Uncertainty Quantification in Accelerated Climate Model for Energy

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Accelerated Climate Modeling for Energy

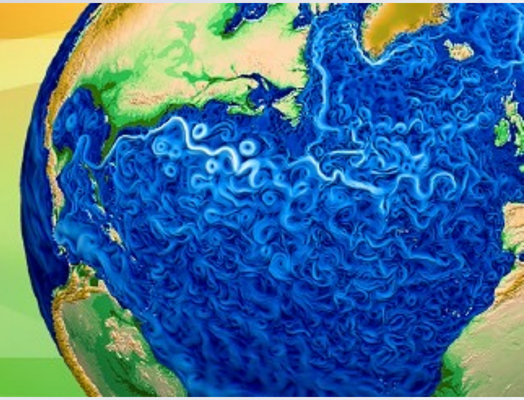
A DOE Model on DOE Machines for the DOE mission

The Accelerated Climate Modeling for Energy is an ongoing, state-of-the-science Earth system modeling, simulation and prediction project that optimizes the use of DOE laboratory resources to meet the science needs of the nation and the mission needs of DOE.

- PI: Dave Bader (LLNL), DOE PM: Dorothy Koch
- Started summer of 2014, funded by **DOE BER**
- 8 DOE Labs, NCAR, a few universities and one company
- 100+ people, ~50 FTE effort, ~$20M per year
- Reformulated effort of existing funding and people
- Branching from existing community models

