

# **Land Model and Biogeochemistry Working Group Meeting 2026**

**Multi-site calibrations of CLM6 for water and carbon fluxes –  
emergence of parameter coherence**

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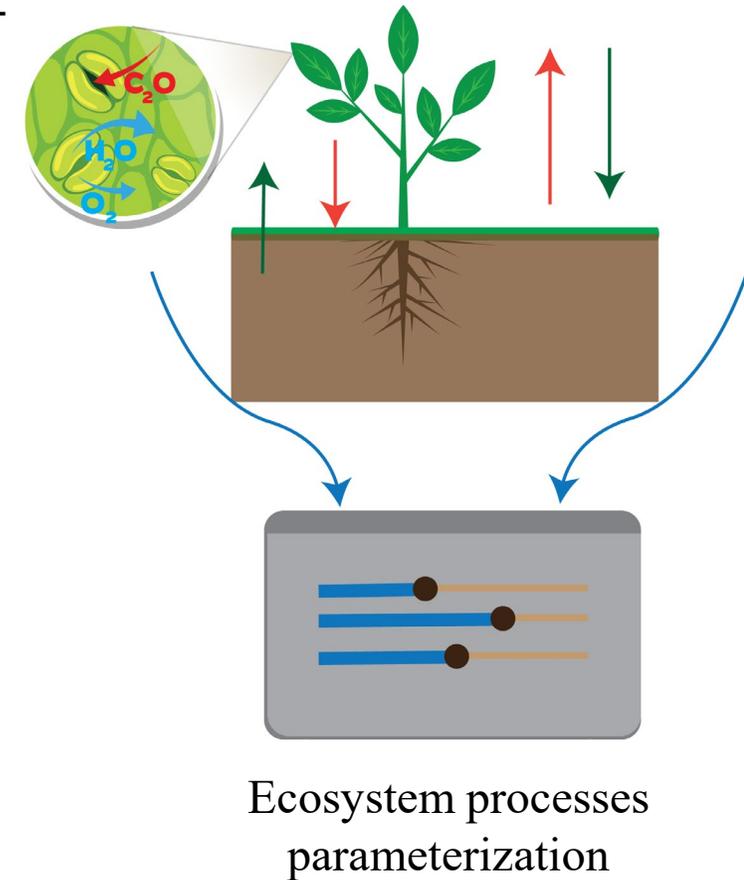
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# Motivation

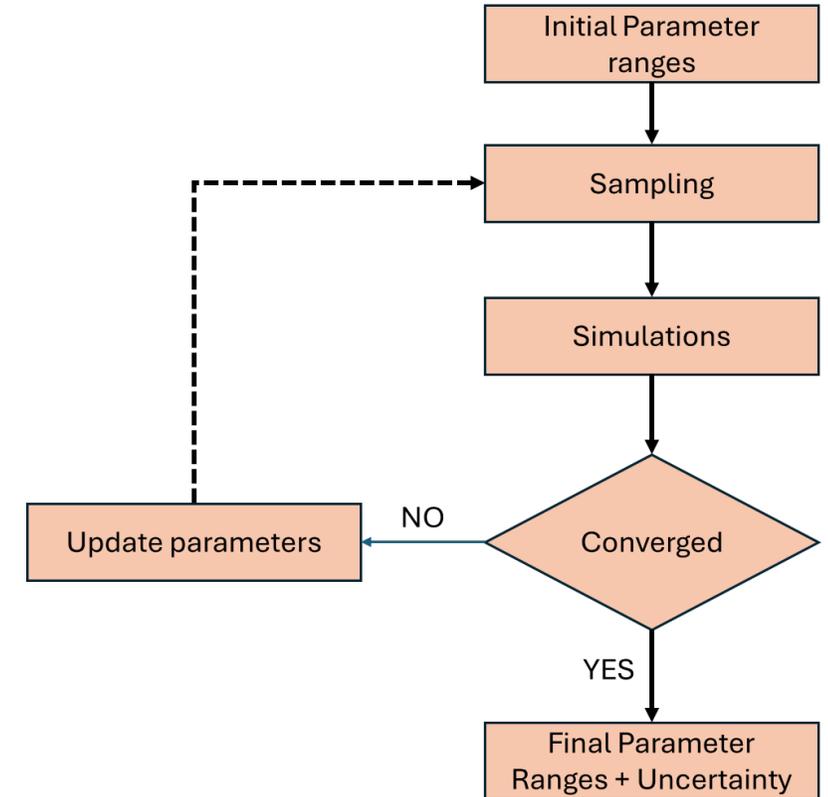
- Many key model parameters controlling photosynthesis, stomatal conductance, and soil-plant hydraulics are poorly constrained at ecosystem scale.
- Large within-PFT variation: e.g.,  $V_{cmax}$  varies 2–3 $\times$  even for the same PFT (Kattge et al., 2009).
- These uncertainties propagate to ecosystem productivity and carbon–water flux estimates (Bonan et al., 2011; Butler et al., 2022).
- Much of this variability is driven by climate, soils, and species, factors not captured by global default values (Kattge et al., 2009; Rogers, 2014).
- Fixed PFT structures impose rigid behavior, limiting representation of physiological diversity and altering water–carbon coupling (Rogers, 2014).





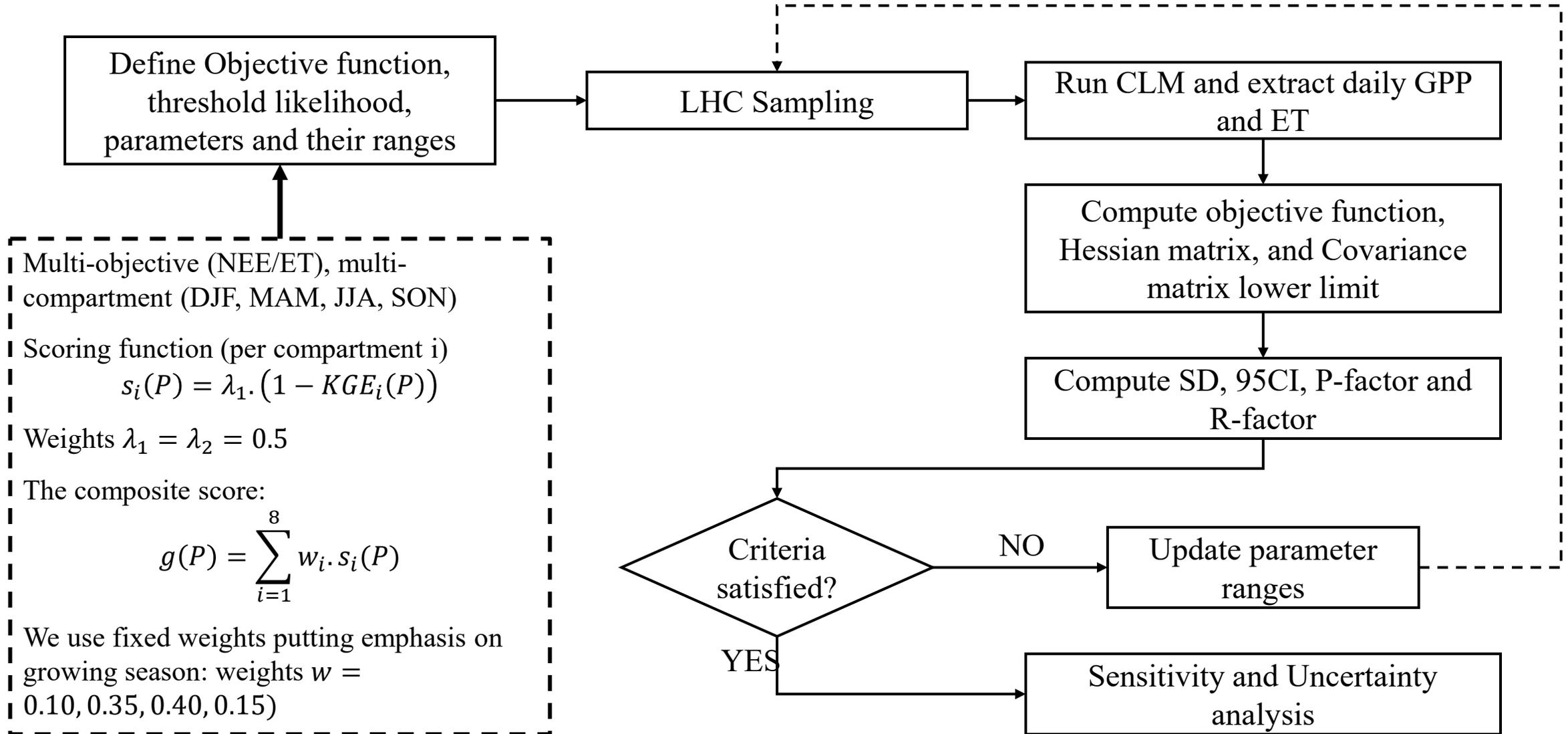
# Sequential Uncertainty Fitting(SUFI) Algorithm

