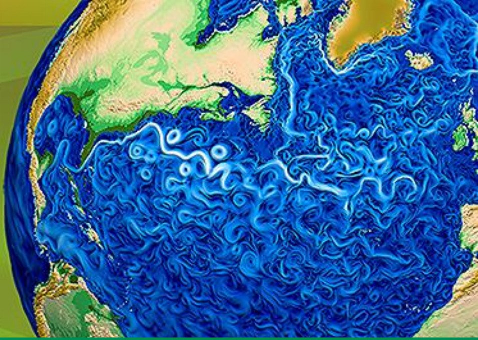
ACME
Accelerated Climate Modeling for Energy




# Uncertainty quantification in the ACME land model

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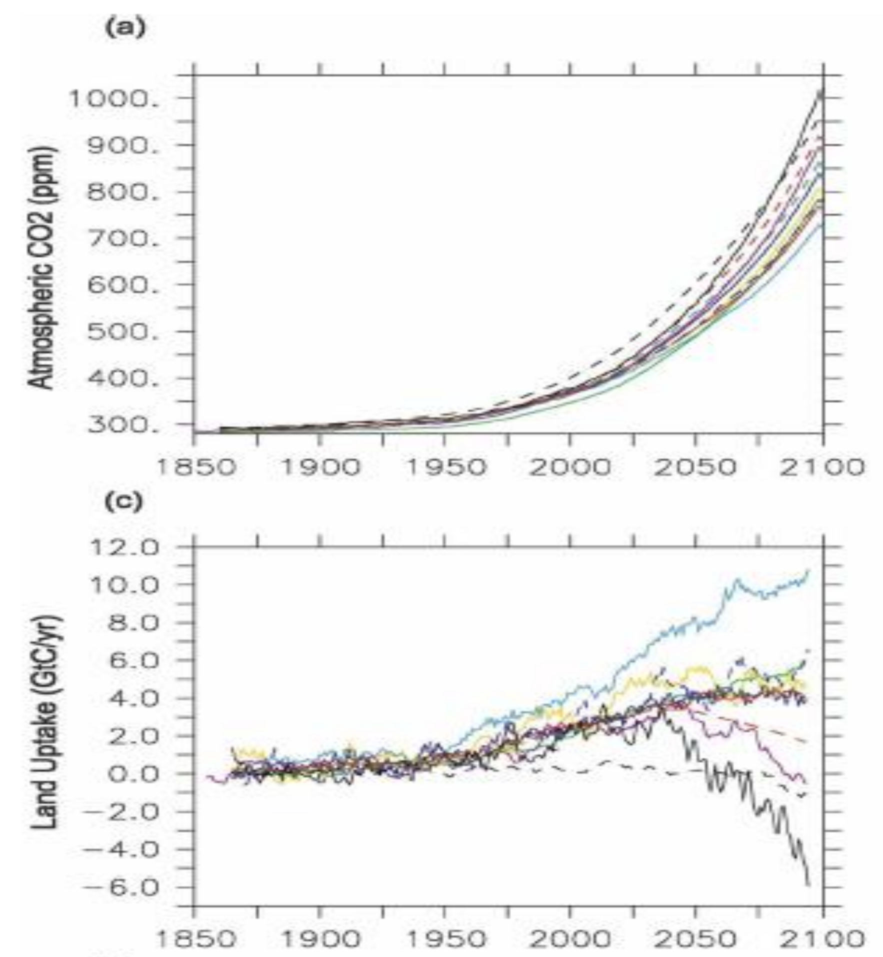
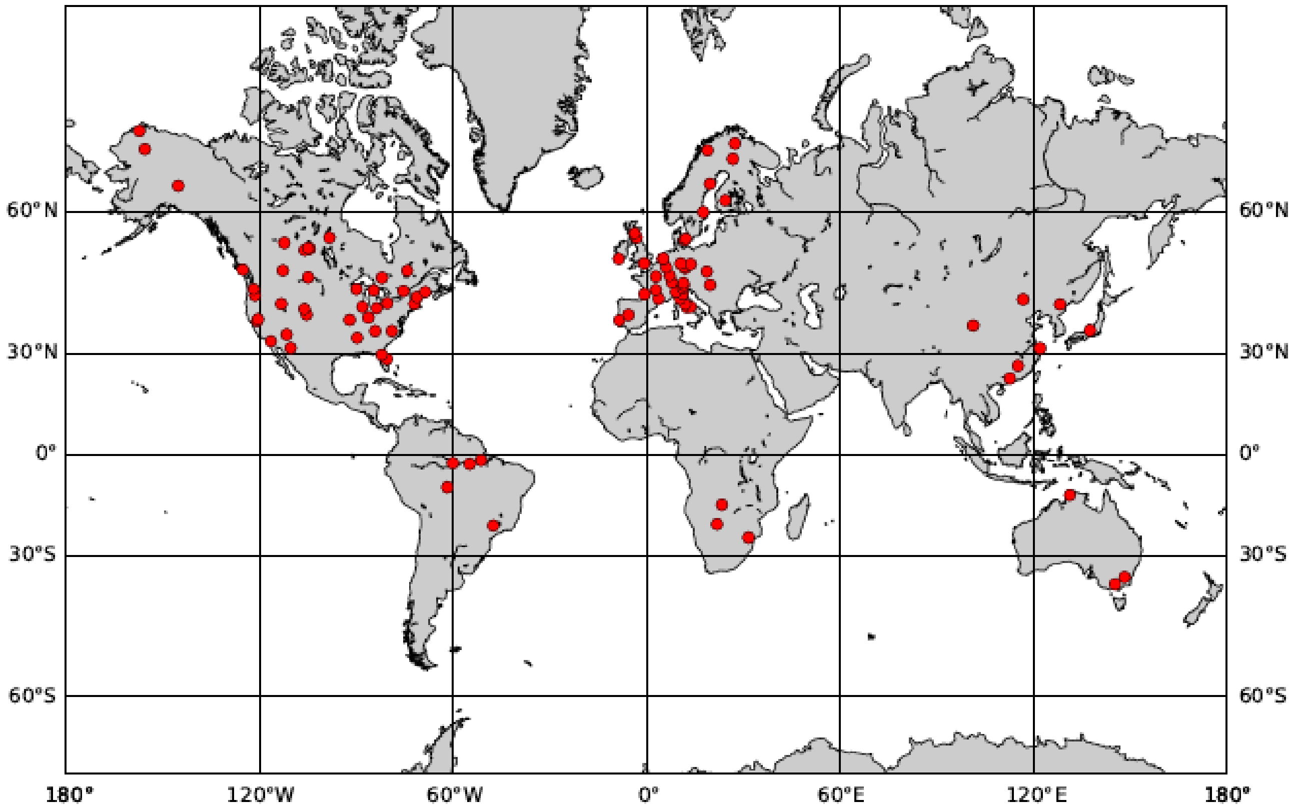
# Evaluating land model uncertainty