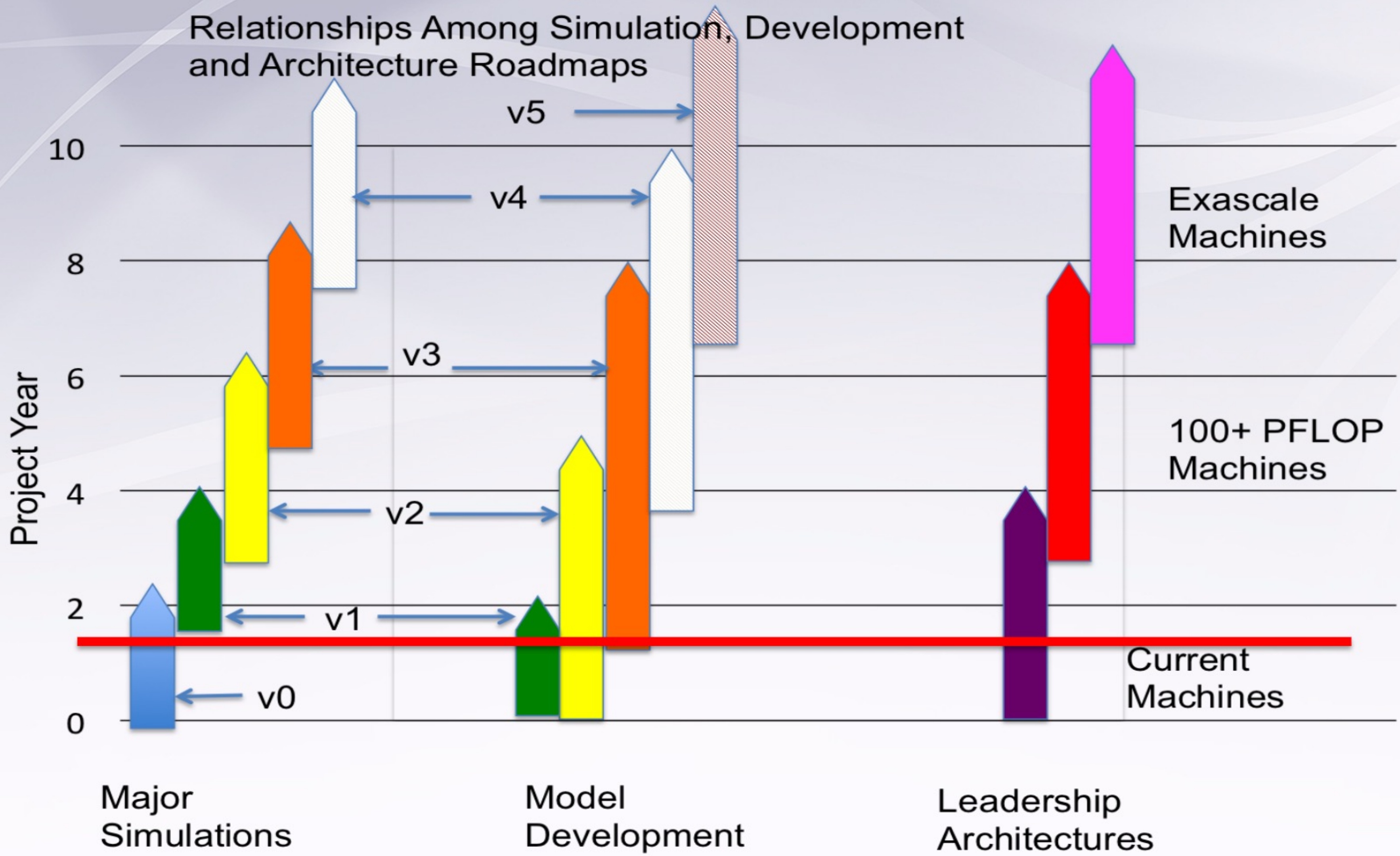
Short overview

ACME
Accelerated Climate Modeling for Energy



- US Department of Energy (DOE) sponsored Earth system model
- Land, atmosphere, ocean, ice, human system components
- High-resolution, employ DOE leadership-class computing facilities
- Addresses energy sector vulnerabilities to climate change and extreme weather

ACME Roadmap



SNL-CA role in ACME: Uncertainty Quantification (UQ) for Land Model

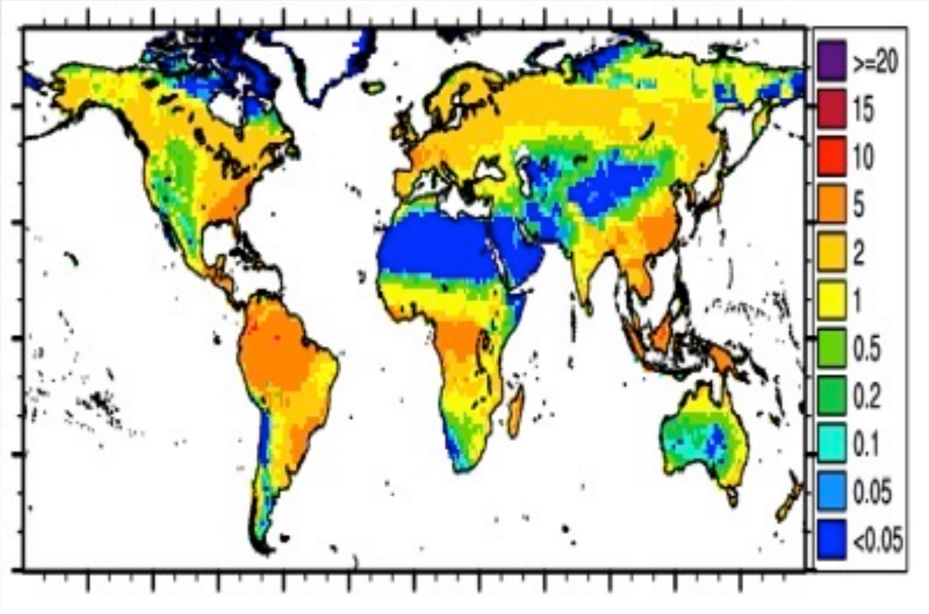
- Current funding based on previous project (CSSEF) with Habib Najm (8351), Bert Debusschere (8351), Cosmin Safta (8954)
- ACME focus is on science development, but still….