- **Wide applications in hydrology** – calibration and uncertainty analysis (Abbaspour et al. 2007)
- **Iteratively constrains parameter ranges** based on model data mismatch using key performance indicators (Abbaspour et al. 2007):
  - Proportion of observation data points that fall within 95% prediction uncertainty band.
  - Average thickness of the 95% prediction uncertainty band divided by SD of observations.
- **Computationally efficient in high-dimensional space:** enabling exploration of many interacting parameters without prohibitive computation cost

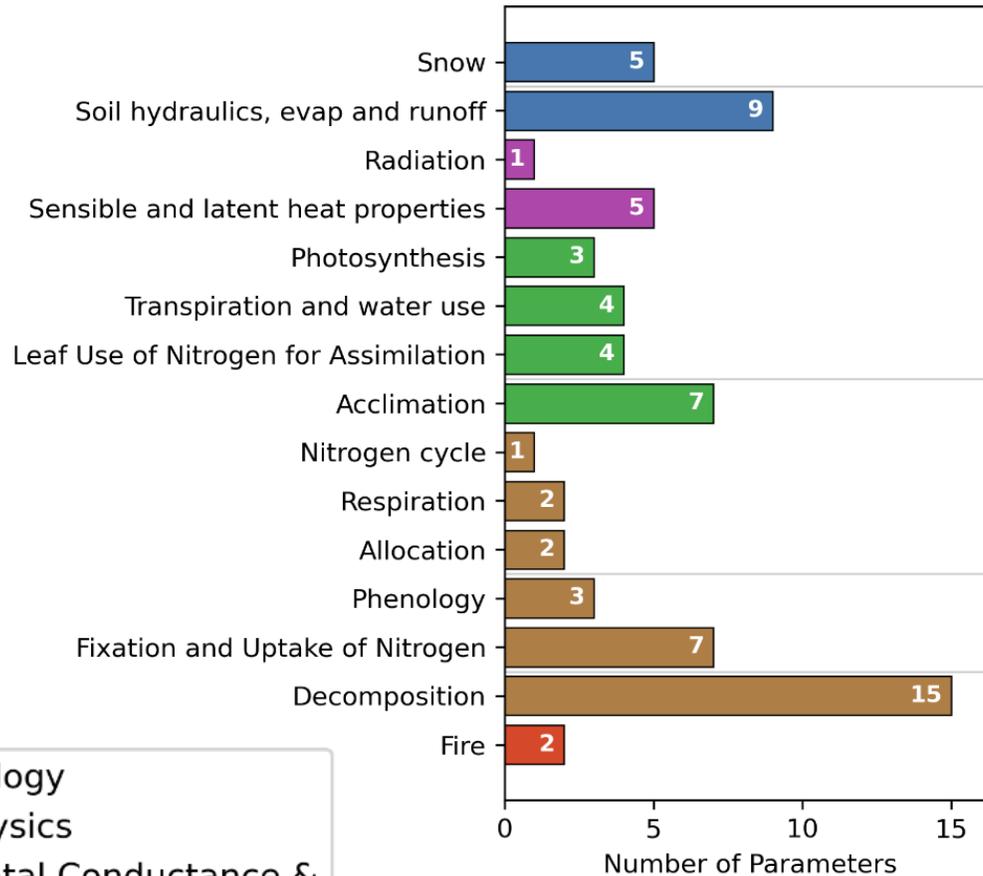


SUFI workflow schematic

# SUFI Implementation Workflow for CLM-NEON



# Multi-Site PPE Setup



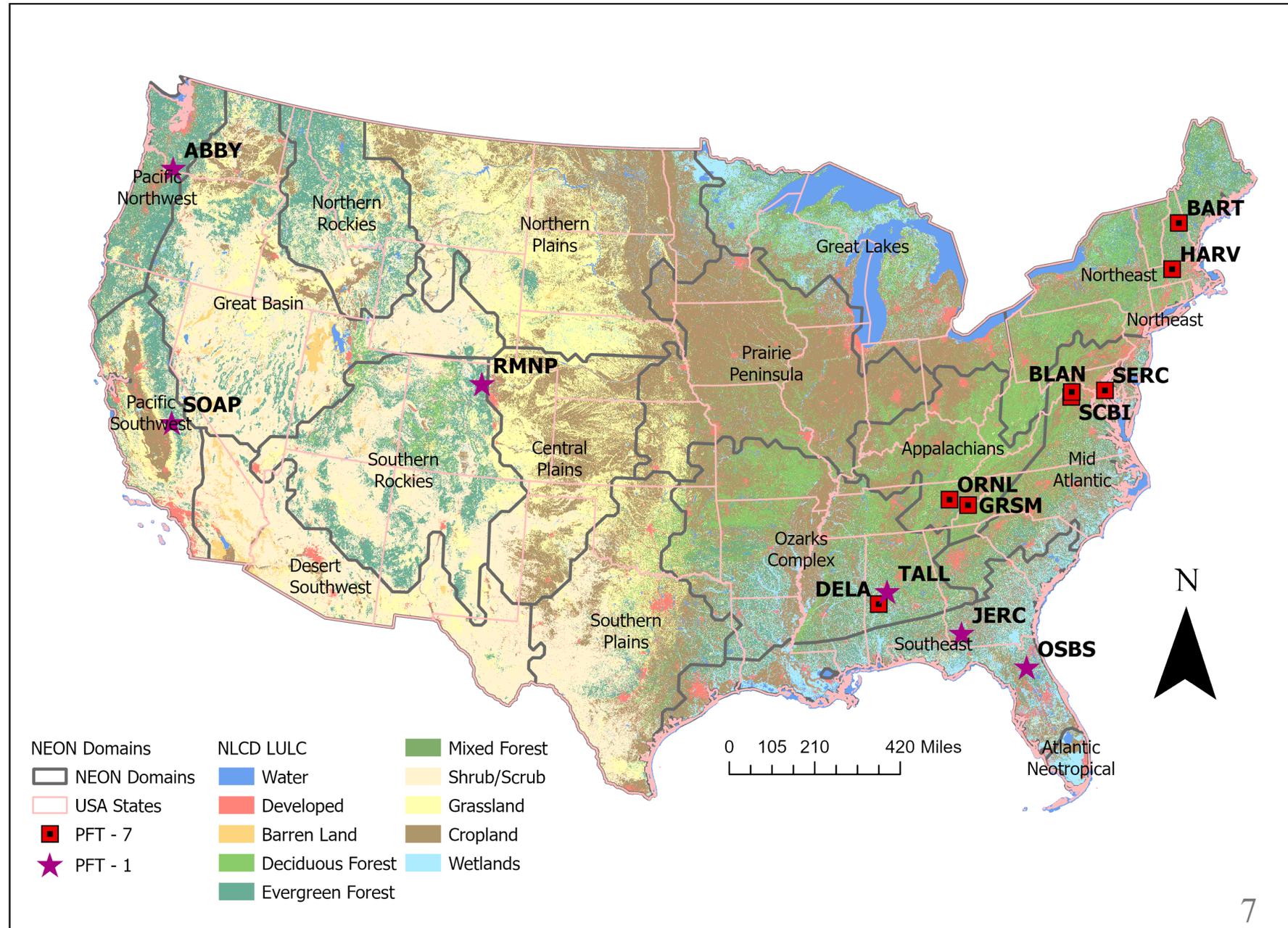
## Multi-objective calibration:

