

# Modeling bioenergy crops in ELM

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## Background

### Motivation:

- ▶ Bioenergy crops cultivation is projected to increase in the future due to their potential for mitigating climate change.
- ▶ Agriculture can alter the climate through its impact on biogeophysical and biogeochemical properties of the terrestrial ecosystem and therefore should be adequately represented in Earth System Models.
- ▶ Although, the Energy Exascale Earth System Model (E3SM) Land Model (ELM) includes representation of select cereal crops, bioenergy crops are not yet included.

### Objective:

- ▶ Expand ELM's crop model to include bioenergy crops - *Miscanthus* and switchgrass.
- ▶ Perform global sensitivity analysis to identify and optimize the bioenergy crop parameters.

### Challenges:

- ▶ Large number of parameters control the plant growth and associated carbon fluxes.

## Approach

### Sensitivity analysis:

Uncertainty Quantification Toolkit (UQTK) was used for optimizing eighteen crop parameters. The steps for performing global sensitivity analysis were:

- ▶ Eighteen different crop parameters associated with carbon nitrogen allocation, crop phenology, and photosynthetic capacity and their approximate ranges were identified for the sensitivity analysis.
- ▶ A sample file was created containing a large sample of randomly distributed parameters within their specified range.
- ▶ Offline Land Model Testbed (OLMT) used for submitting, managing, and post processing a large ensemble of ELM model runs (2000).
- ▶ Surrogate models developed for ELM simulations (*forward modeling*) (Figure 1).
- ▶ Sobol indices (variance based decomposition) estimated for parameter selection (Figure 2).
- ▶ Observational data utilized for optimizing parameters (*inverse modeling*) (Figure 3).

## Future work

- ▶ Modify the *Miscanthus* crop model to better represent the observed longer growing season.
- ▶ Develop surrogates models for daily outputs from ELM to achieve better calibration of the model parameters.

## Results

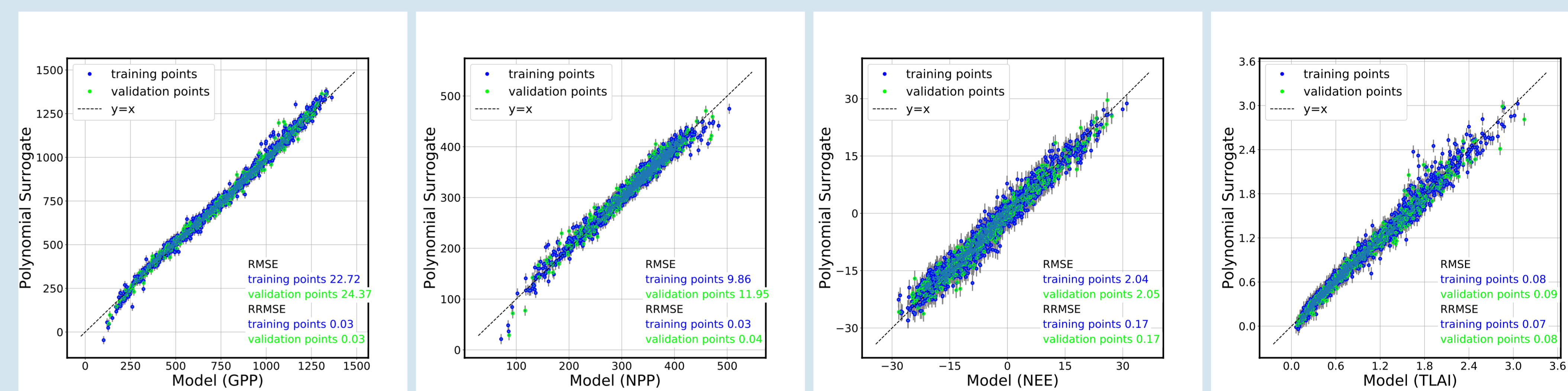


Figure 1: ELM outputs vs. surrogate model outputs for the 10-year average annual GPP, NPP, NEE, and TLAI. The surrogate model is fairly accurately representing the ELM outputs.

