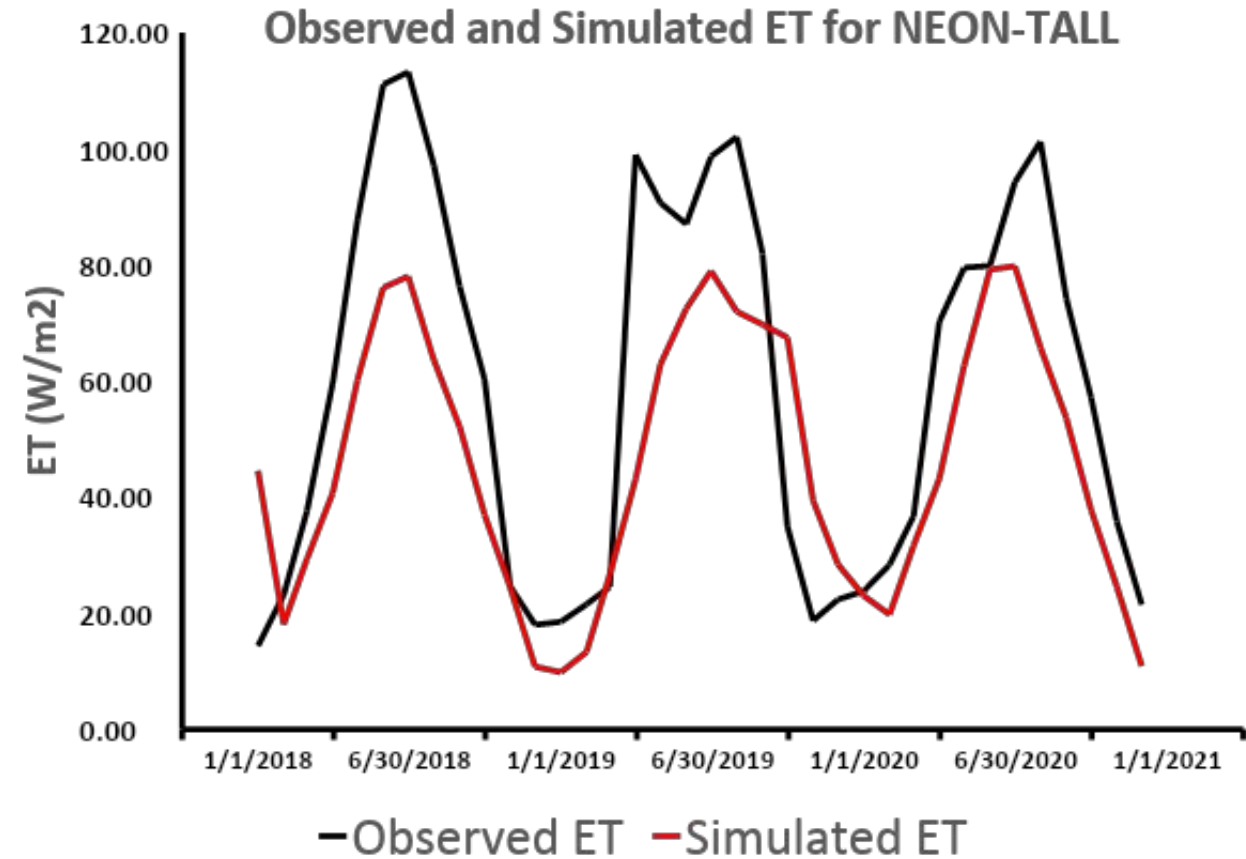


# OUTLINE

- Introduction
- Addressing ET uncertainties
- Methods and Data
- Results

# INTRODUCTION

- Estimates of change in ET are key for understanding the terrestrial hydrological cycle under changing environments.
- There are significant uncertainties between simulated and observed ET fluxes