- Via Perturbed Parameter Ensemble (PPE)
- 14 sites (Needleleaf - 6, broadleaf 8)
- 1000 simulations: Sampled using (LHC)
- 56 parameter groups (reduced from 70)

## Setup

- Spin-up: PLUMBER2 protocol (pre-industrial CO<sub>2</sub>, Ndep)
- Transient run: 1850 – 2018
- Production run: 2018 - 2024

# Study Area

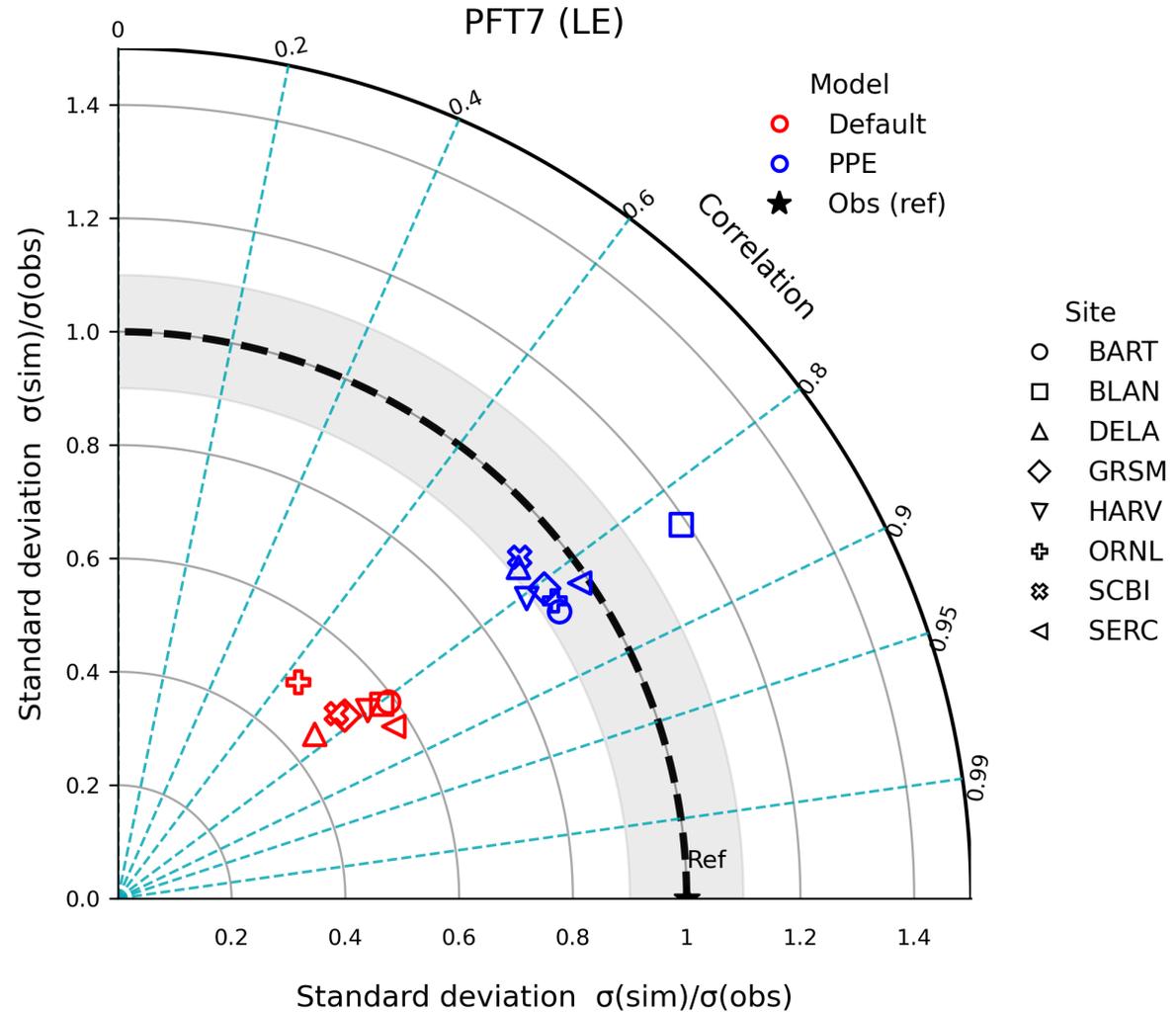


# Results: Performance (PFT 7 - BDT)

Improvements 13% overall

## Latent Heat Flux (8/8 sites)

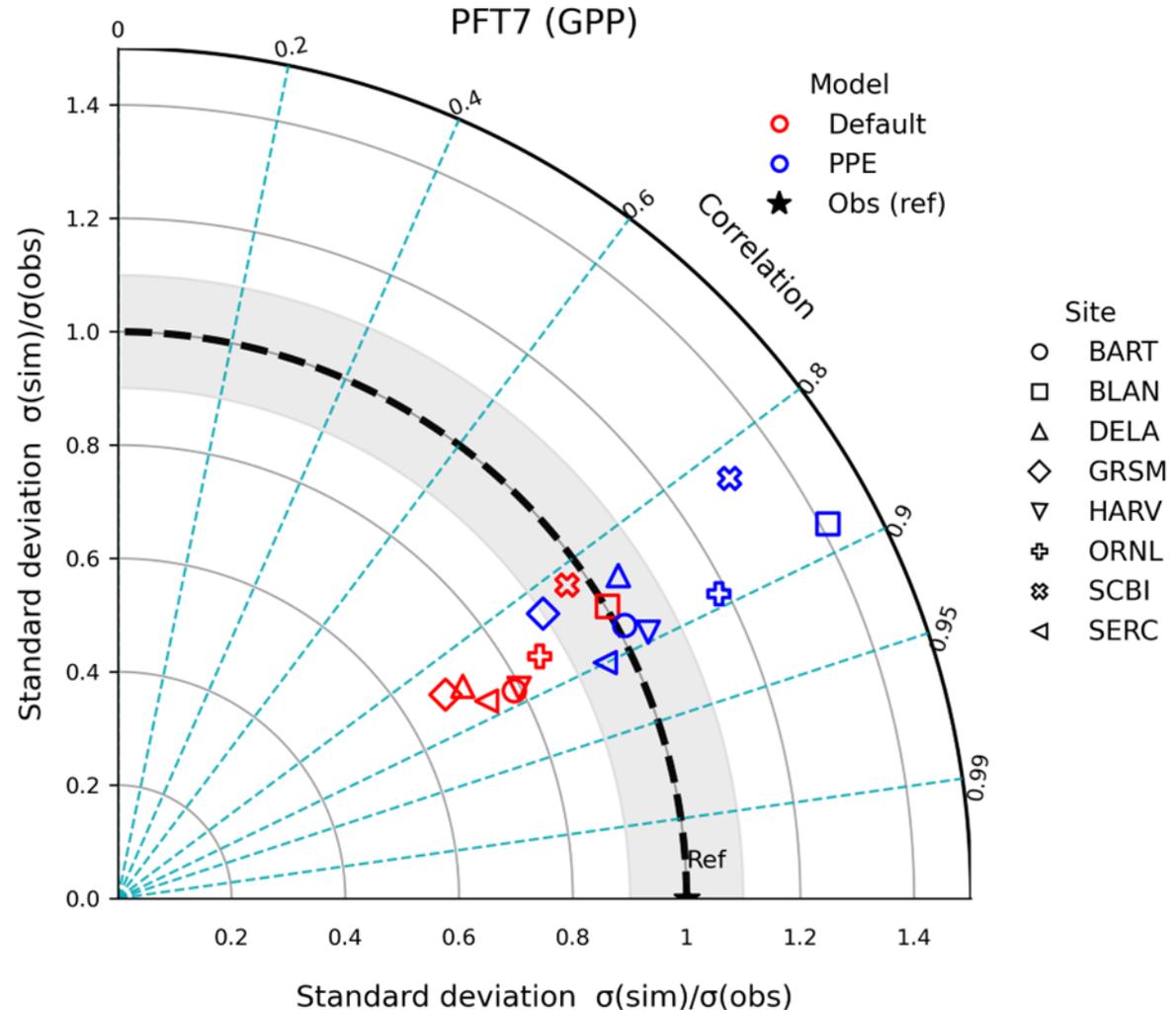
- Default means: Corr=0.788,  $\sigma$  ratio =0.532, CRMSD\_norm =0.667