- Traditionally, uncertainty has been estimated using multi-model comparisons
- Large uncertainties about future carbon flux
- Hard to distinguish various types of uncertainty (e.g. structural vs. parametric)
- Within-model uncertainty not well characterized
- Need for formal UQ methods




*Friedlingstein et al 2006*

# FLUXNET sensitivity analysis – ALM-CN

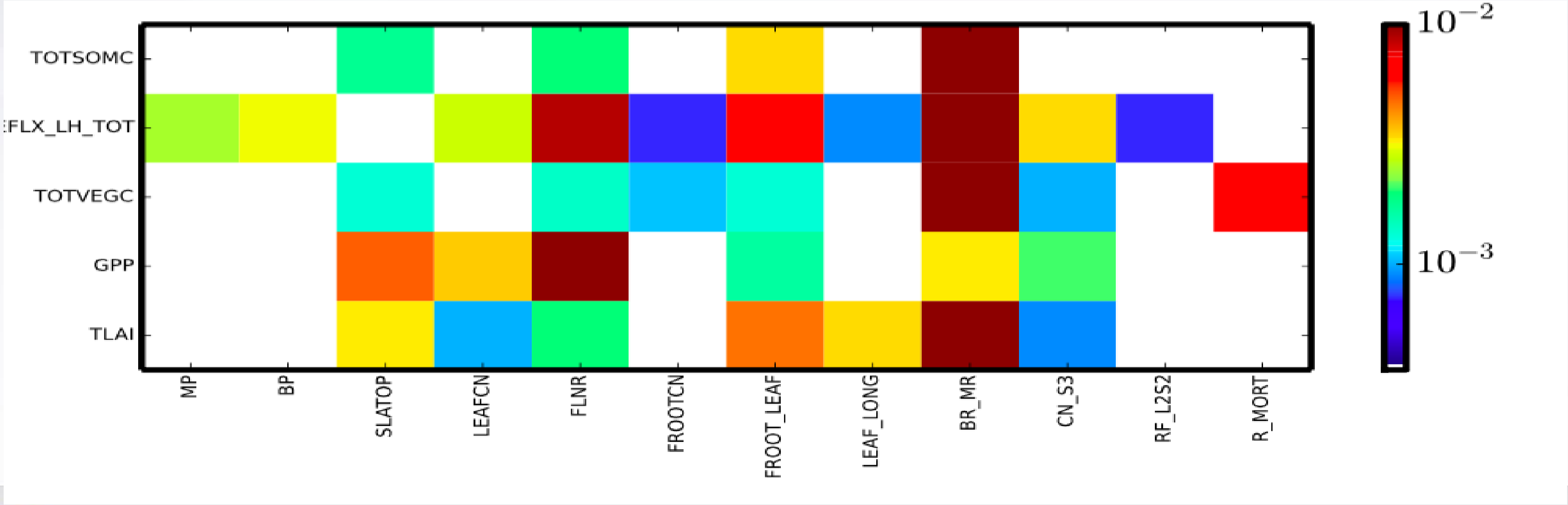


FLUXNET sites

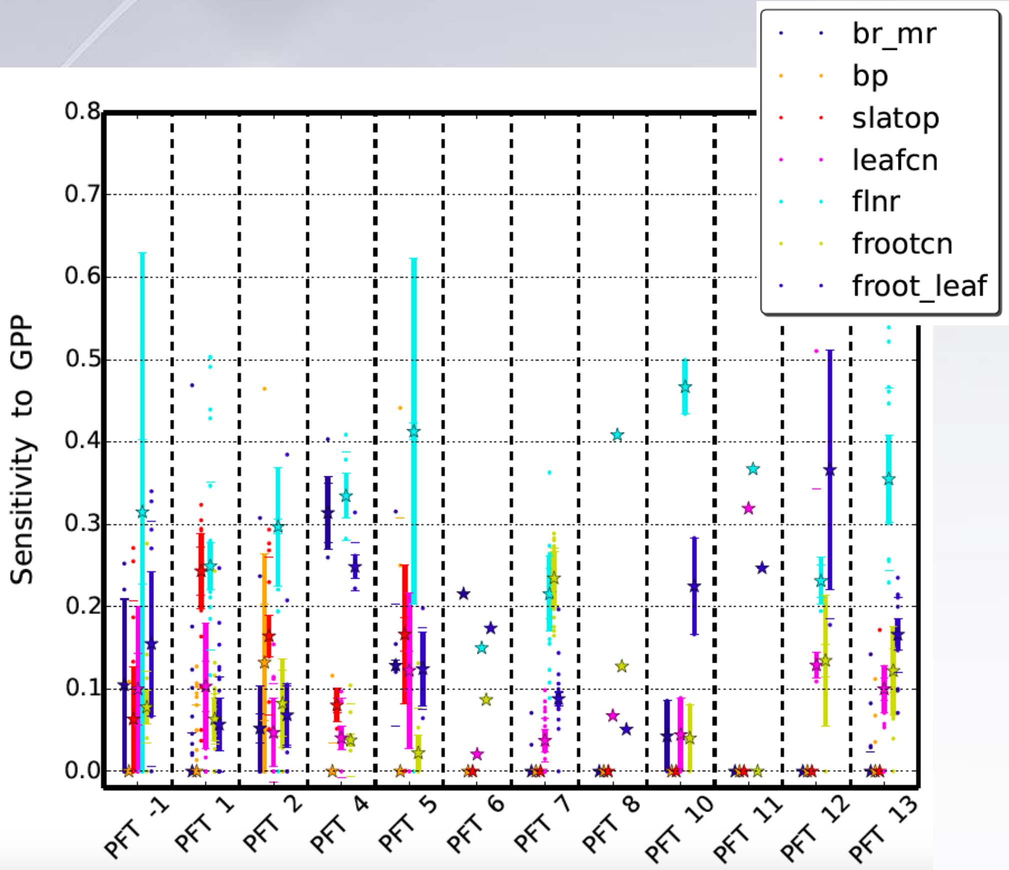
- 96 FLUXNET sites covering major biomes and plant functional types
- 68 input parameters varied over uniform prior ranges
- Sensitivity analysis with Bayesian Compressive Sensing (Sargsyan et al., 2014)
- Site-specific PFT, but reanalysis forcings/soil properties