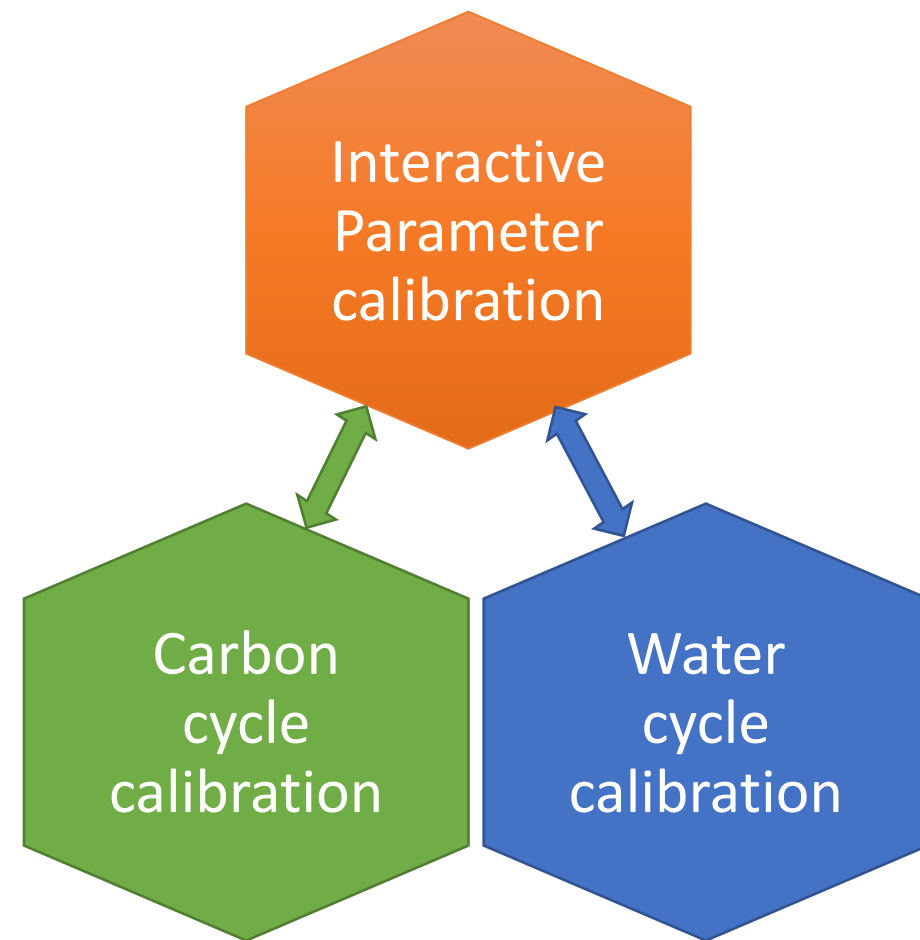


# ADDRESSING ET UNCERTAINTY

- High-resolution forcing datasets
- Model calibration and parameterization
- Use of AI and Machine learning techniques to optimize model parameters

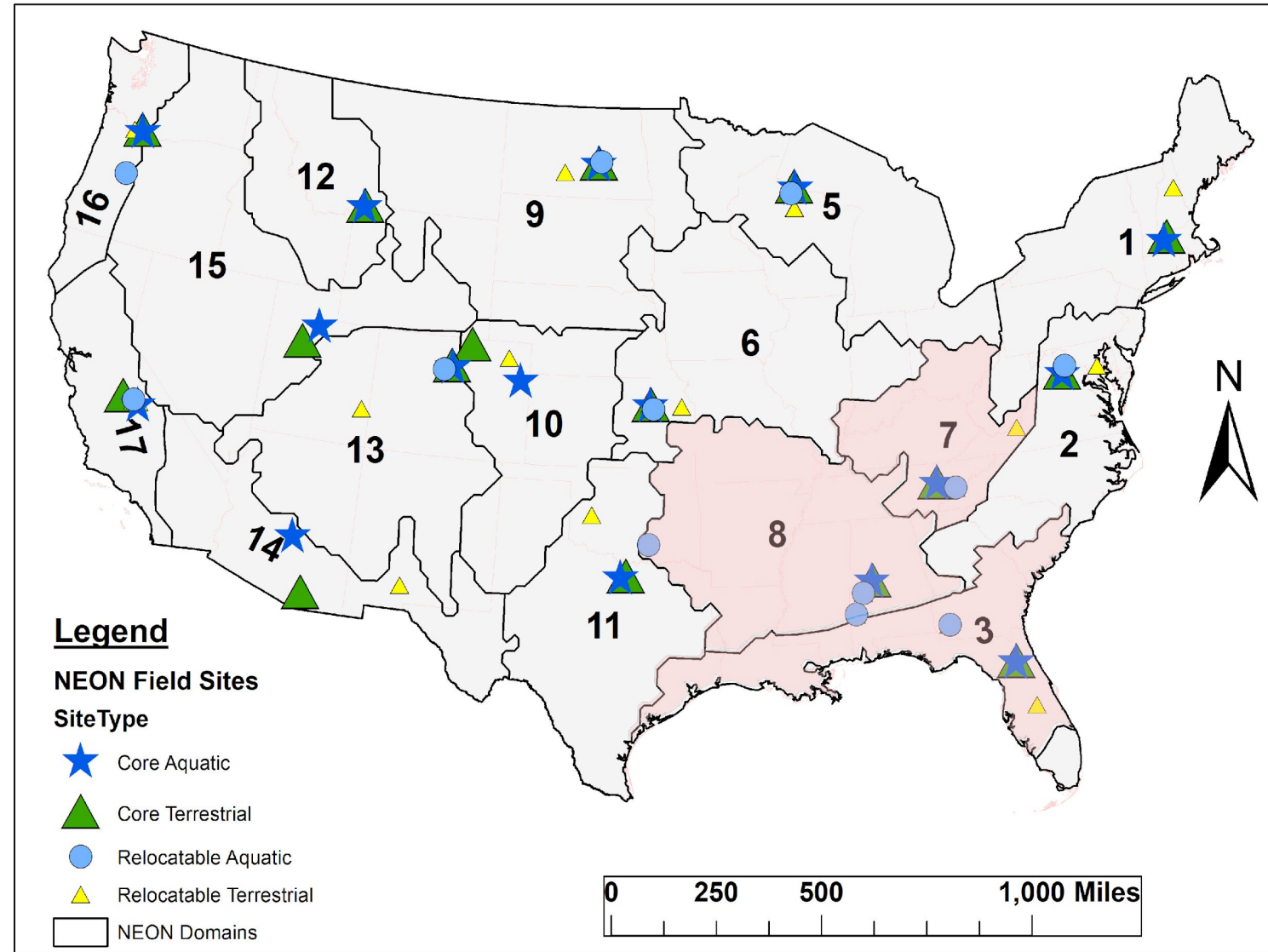
However, global calibration is a challenge – many parameter sets and high computational demands