- PPE means: Corr=0.816,  $\sigma$  ratio =0.928, CRMSD\_norm =0.600
- **Overall  $\Delta$  (PPE – Default)**
  - $\Delta$ Corr =0.028
  - $\Delta$  $\sigma$  Ratio =0.396
  - $\Delta$ CRMSD\_norm =-0.066



# Results: Performance (PFT 7 - BDT)

## Gross Primary Productivity (5/8 sites)

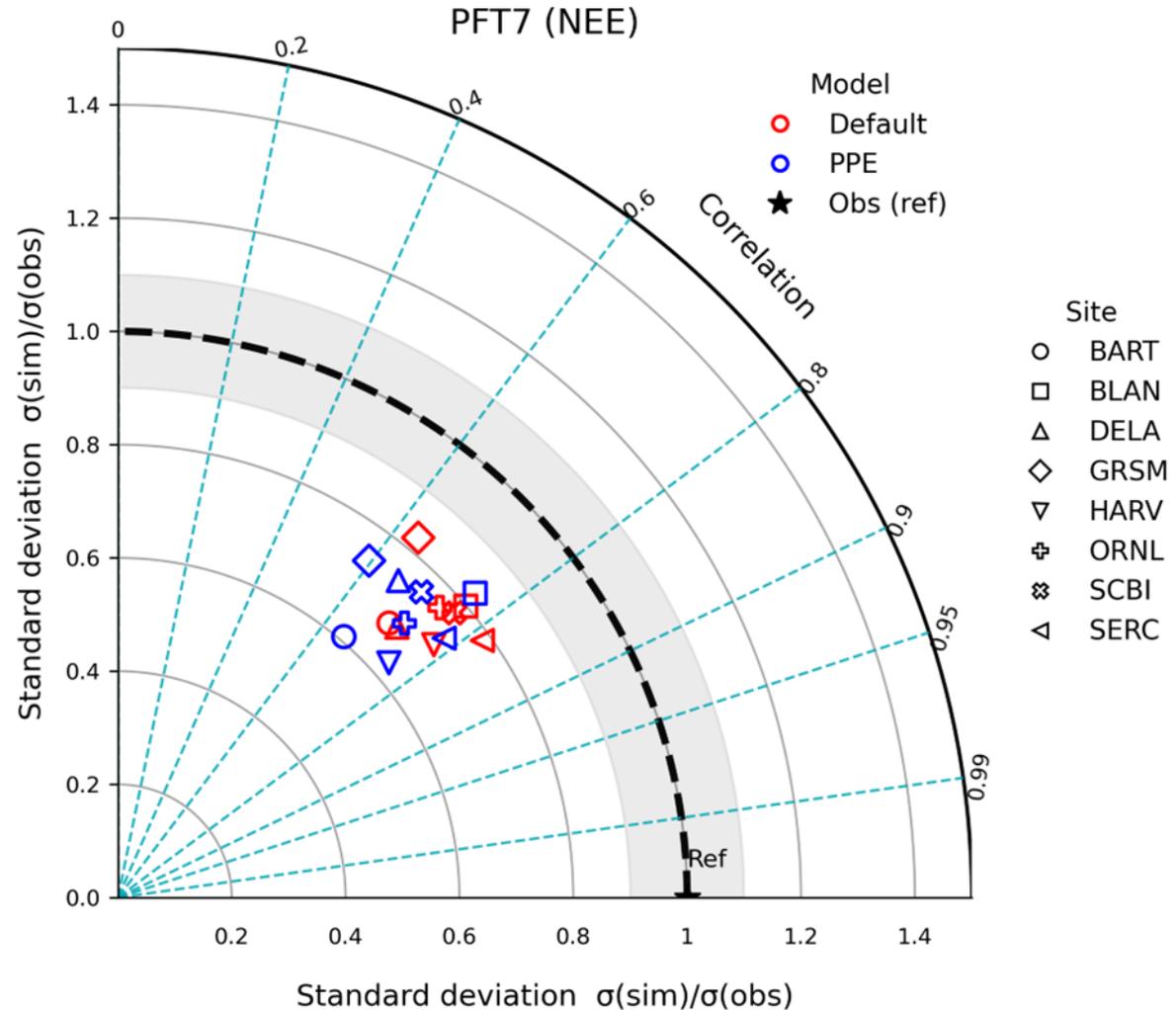
- Default medians: Corr=0.862,  $\sigma$  ratio =0.792, CRMSD\_norm =0.516
- PPE medians: Corr=0.882,  $\sigma$  ratio =1.046, CRMSD\_norm =0.552
- **Overall  $\Delta$  (PPE – Default)**
  - $\Delta$ Corr =0.020
  - $\Delta\sigma$  Ratio =0.254
  - $\Delta$ CRMSD\_norm =0.035