# Interpreting the results

- Variation in sensitivity with quantity of interest
  - Steady state fluxes and pools
  - Top 10-15 parameters vary, but remaining 50 are always insensitive
  - Maintenance respiration base rate (br_mr)
  - R_mort (mortality) only important for total vegetation biomass
  - Indirect controls:  br_mr affects total SOM carbon



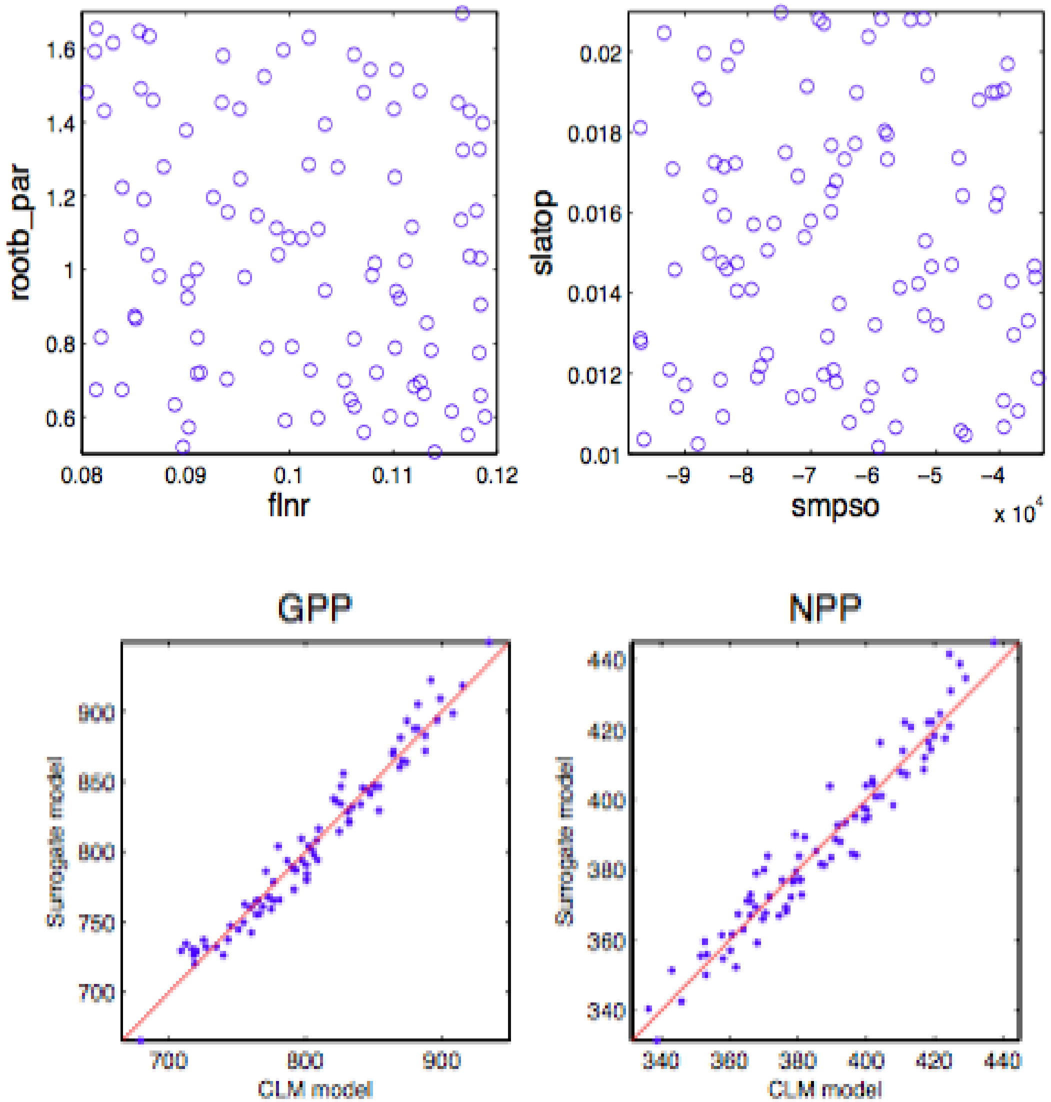
# Sensitivity analysis: Interpreting the results