***Can point scale calibration improve coupled carbon-water cycle in CLM?***

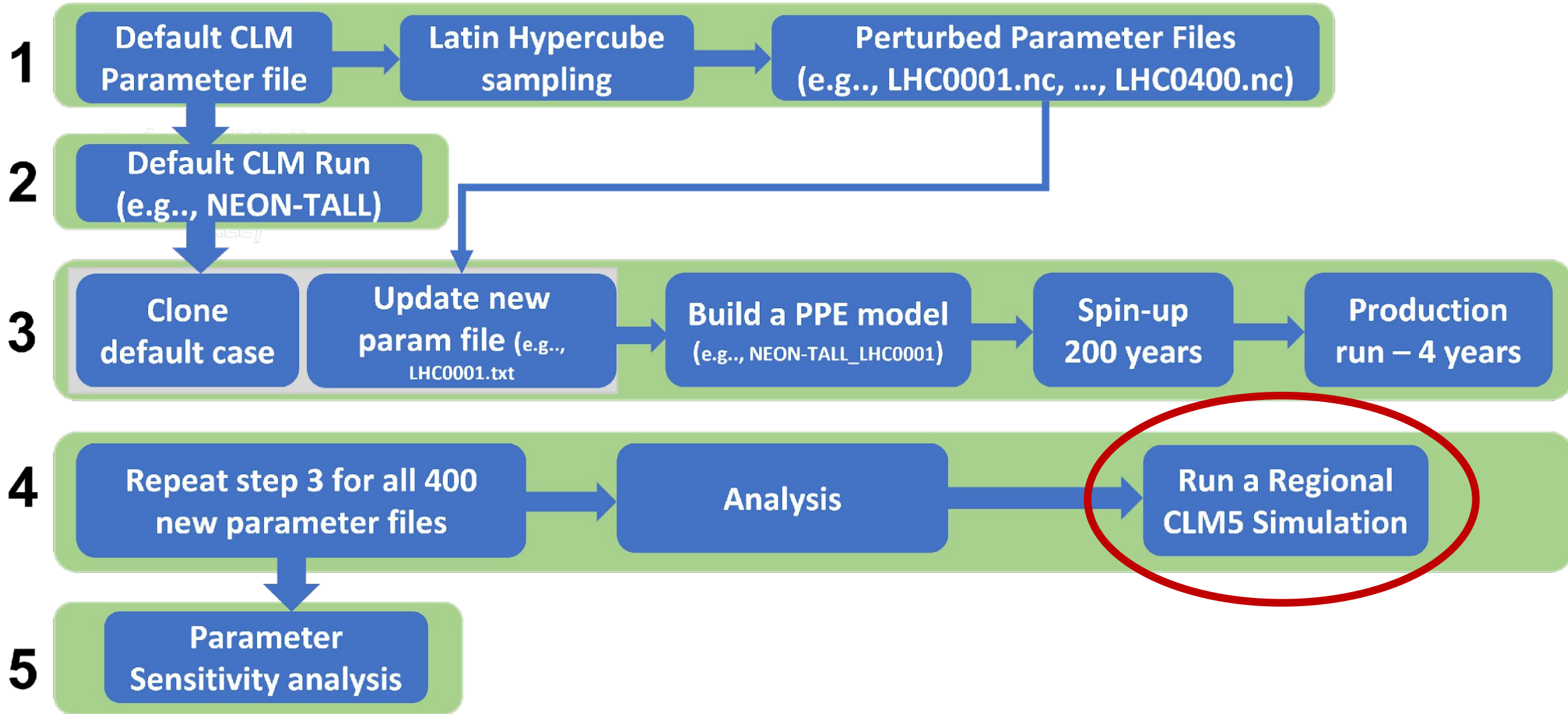


# METHODS & DATA

- NEON data is a new resource that can be utilized to constrain land surface model parameters
- CLM-NEON Tool has enabled use of NEON data to test various hypothesis