# Results: Performance (PFT 7 - BDT)

## Net Ecosystem Exchange (5/8 sites)

- Default means: Corr=0.751,  $\sigma$  ratio =0.770, CRMSD\_norm =0.660
- PPE means: Corr=0.712,  $\sigma$  ratio =0.737, CRMSD\_norm =0.704
- **Overall  $\Delta$  (PPE – Default)**
  - $\Delta$ Corr =-0.040
  - $\Delta$  $\sigma$  Ratio =-0.032
  - $\Delta$ CRMSD\_norm =0.044

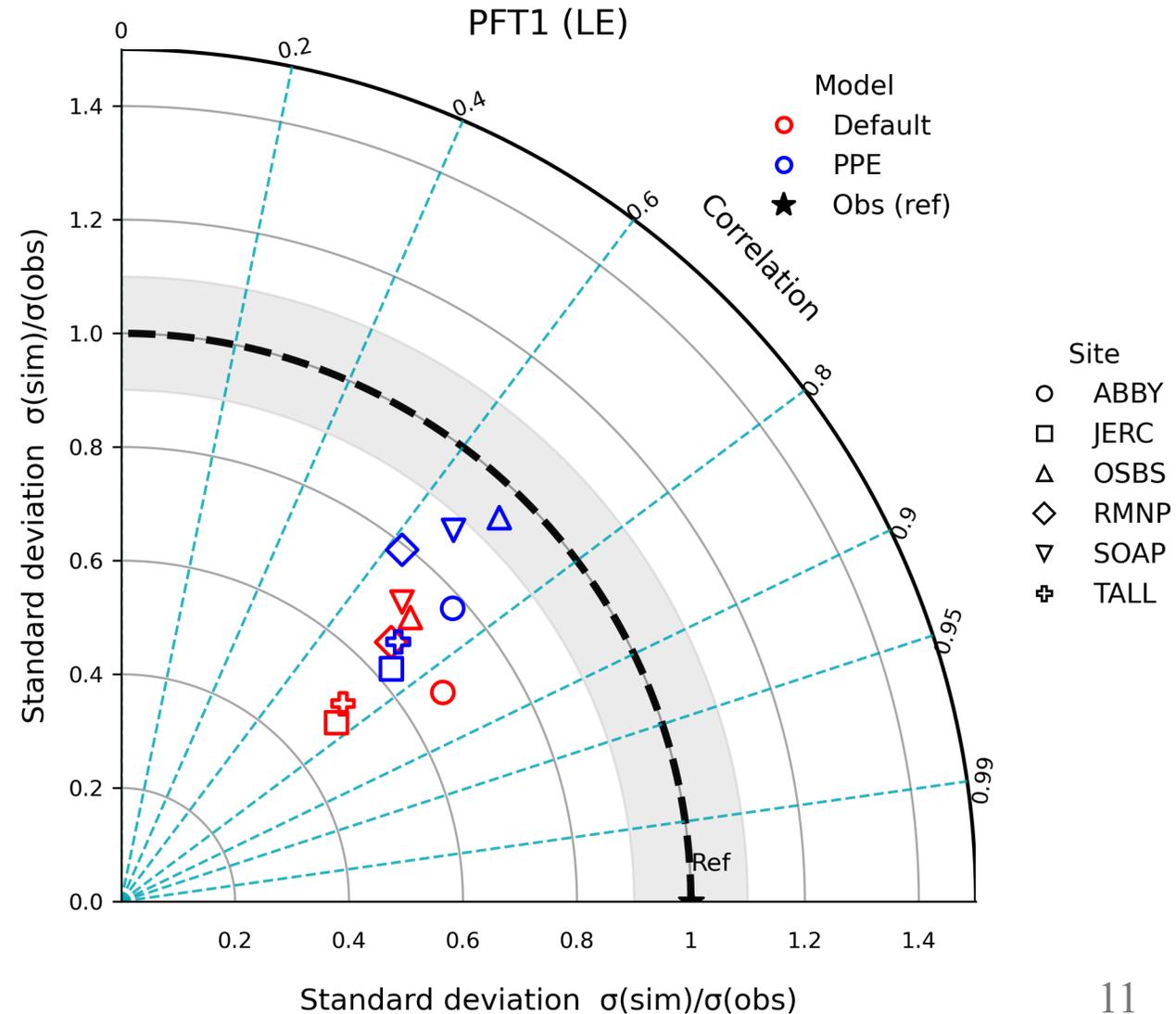


# Results: Performance: PFT 1 (NET)

Improvements 5% overall

## Latent Heat Flux 6/6 sites

- Default medians: Corr=0.733,  $\sigma$  ratio =0.666, CRMSD\_norm =0.699
- PPE medians: Corr=0.715,  $\sigma$  ratio =0.785, CRMSD\_norm =0.721
- **Overall  $\Delta$  (PPE – Default)**
  - $\Delta$ Corr =-0.018
  - $\Delta\sigma$  Ratio =0.119
  - $\Delta$ CRMSD\_norm =0.022



