R: Parametric Uncertainty Quantification Workflow for ALM

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Objective

Multi-site, Multi-output Uncertainty Analysis

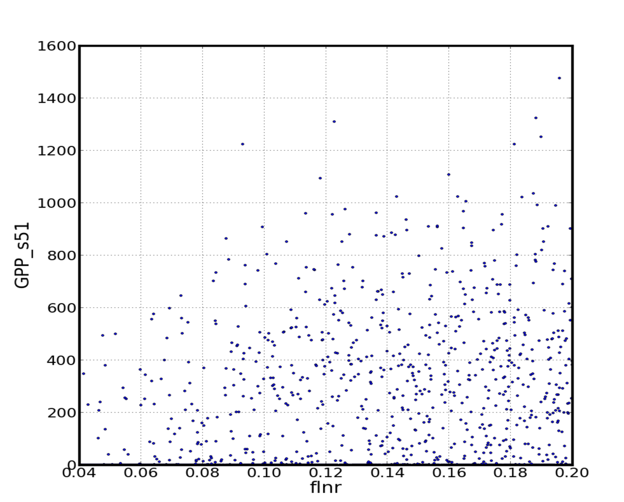
- Decompose output uncertainties into fractional input contributions
- Vary 68 input parameters simultaneously over selected ranges
- Perform global sensitivity analysis for 96 sites and 5 steady state outputs

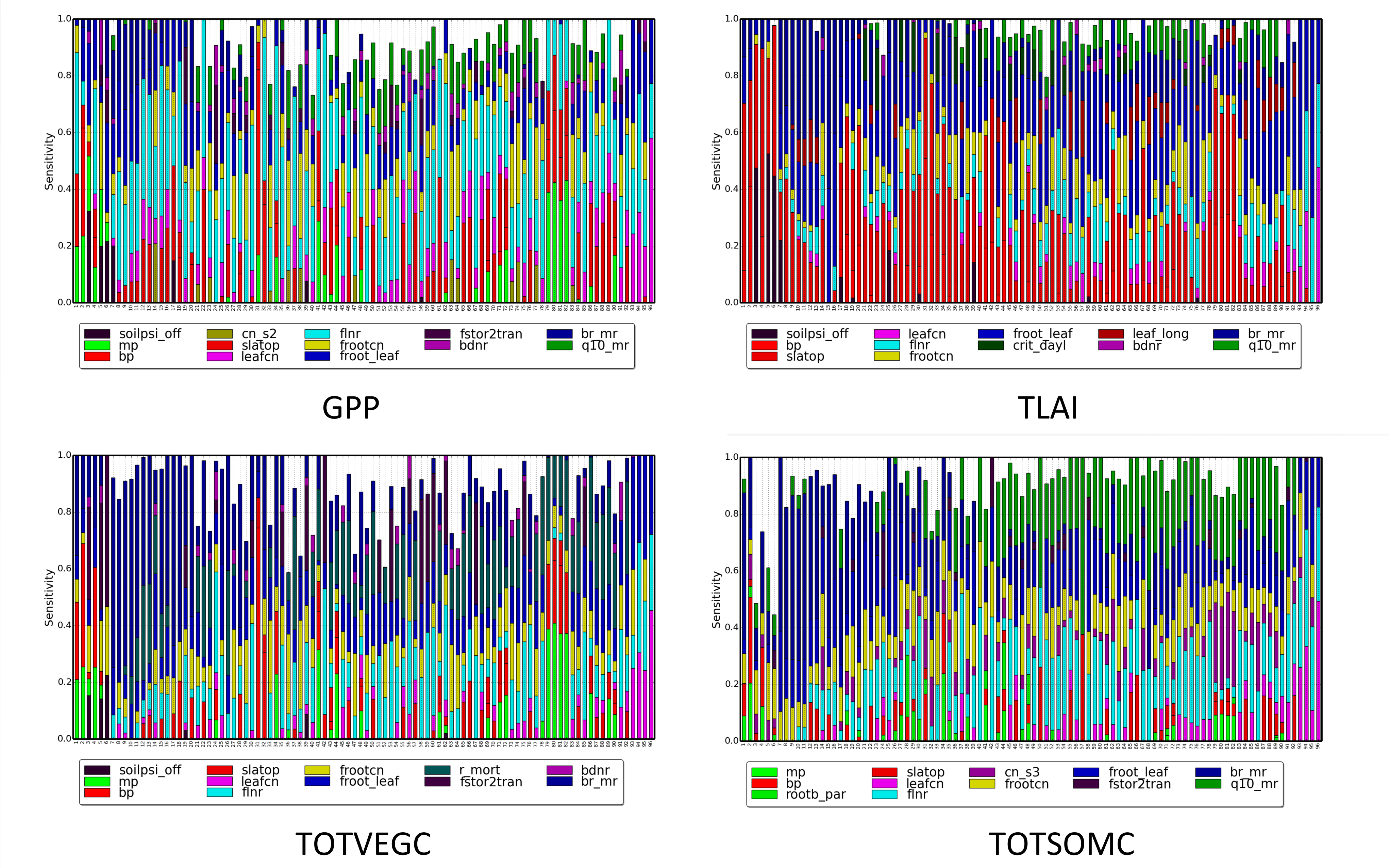
Create a Forward UQ Workflow for ACME v1.0