# NEON-PPE EXPERIMENT DESIGN



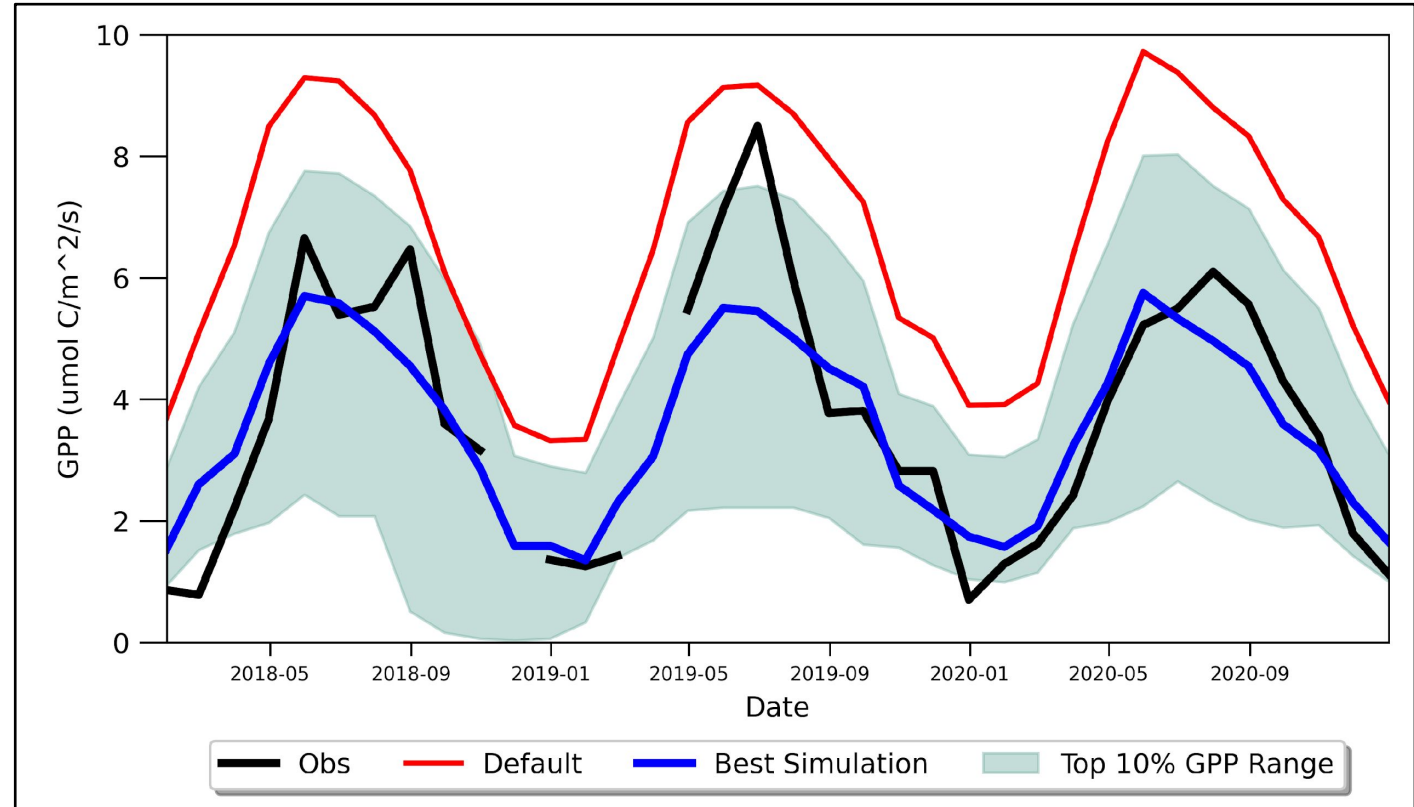
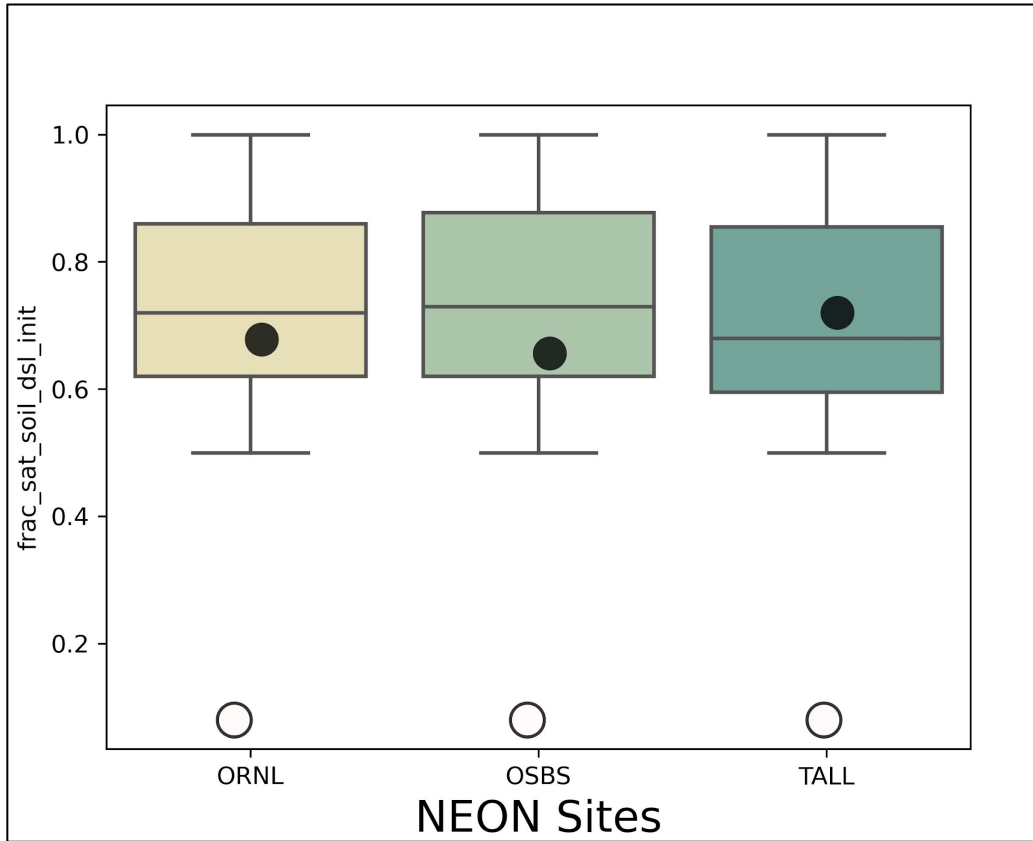
# PARAMETER SENSITIVITY ANALYSIS

- Method applied – Variance-based Sensitivity analysis using COpulaS (VISCOUS) (Sheikholeslami et al., 2021)
- Recycles existing data (400 model runs and 30 parameter files) to determine parameter sensitivity
- Approximates joint PDF of given data and characterizes its dependency structure using copulas.

$$E[Y|X = x_c] \approx 1/N_{MC} \sum_{j=1}^{N_{MC}} F_Y^{-1}(v^{(j)} c_g(v^{(j)} u_i; \Theta))$$

$$Var[E(Y|X = x_c)] \approx 1/2N_{MC}^3 \sum_{j=1}^{N_{MC}} \sum_{i=1}^{N_{MC}} \left( \sum_{k=1}^{N_{MC}} F_Y^{-1}(v^{(k)} c_g(v^{(k)}, u_c^{(i)}; \Theta)) - \sum_{k=1}^{N_{MC}} F_Y^{-1}(v^{(k)} c_g(v^{(k)}, u_c^{(j)}; \Theta)) \right)^2$$