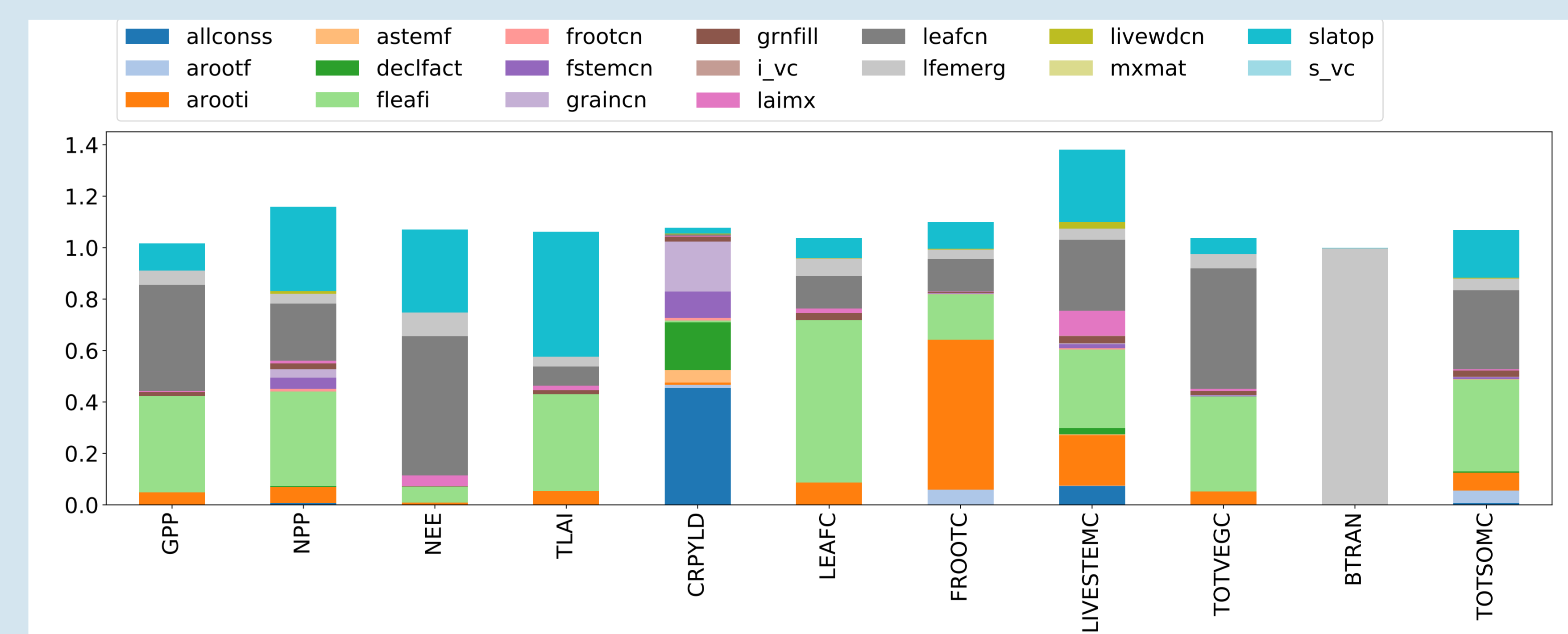


Figure 2: Total-effect Sobol sensitivity indices of the eighteen parameters for the eleven output quantities of interest. ELM output variables are most sensitive to 1) *fleafi* - leaf allocation parameter used in CNAllocation 2) *leafcn* - leaf C:N 3) *slatop* - specific leaf area (SLA) at top of canopy that impacts water uptake and transpiration.

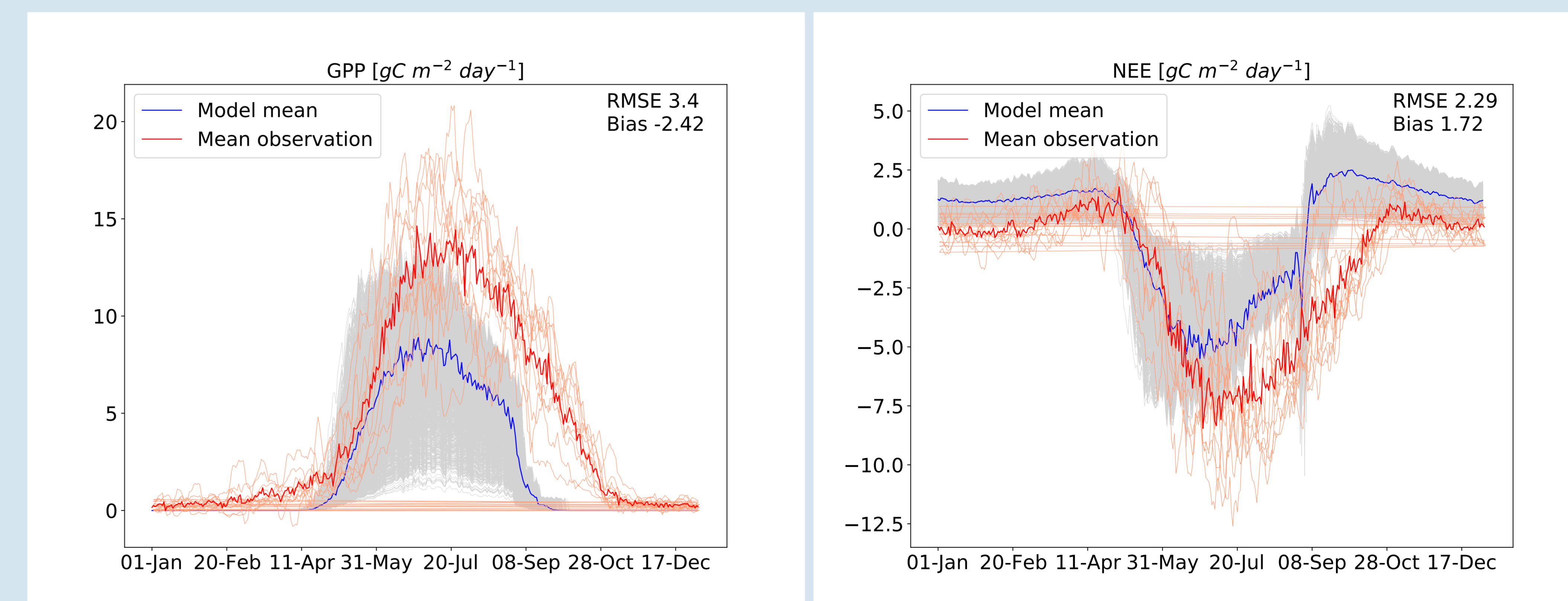


Figure 3: Simulated (grey and blue lines) and observed (red lines) daily GPP ( $gC m^{-2} day^{-1}$ ) and NEE ( $gC m^{-2} day^{-1}$ ) for *Miscanthus*. Grey lines represent the simulated values for the 2000 ensemble members while the thick blue line is average simulated value across the ensemble. Light red lines represent daily observed values from 2009-2018 while the thick red line is the daily average across the ten years. The observational data was collected at the University of Illinois Energy Farm from 2008-2018.