… automated parameter sensitivity, tuning and prediction uncertainty assessment are needed.

- UQ Lead: K. Sargsyan, 0.5 FTE
- Direct collaboration with ORNL and PNNL scientists

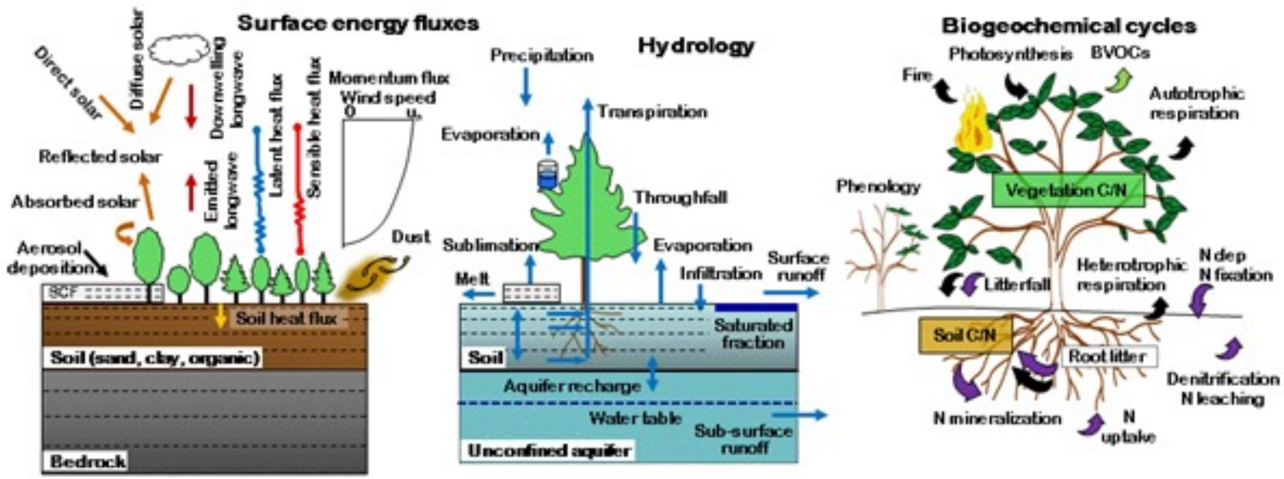
Relevance of Land Model for Climate

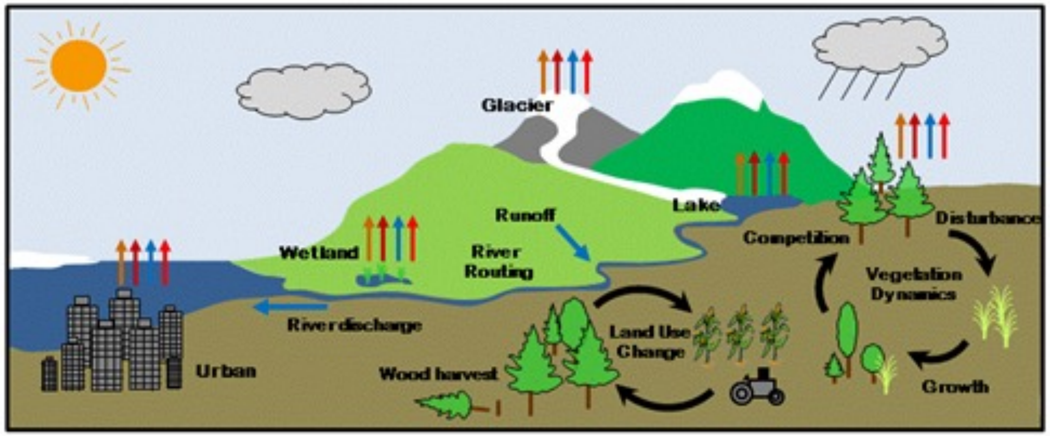
- Carbon fluxes: how much CO2 is taken up/released by ecosystems?
- Energy fluxes: sensible and latent heat from land surface
- Land surface albedo: soil and vegetation
- All of these processes have high uncertainty