- Analyze ALM outputs with UQTk v2.2 and Python scripts to interface
- Full workflow is non-intrusive, i.e. model runs as a black-box

Major Challenges

- Large number of parameters / curse of dimensionality
- Expensive simulations / scarce information
- Input parameter dependencies
- Non-linear input-output maps



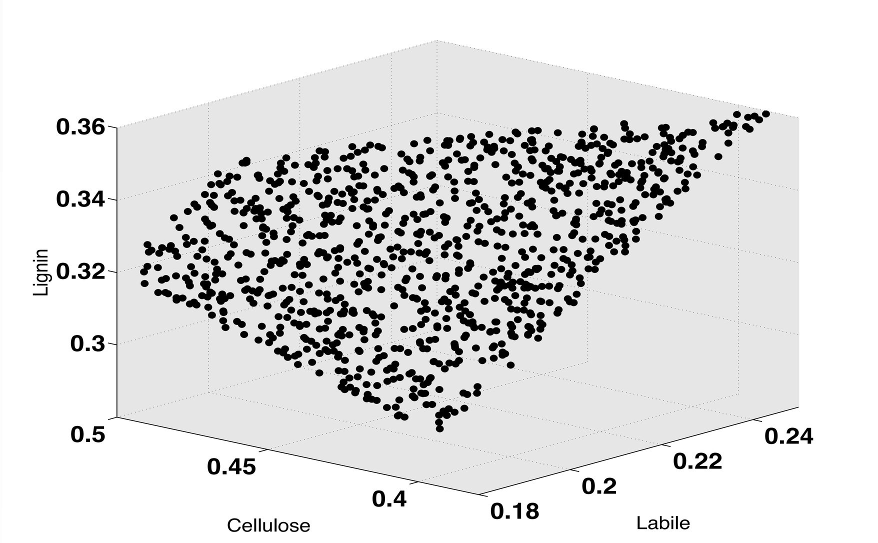


- Multisite sensitivities help extract the most impactful inputs
- The results indicate some site-to-site variability
- Overall coherence of sensitivities across sites covering different climates and PFTs

Approach

Rosenblatt Transformation:

- Create dependent input configurations
- High-D generalization of CDF transform
- Probability-preserving map



Polynomial Chaos Surrogate:

- Cast input/outputs as random variables
- Flexible representation for both forward and inverse UQ

$$y = u(\boldsymbol{x}) \approx \sum_{k=0}^{K-1} c_k \Psi_k(\boldsymbol{x})$$

$$\Psi_k(x_1, x_2, ..., x_d) = \psi_{k_1}(x_1)\psi_{k_2}(x_2)\cdots\psi_{k_d}(x_d)$$

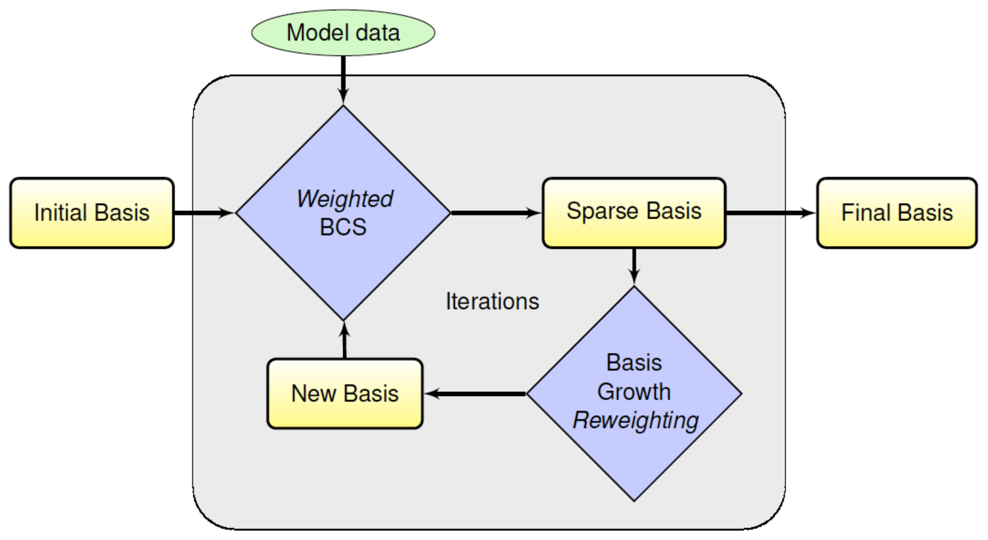
Bayesian Approach:

- Uses any number of model simulations
- Provides an uncertain surrogate with quantified error

$$\underbrace{P(c_k|u(x_j))}_{\text{Posterior}} \propto \underbrace{P(u(x_j)|c_k)}_{\text{Likelihood}} \underbrace{P(c_k)}_{\text{Prior}}$$

Weighted Iterative Bayesian Compressive Sensing:

- Iterative search for most relevant polynomial bases



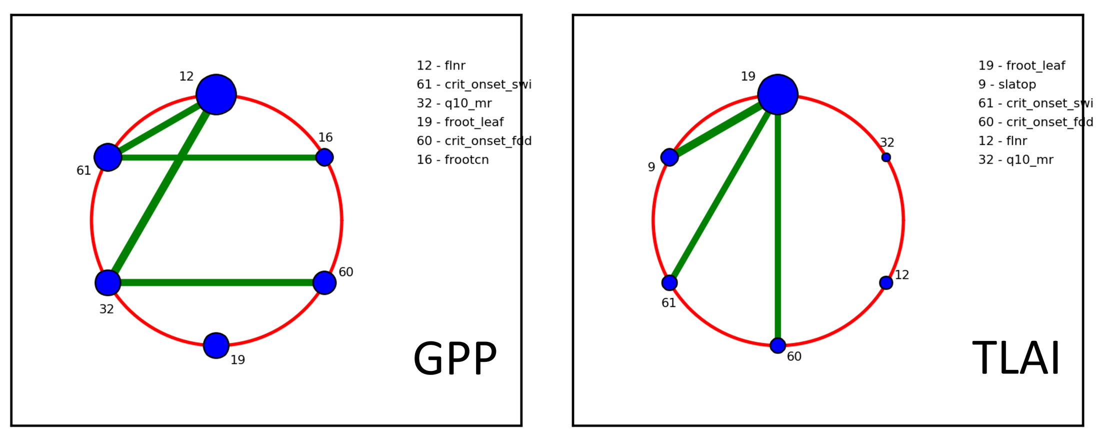
Variance-based Decomposition:

- Sobol sensitivities attribute output uncertainties to input parameters

Impact

Parameter Ranking:

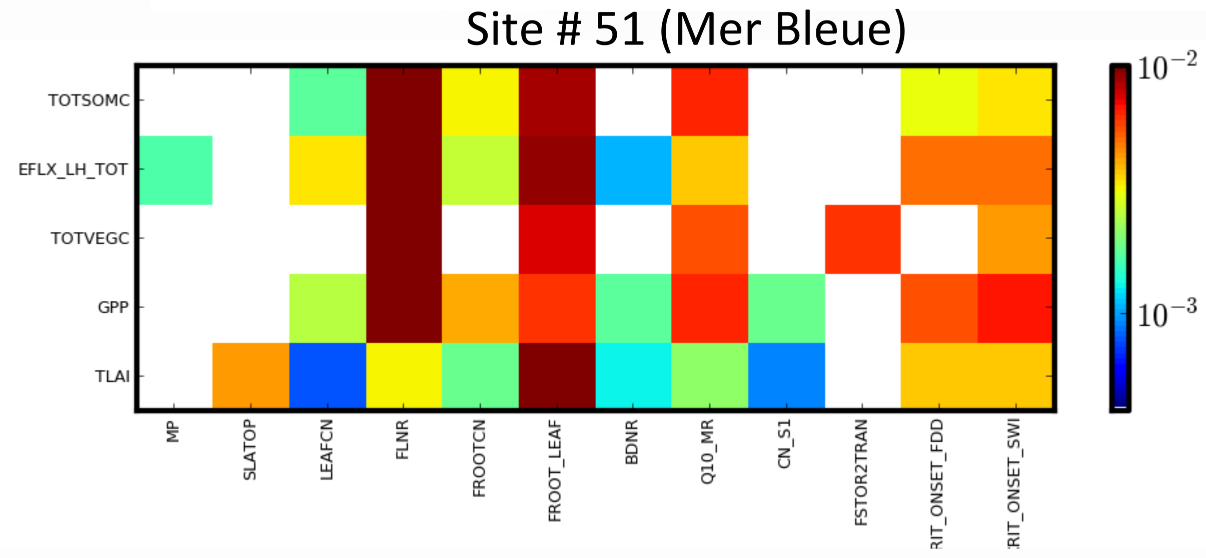
- Provides an efficient parameter ranking by their impact to each output QoI across multiple sites



Dimensionality Reduction:

- Large number of input parameters can be reduced to about 10 without much loss of information

Site # 51 (Mer Bleue)



Key Parameters:

- Leaf and fine root nitrogen
- Fine root allocation
- Leaf longevity, denitrification
- Autotrophic respiration
- Stomatal conductance

Model Surrogate for Multirun Studies:

- Calibration and optimization can proceed using the uncertain model surrogate
- More accurate surrogate in lower-dimensional parameter space

Automated Forward UQ Workflow as a part of ACME v1.0

ACME Accelerated Climate Modeling for Energy

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