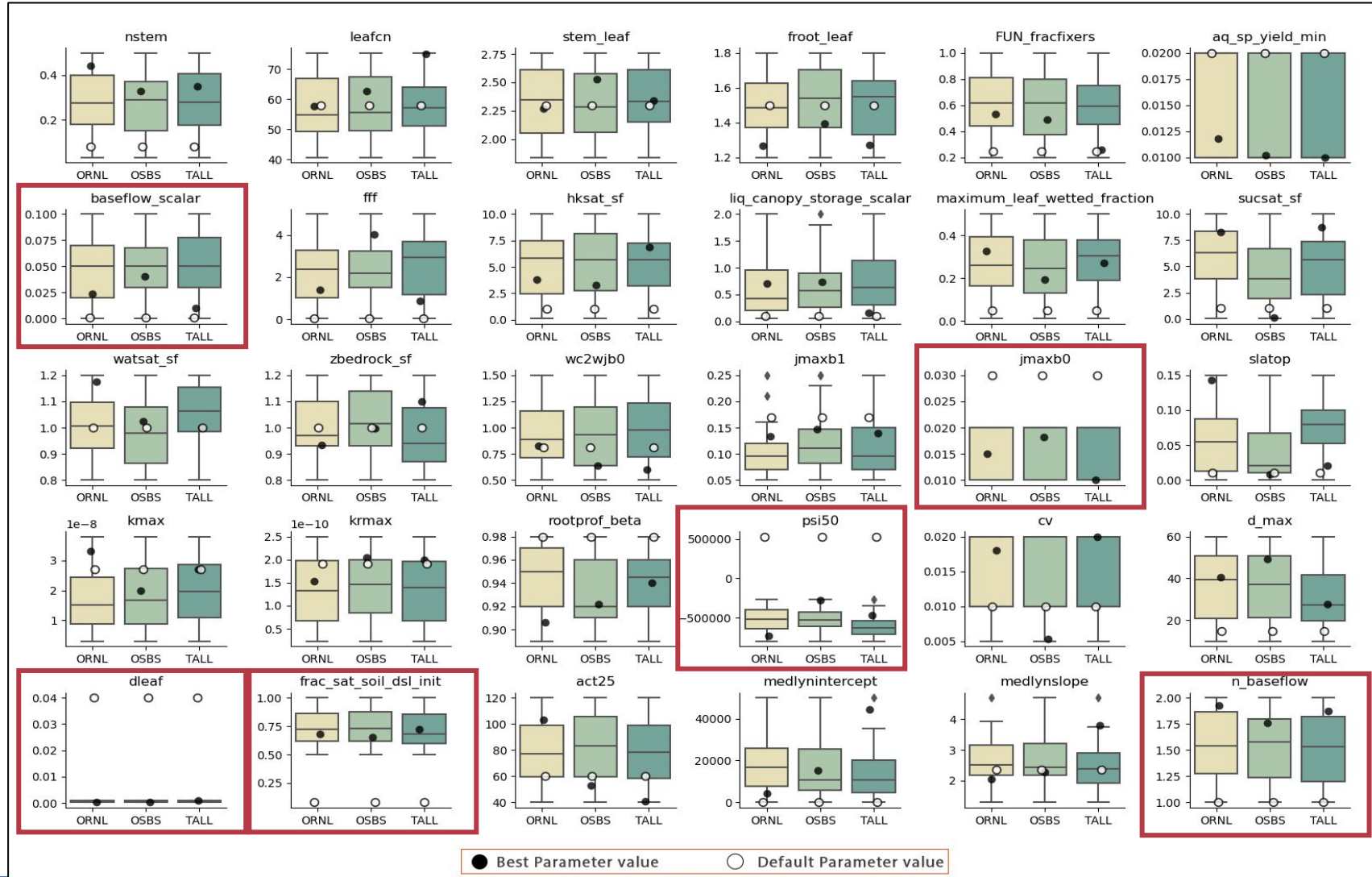
# RESULTS PRESENTATION





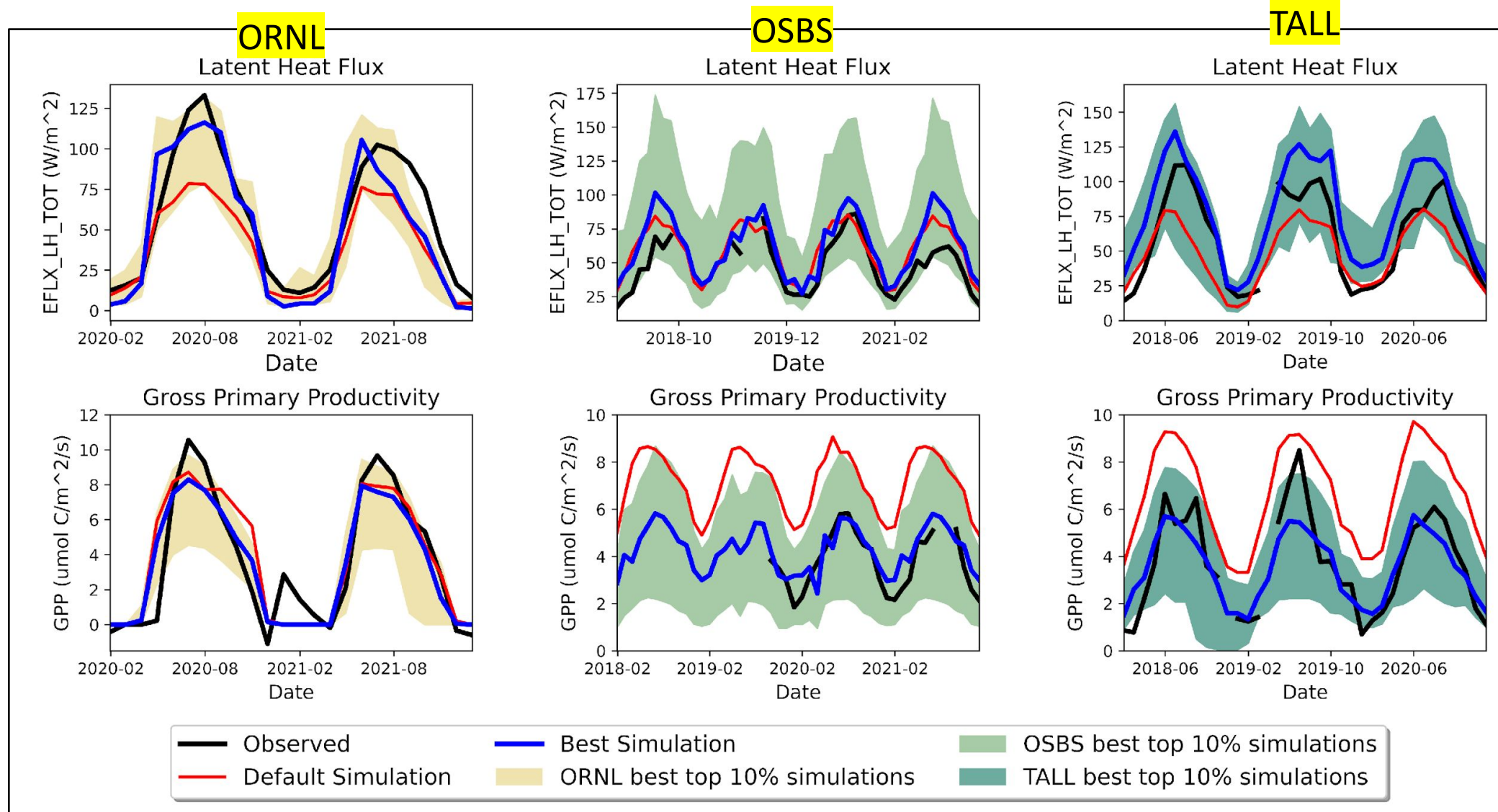
# RESULTS 1: MODEL PERFORMANCE - PARAMETER OPTIMIZATION

Optimized parameters