- Some parameters are sensitive everywhere (flnr)
- Maintenance respiration base rate (br_mr) is critically important in tropical rainforests but not in other ecosystems.
- Relative consistence within PFTs

- Can provide guidance about where specific measurements or data are more valuable
- Reduction of parameter space for optimization

# Surrogate modeling applications




- Goal: Model calibration
- CLM/ALM are too slow for methods to estimate posterior uncertainties (MCMC)
- Evaluate model at given sample points
- Construct a set of basis functions to represent the full model for a subset of outputs

- Additional uncertainty introduced, but high accuracy is achievable
- Combine with optimization approaches (e.g. GA)

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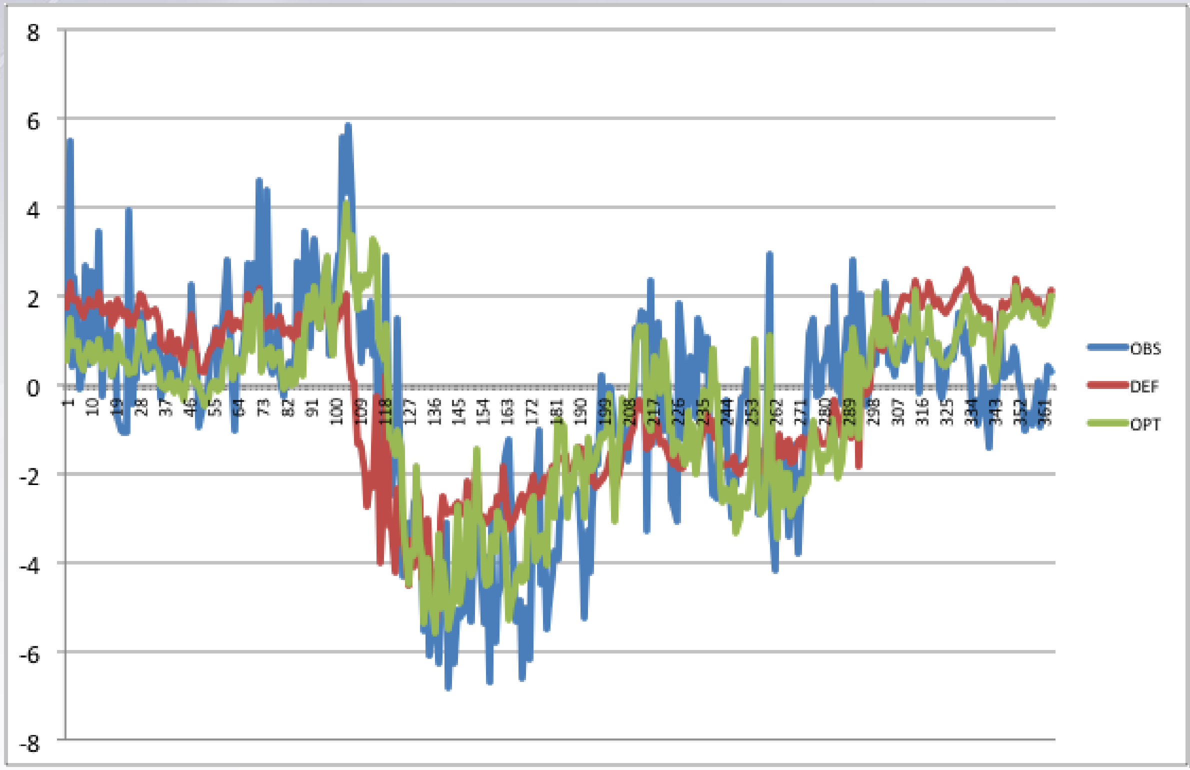
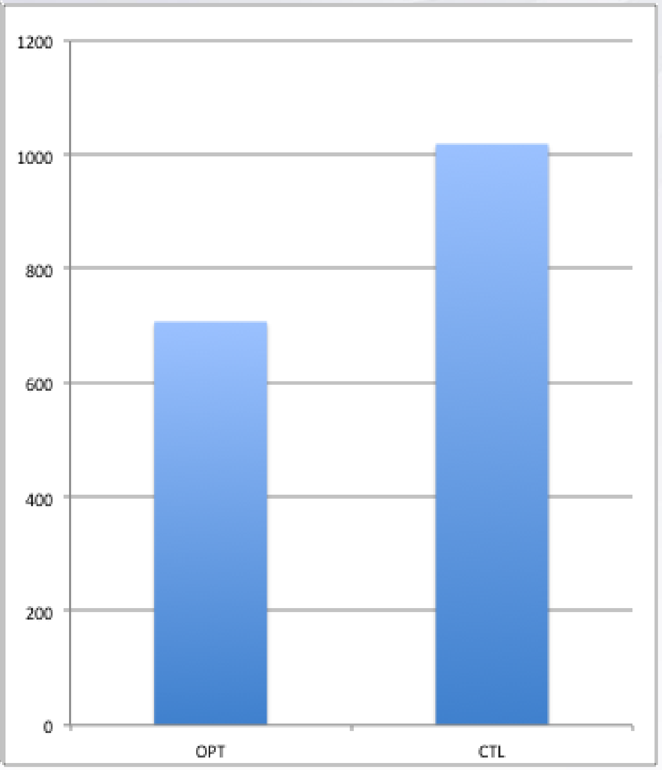
# Model optimization and benchmarking

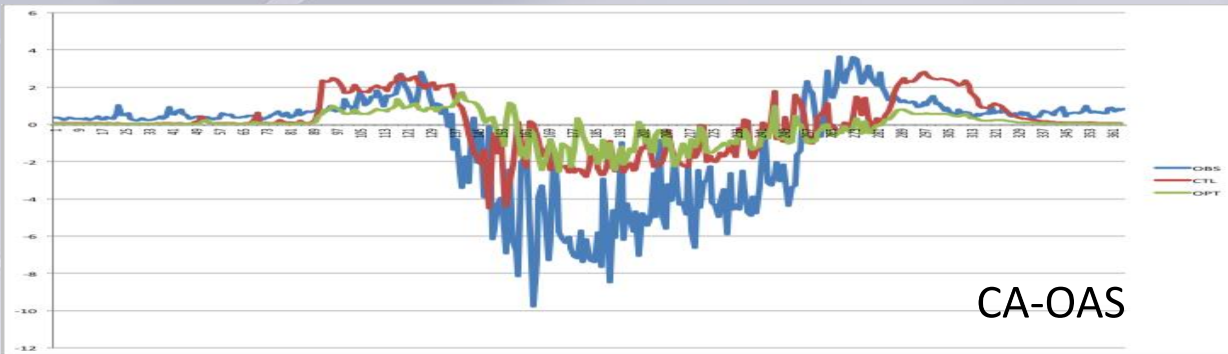
- Example at US-MOz flux site
- Optimized ALM using 2006 NEE data, 30% RMSE reduction
- 1928-2006 simulation, 14 parameters (GA, full model)