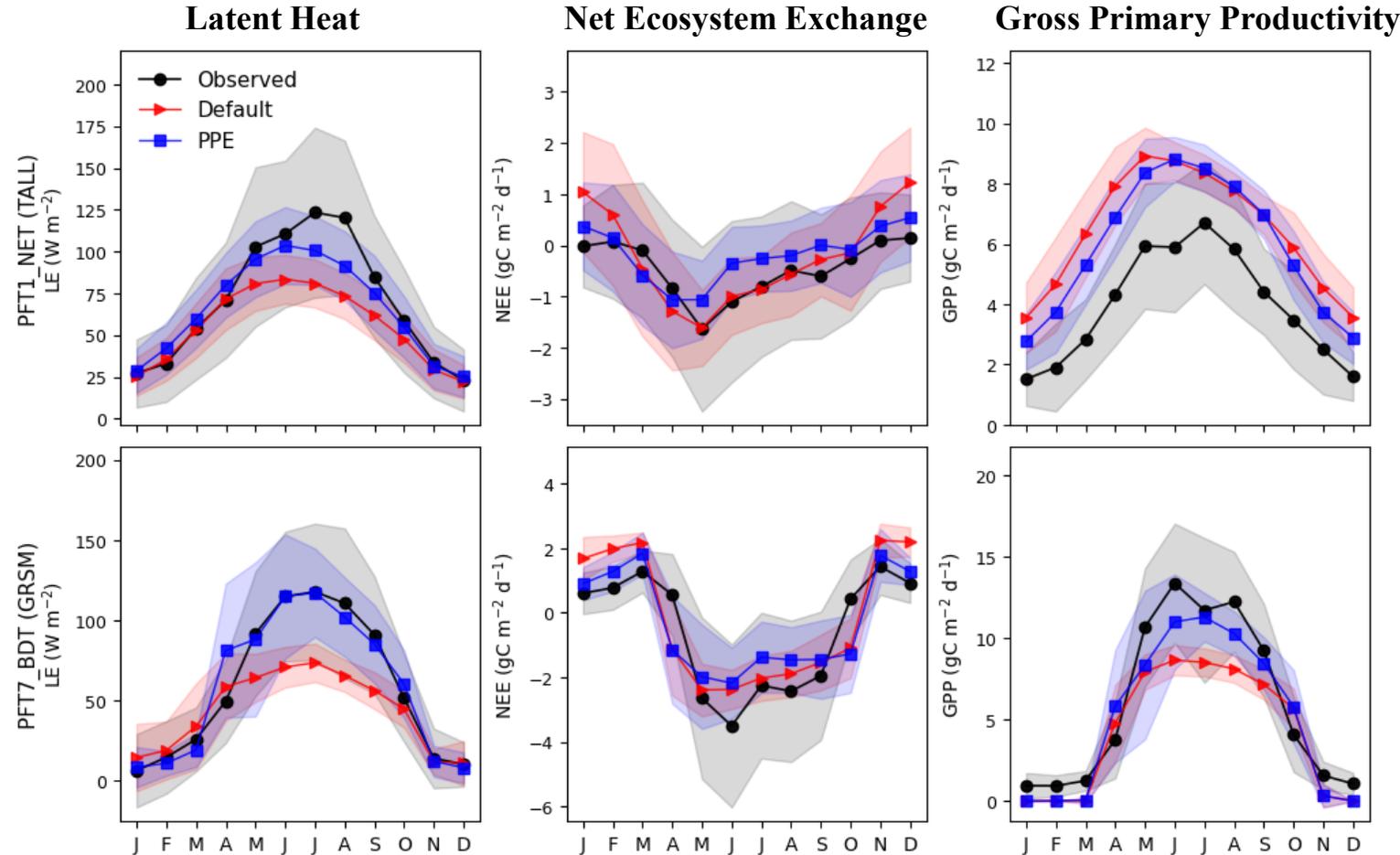
# Seasonal Fluxes and Skill score

## Model data alignment: PPE

matches summer GPP & LE  
better.

## Large error reductions (PFT 7):

RMSE drops by 8–11  $\text{W m}^{-2}$  (LE)  
and 0.5 - 0.6  $\text{g C m}^{-2} \text{d}^{-1}$  (GPP).



# Impact of PPE on Simulated LE: PFT 7 (BDT)

## Hexbin Meaning:

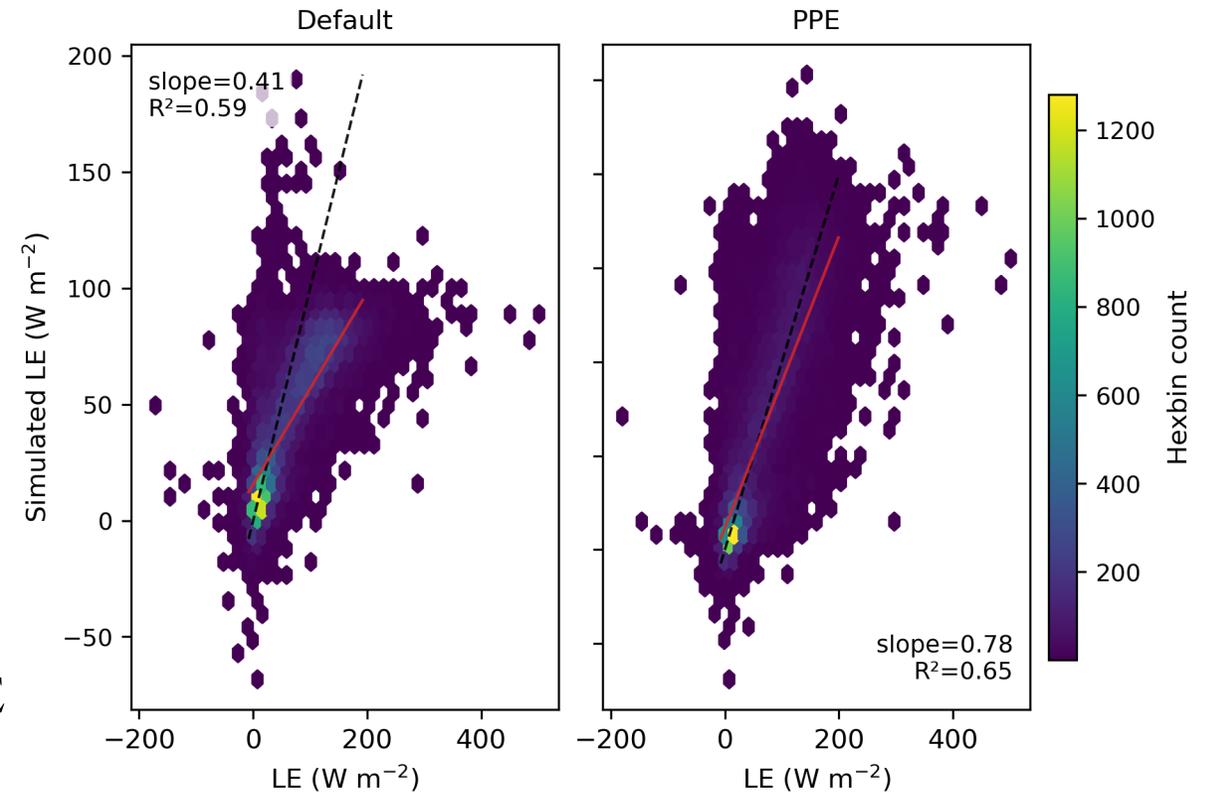
- Color indicates how many points fall in that area.
- Overall distribution of daily model–observation pairs

## Reference Lines:

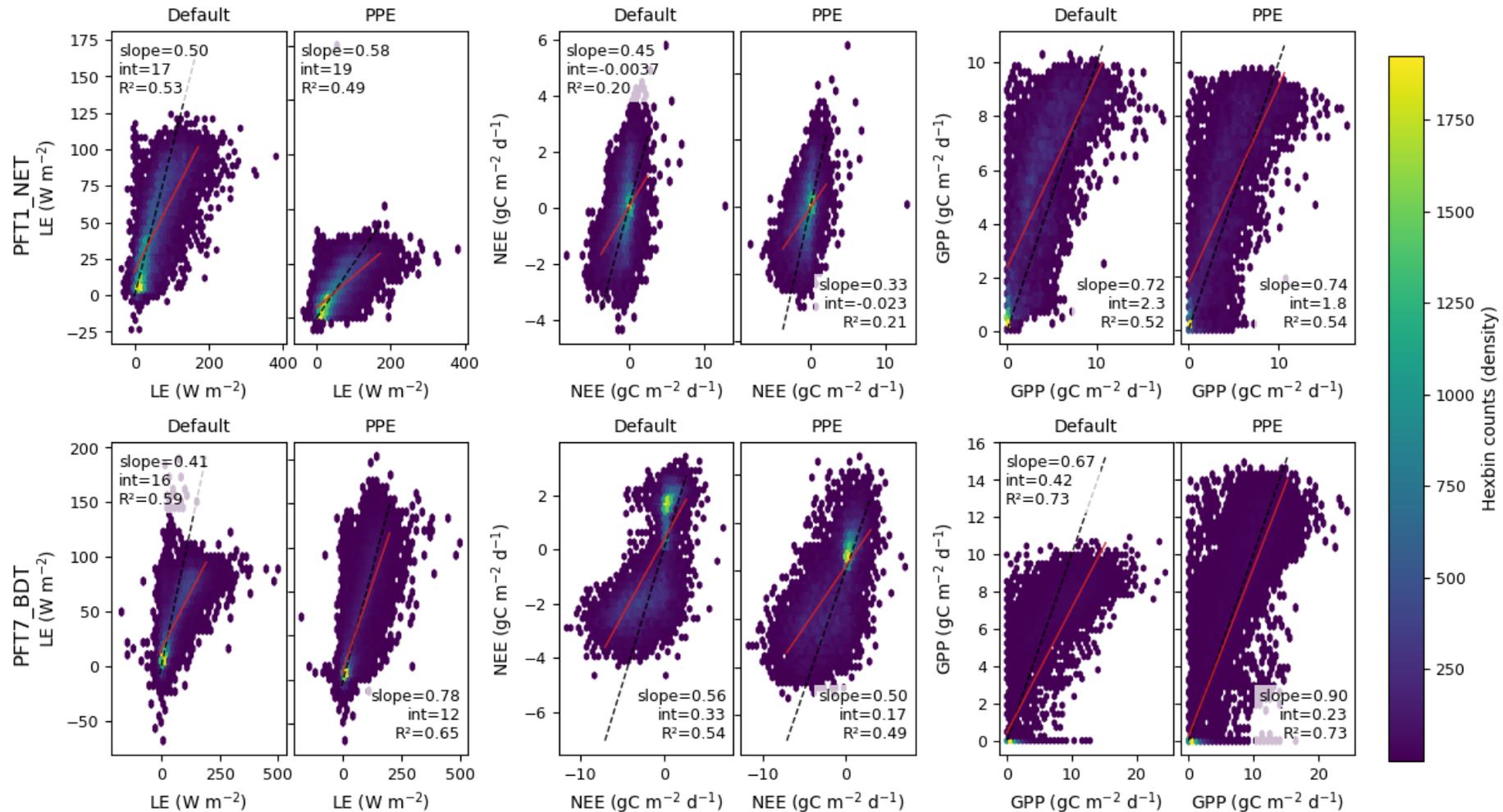
- 1:1 line: perfect agreement.
- Red line: regression fit (model behavior)