Gross Primary Productivity, gC/(m² day)

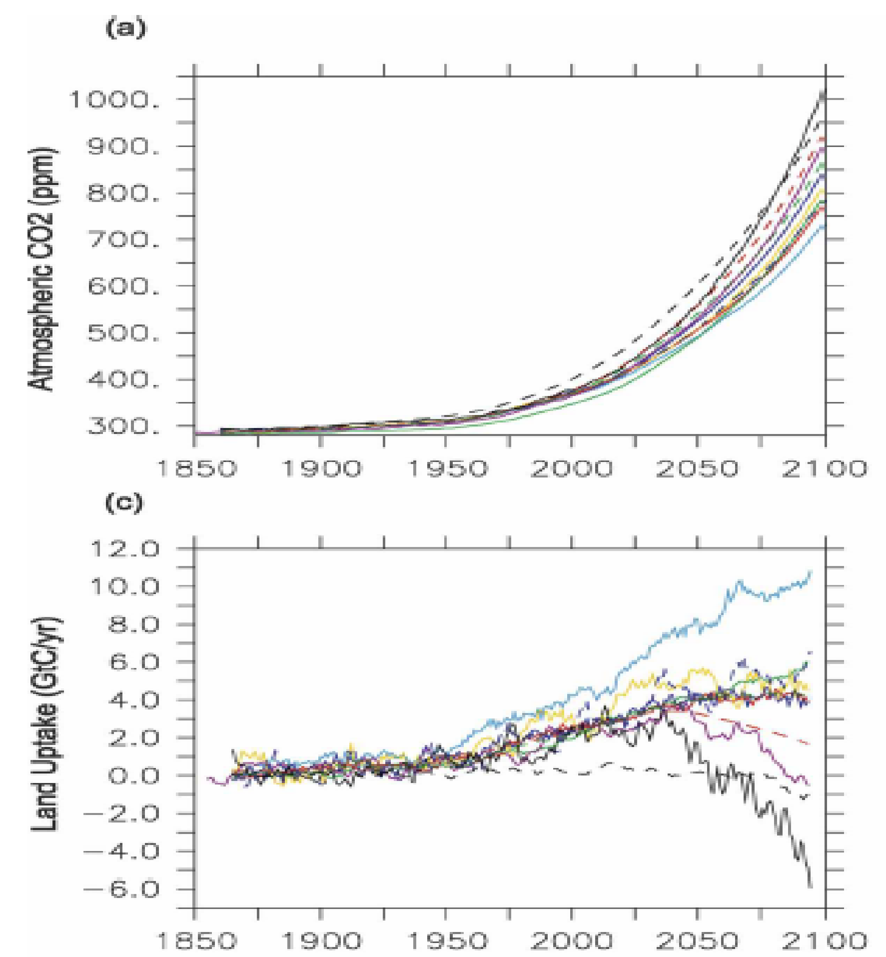
ACME Land Model





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

Major UQ challenges for climate models

- High dimensionality (too many parameters)
- Expensive models (a single run is a few hours)
- Scarce information
- Inputs are very uncertain, and not independent
- Strongly nonlinear response
- [Elephant in the room] Structural uncertainties!

What we do:

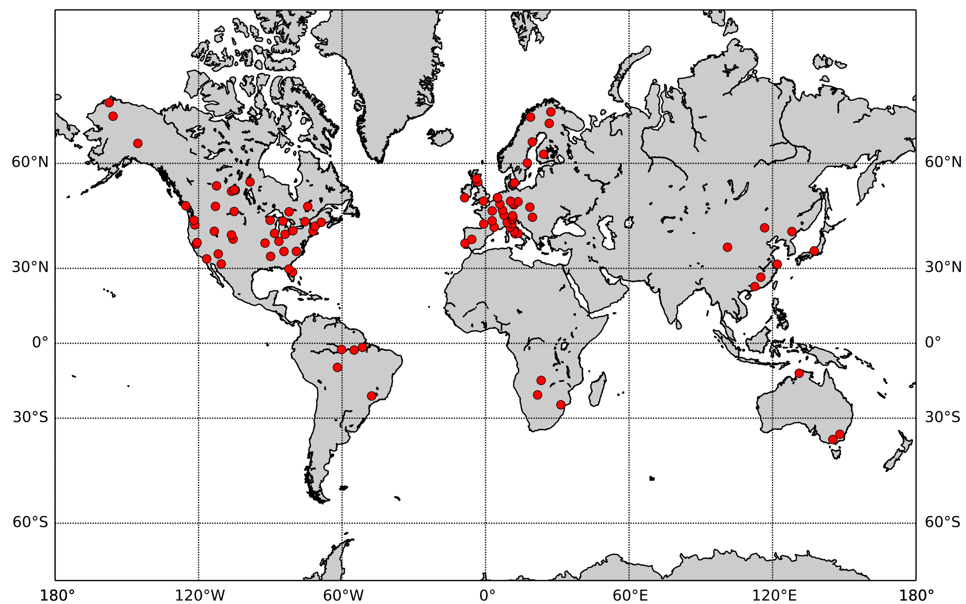
- Developing/enhancing statistics and machine learning tools for UQ in physical models

Technical details

- Expensive model
  - Create surrogate (response surface, emulator, metamodel, …)
    - Polynomial Chaos surrogate
- High-dimensionality
  - Sparse learning methods (compressive sensing)
    - **Weighted Iterative Bayesian Compressive Sensing**
- Non-linear, non-differentiable response
  - Prepend data classification
- Input dependence
  - Non-trivial sampling approaches, e.g. Rosenblatt transformation

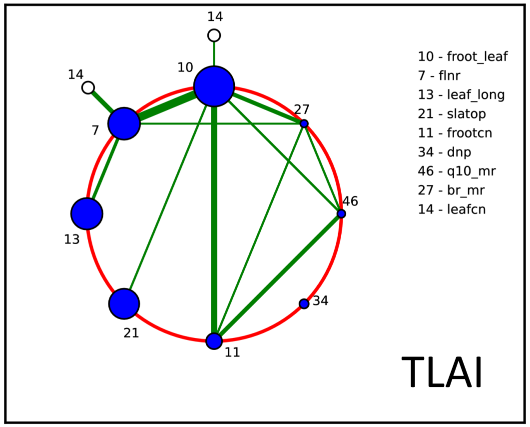
Forward UQ Analysis for Multiple Sites

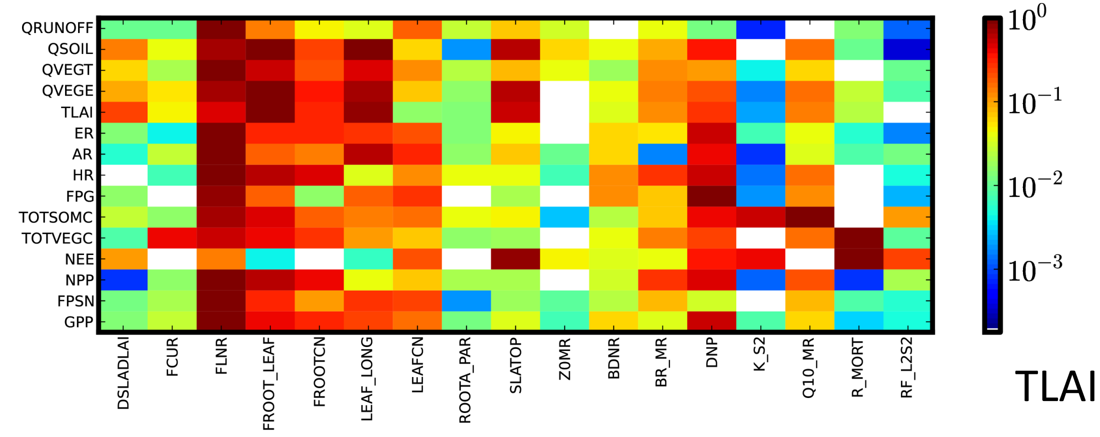
- 96 FLUXNET sites covering major biomes and plant functional types
- Varying 68 parameters over given ranges
- Ensemble of 3000 ACME Land Model runs on Titan (ORNL supercomputer)
- The goal is to build surrogate models and to perform parametric uncertainty decomposition