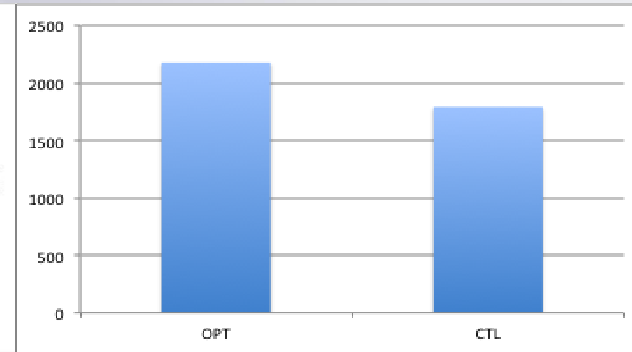


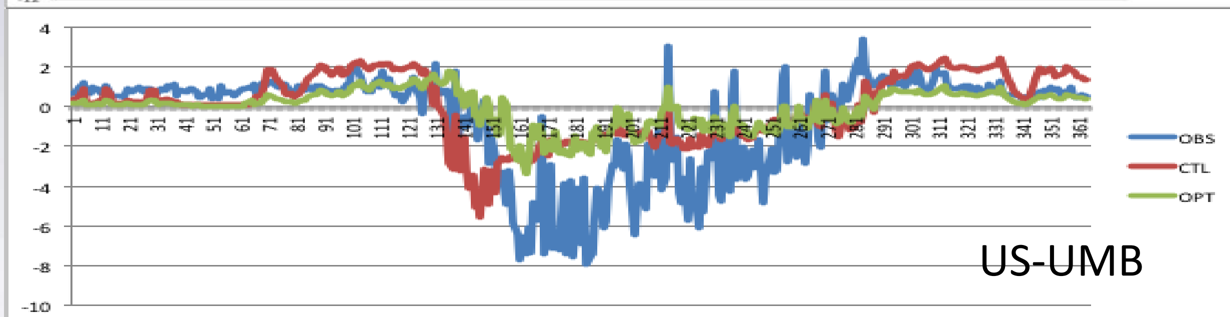



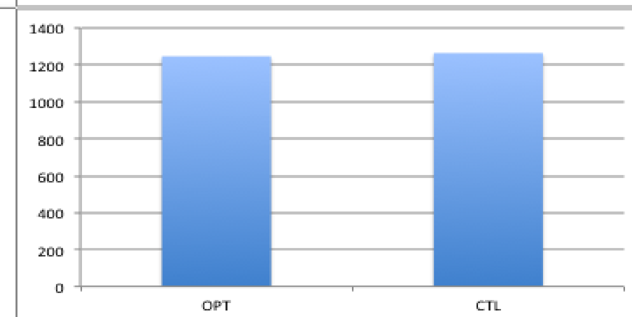
# Model optimization and benchmarking

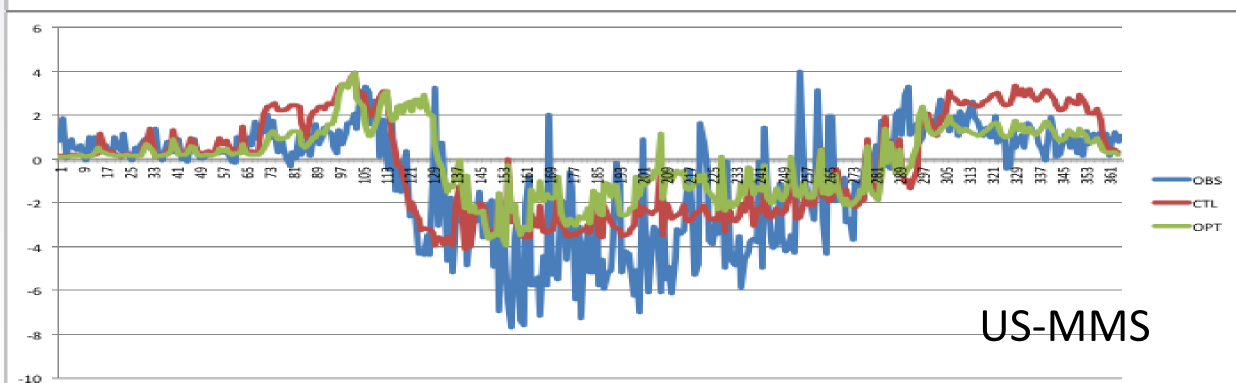
Default “PFT” parameters (benchmark) vs. optimized parameters

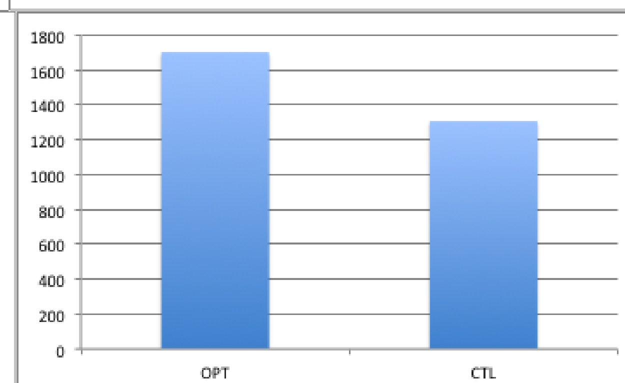


# Multivariate optimization example: CLM at PiTS experimental site

- Pre-treatment observations of variables below
- A single spin-up and transient simulation through 2002 (default PFT-level parameters)
- Ensemble simulations 2002-2012
- 100 iterations of genetic algorithm
- Mao et al (2015)
- Can we increase predictive skill at other sites?

| State variable | Units | Observed | PRE_STD | PRE_OPT | Bias reduction (%) |
|---|---|---|---|---|---|
| Leaf carbon | $\mathrm{g\,C\,m^{-2}}$ | [182, 221] | 419 | 209 | 96.55 |
| Stem carbon | $\mathrm{g\,C\,m^{-2}}$ | [973, 1220] | 1455 | 1027 | 88.49 |
| Root carbon | $\mathrm{g\,C\,m^{-2}}$ | 488 | 859 | 408 | 78.44 |
| Aboveground biomass | $\mathrm{g\,C\,m^{-3}}$ | [728, 1758] | 1645 | 1236 | 98.26 |