can be considerably different and can be constrained



● Best Parameter value ○ Default Parameter value

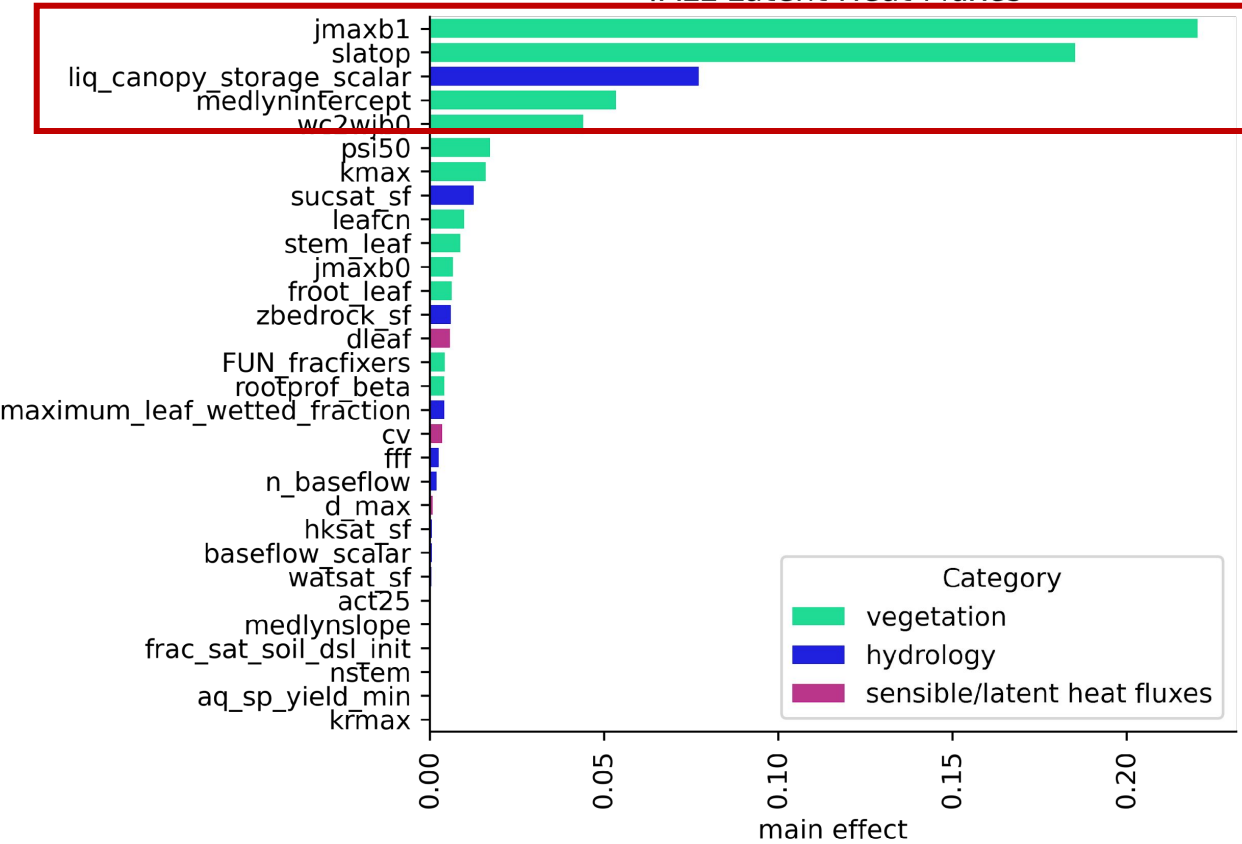
# RESULTS 1: MODEL PERFORMANCE – ET & GPP