## Example Latent Heat:

- Default: slope  $\approx 0.41$ : CLM6 underestimates high LE values
- PPE: slope  $\approx 0.78$ : Simulated LE closer to 1:1 line.

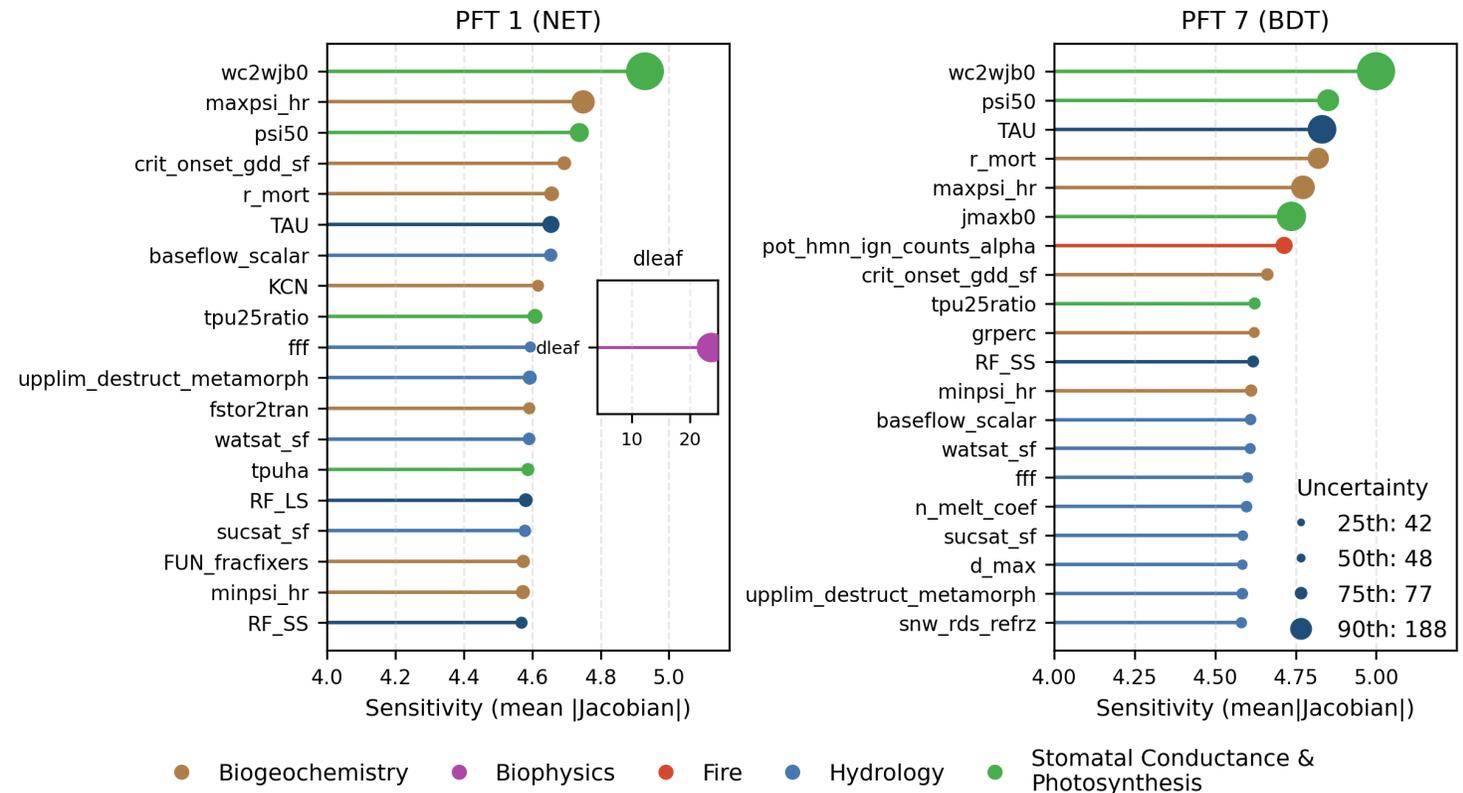


# Impact of PPE on Water – Carbon Fluxes



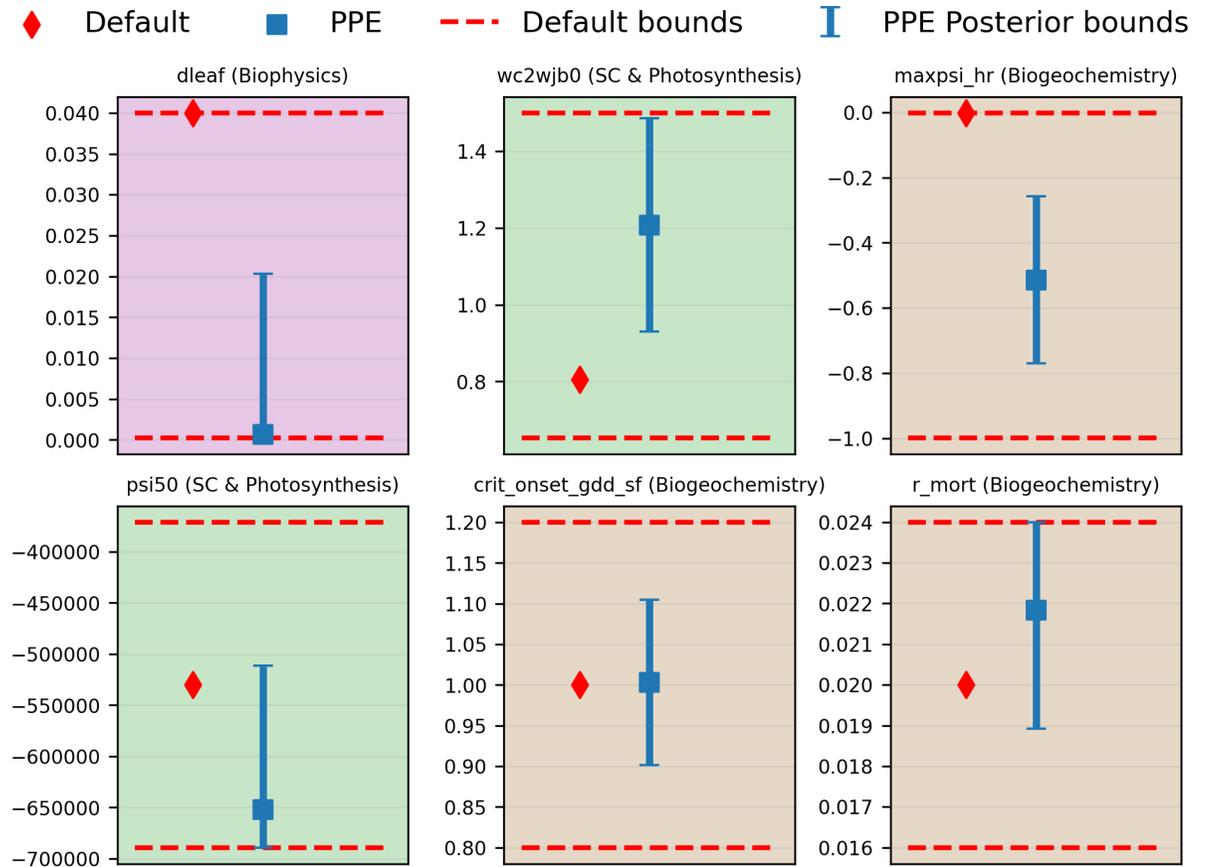
# Parameter Sensitivity

- A small subset of parameters  
(*e.g., wc2wjb0, maxpsi\_hr, psi50, r\_mort*) show consistently high sensitivity.
- The wide uncertainty ranges (colored dots) highlight that not all influential parameters are equally stable.



# A revised parameter Range – A key outcome of this study

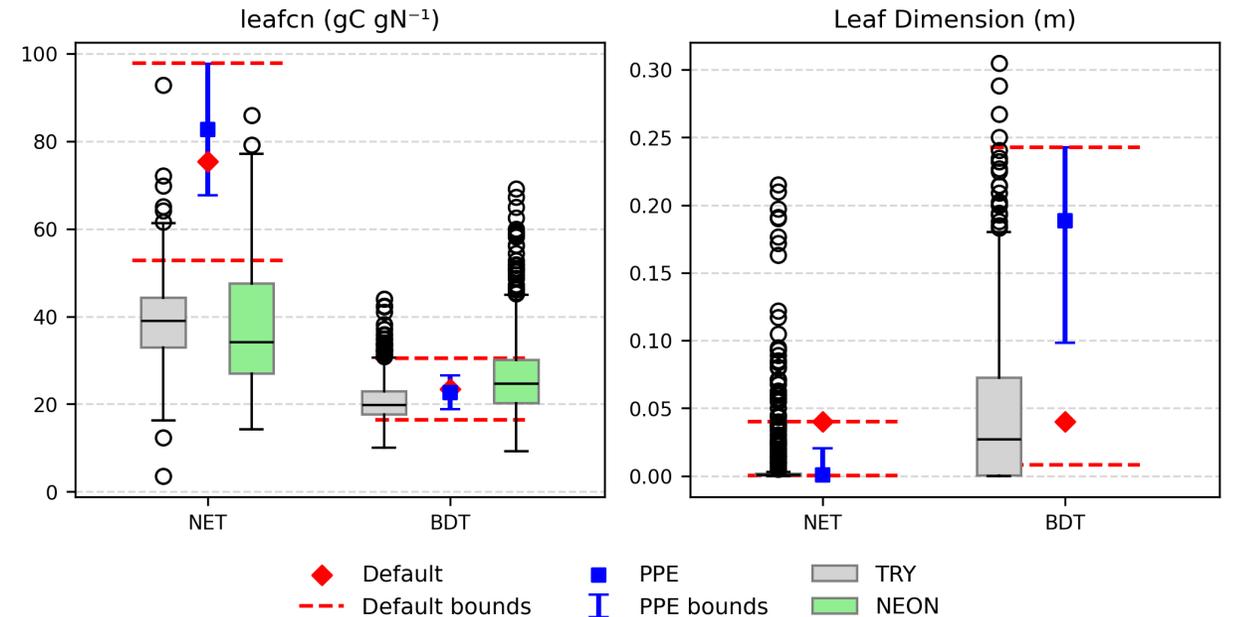
Several parameters (*e.g.*, *dleaf*, *wc2wjb0*, *maxpsi\_hr*) show posterior values that shift substantially from the Default and lie within much narrower posterior bounds, indicating strong identifiability.



# Observed Traits and Parameter Constraints

**Leaf C:N** (*leafcn*): A less sensitive parameter but the default value and bounds sit well above observed TRY/NEON range, limiting how far the posterior could move.

**Leaf dimension** (*dleaf*): highly sensitive parameter especially in PFT 1. The posterior shifts from the default and aligns closely with the median observed trait.



# What I found doing multi-site optimization?

- A revised posterior parameter range
- Non-compensation optimized parameter value
- Getting close to solving long-standing biases in CLM, e.g. ET underestimation
- Does it work on regional / global scale – remain to be tested.

## **Acknowledgments:**

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# References