| $\delta^{13}$C leaf | ‰ | −27.99 | −27.38 | −27.49 | 18.03 |
| $\delta^{13}$C phloem | ‰ | −28.48 | −27.38 | −27.50 | 10.91 |
| $\delta^{13}$C Root | ‰ | −28.86 | −27.36 | −27.39 | 2.13 |
| Sap flow | $\mathrm{mm\,day^{-1}}$ | 2.40 | 3.70 | 2.37 | 97.85 |
| Soil respiration | $\mu\mathrm{mol\,m^{-2}\,s^{-1}}$ | 3.63 | 5.20 | 3.26 | 76.58 |

# UQ, optimization and benchmarking

- Sensitivity analysis:  Determining which model parameters are sensitive for given benchmarks
  - ALM:  Coherence of sensitivity within and among PFTs
  - Multi-model application will be useful (e.g. PecAn)
- Ensemble benchmarking
  - Consider parameter, driver, and structural uncertainty (compare PDFs of scores rather than individual numbers)
- Model calibration:  Improving predictions
  - Use of a single dataset probably won't increase predictive skill
  - Multivariate optimization, use of emergent constraints
  - Independent data must be reserved for validation/benchmarking
  - Complex LSMs require more sophisticated approaches
  - Opportunity for standardization of workflows