# RESULTS 3: SENSITIVITY ANALYSIS

## Latent Heat Flux

TALL Latent Heat Fluxes

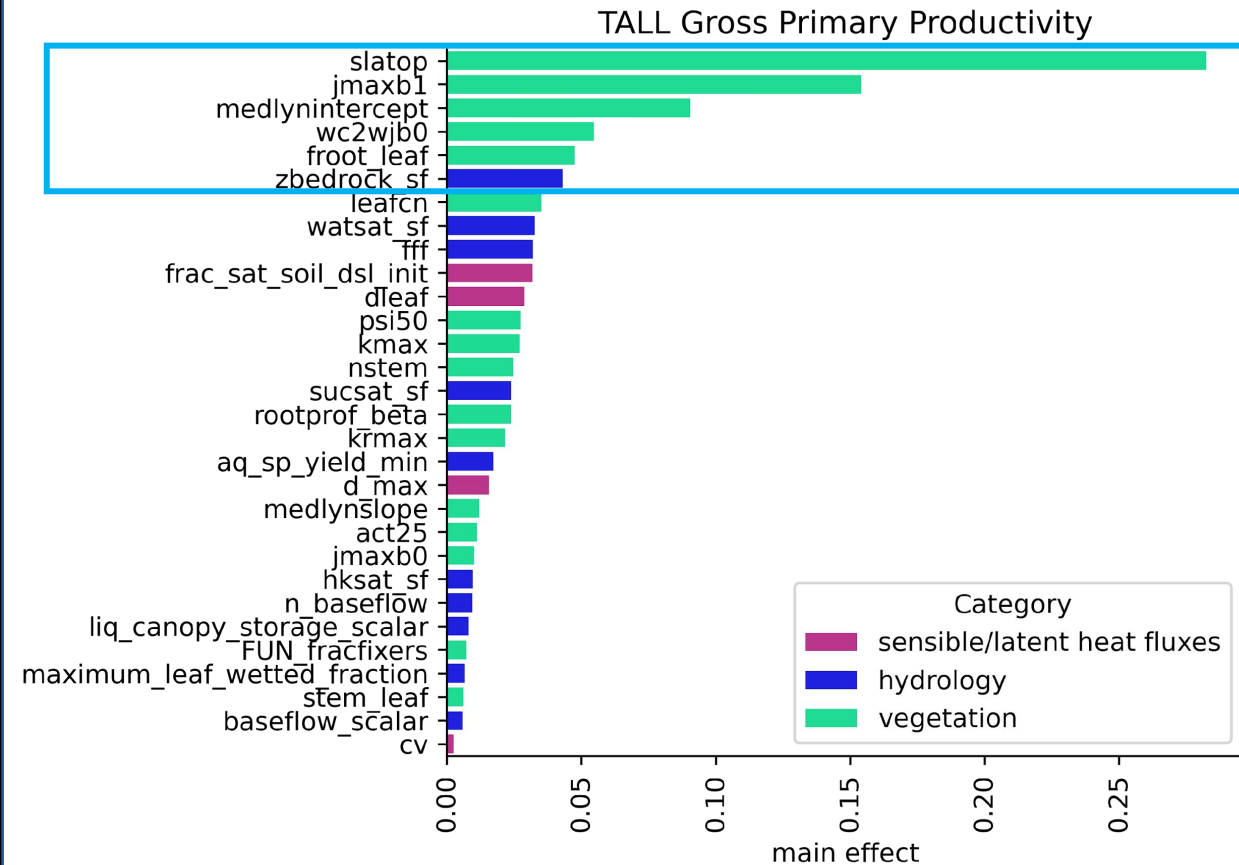


- Out of the selected parameter sets, vegetation, and hydrology related have strong influence on Latent Heat fluxes
- These include; jmaxb1, slatop, liq\_canopy\_storage\_scalar, medlynintercept, and wc2wjb0

# RESULTS 3: SENSITIVITY ANALYSIS CONT'

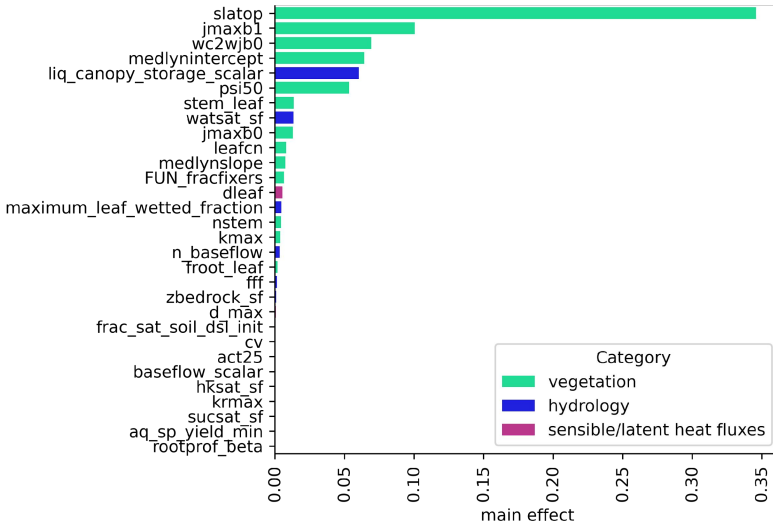
## Gross Primary Productivity

- Only vegetation and hydrology-related parameters have a significant influence on gross primary productivity
- These include; slatop, jmaxb1, medlynintercept, wc2wjb0, froot\_leaf, and zbedrock\_sf