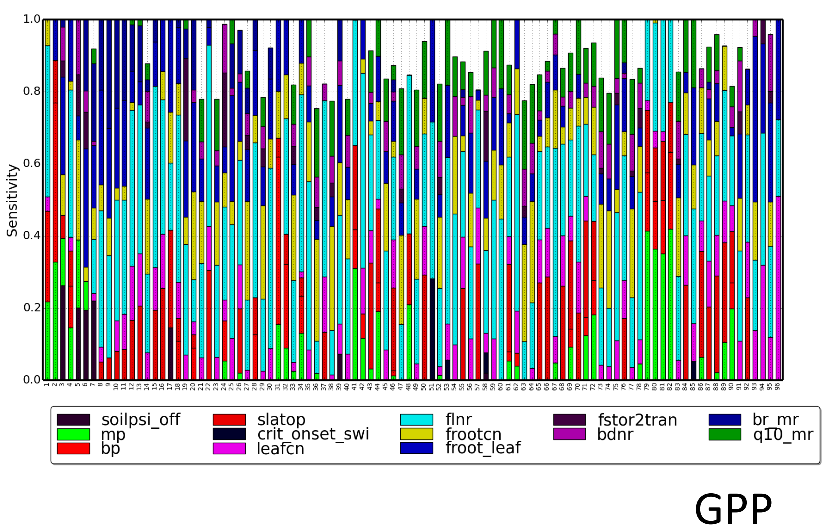


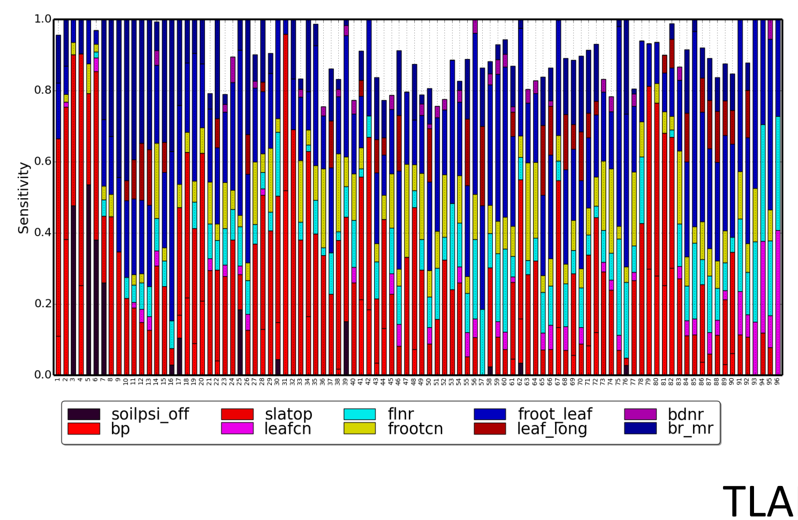
FLUXNET sites

Uncertainty Decomposition / Global Sensitivity Analysis









Current / Future

- Forward UQ workflow for automatic parameter ranking
- Interface to UQTk v2.2 (www.sandia.gov/uqtoolkit)
- Uncertainty decomposition, global sensitivity analysis
- Dimensionality reduction

- Create automatic workflow for Inverse UQ
- Calibration: parameter tuning with surrogates
- More accurate, adaptive surrogates

- Structural errors, extrapolative scenarios