- 1) Abbaspour, K. C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., et al. (2007). Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. *Journal of Hydrology*, 333(2–4), 413–430. <https://doi.org/10.1016/j.jhydrol.2006.09.014>
- 2) Bonan, G. B., Lawrence, P. J., Oleson, K. W., Levis, S., Jung, M., Reichstein, M., et al. (2011). Improving canopy processes in the Community Land Model version 4 (CLM4) using global flux fields empirically inferred from FLUXNET data. *Journal of Geophysical Research*, 116(G2), G02014. <https://doi.org/10.1029/2010JG001593>
- 3) Butler, E. E., Wythers, K. R., Flores-Moreno, H., Ricciuto, D. M., Datta, A., Banerjee, A., et al. (2022). Increasing Functional Diversity in a Global Land Surface Model Illustrates Uncertainties Related to Parameter Simplification. *Journal of Geophysical Research: Biogeosciences*, 127(3), e2021JG006606. <https://doi.org/10.1029/2021JG006606>
- 4) Kattge, J., Knorr, W., Raddatz, T., & Wirth, C. (2009). Quantifying photosynthetic capacity and its relationship to leaf nitrogen content for global-scale terrestrial biosphere models. *Global Change Biology*, 15(4), 976–991. <https://doi.org/10.1111/j.1365-2486.2008.01744.x>
- 5) Kavoo, T., Kennedy, D., Kumar, S., Wieder, W. R., & Lombardozzi, D. (2026). Reducing Uncertainties in Coupled Carbon-Water Cycle Predictions—A Parameter Perturbation Ensemble Experiment at Three NEON Tower Sites in the Southeastern United States. *Journal of Geophysical Research: Atmospheres*, 131(4), e2025JD043780. <https://doi.org/10.1029/2025JD043780>
- 6) Rogers, A. (2014). The use and misuse of  $V_{c,max}$  in Earth System Models. *Photosynthesis Research*, 119(1–2), 15–29. <https://doi.org/10.1007/s11120-013-9818-1>