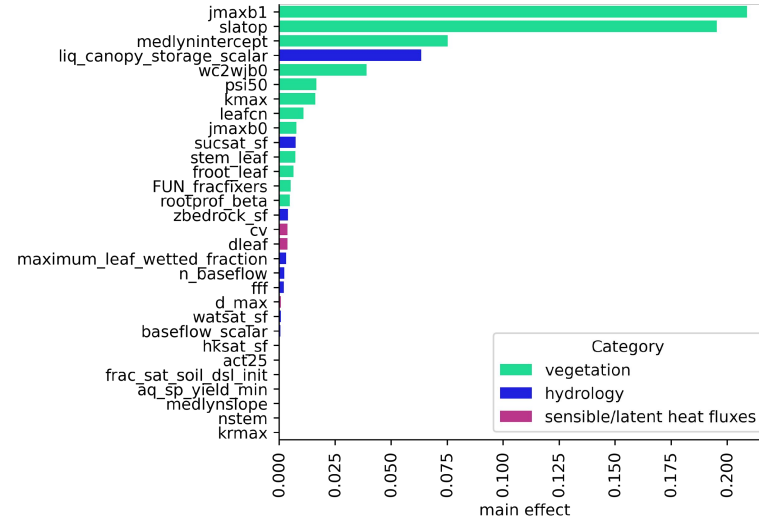


# RESULTS 3: SENSITIVITY ANALYSIS CONT'

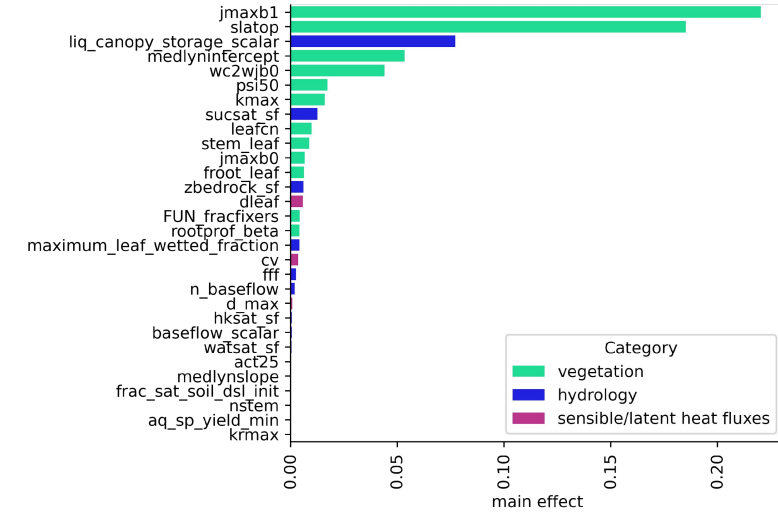
ORNL Latent Heat Fluxes



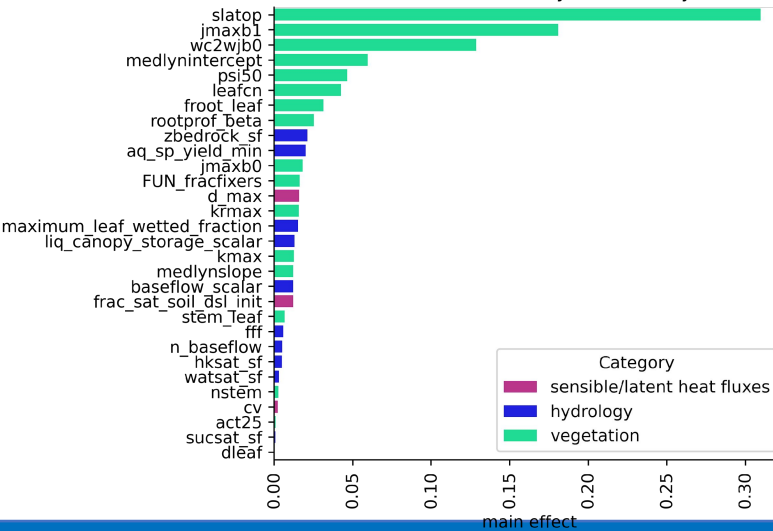
OSBS Latent Heat Fluxes



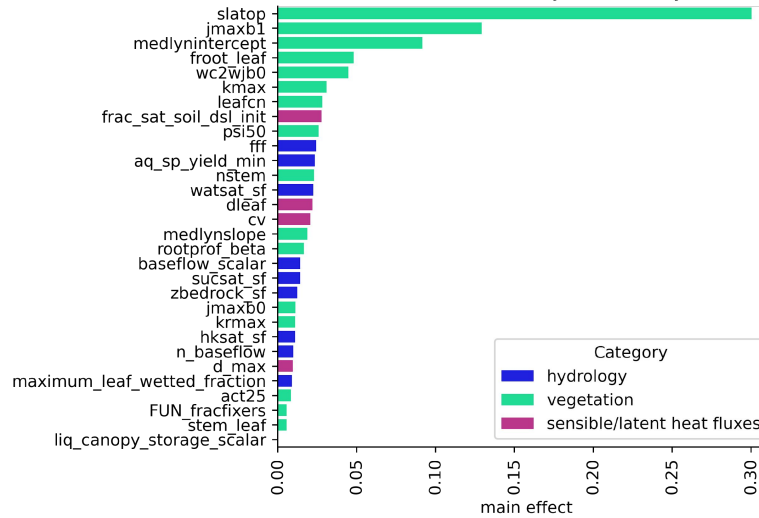
TALL Latent Heat Fluxes



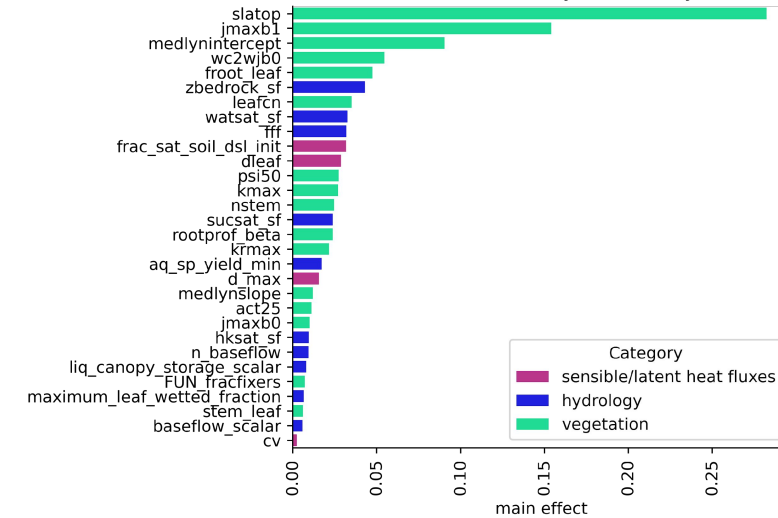
ORNL Gross Primary Productivity



OSBS Gross Primary Productivity



TALL Gross Primary Productivity



Thank you

