Development of optimization and posterior inference tools in NASA Land Information System (LIS)

Sujay V. Kumar^a, Ken W. Harrison^a, Soni Yatheendradas^a, Joseph A. Santanello^a, Christa D. Peters-Lidard^a and Rolf H. Reichle^b

a – Hydrological Sciences Branch, NASA Goddard Space Flight Center, Greenbelt, MD b-Global Modeling and Assimilation Office, NASA Goddard Space Flight Center, Greenbelt, MD

LIS Overview

- A comprehensive land surface modeling and data assimilation system (Kumar et al. 2006, Peters-Lidard et al. 2007, <u>http://lis.gsfc.nasa.gov</u>).
- Integrates satellite- and ground-based observational data products with land surface modeling techniques.
- Capable of modeling at different spatial (up to 1km and finer) scales, over global, regional, and point scales.
- Incorporates a large suite of land surface models, a variety of meteorological and land surface parameter data, and computational infrastructure for fine scale modeling.



- Coupled land-atmosphere systems using the Earth System Modeling Framework (ESMF)that employ LIS as the land surface component (Kumar et al. 2007).
- LIS-WRF (Weather Research and Forecasting model).
- Forward modeling and radiance assimilation capabilities through radiative transfer models (e.g. CRTM).
- Infrastructure for optimization/inverse modeling and uncertainty estimation.

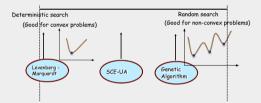




- Advanced algorithms such as the Ensemble Kalman Filter (EnKF).
- Interoperable system that allows the integrated use of multiple land surface models, multiple observations, and multiple data assimilation algorithms.
- th and the deal of the set of t

Optimization/Uncertainty Estimation Infrastructure

- To improve the representation of parameters at the spatial scale of interest and to improve the efficiency of data assimilation by enabling unbiased model predictions.
- The current infrastructure includes a suite of optimization algorithms that capture the spectra of search strategies, ranging from techniques such as Levenberg-Marquardt (LM; suited for convex optimization problems) to techniques better suited for non-convex optimization problems such as Genetic Algorithm (GA) and Shuffled Complex Evolution from University of Arizona (SCE-UA).



The uncertainty estimation component is designed to include a range of techniques ranging from simple informal approaches of Generalized Likelihood Uncertainty Estimation (GLUE) to more complex, formal Bayesian approaches such as the Differential Evolution Adaptive Metropolis (DREAM) Markov Chain Monte Carlo (MCMC) scheme (Vrugt et al. 2009).

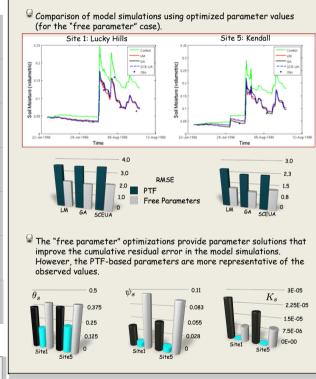
Case Study

- Objective : Parameterize soil properties for estimation of soil moisture.
- Observations: Estimates of near surface soil moisture derived from passive (Lband) microwave remote sensing using NASA's push broom microwave radiometer (PBMR) during Monsoon'90 experiment (23 July - 9 Aug, 1990) in Southeastern Arizona.



- Noah land surface model employed at 40m spatial resolution across the Walnut Gulch experimental watershed.
- Two sets of optimization simulations: (1) that adjust the sand, clay soil fractions, which in turn control the hydraulic properties through the use of pedotransfer functions (PTF) and (2) that adjust the soil hydraulic properties themselves ("Free parameters").

Results



Ongoing Work

- Implementation of a suite of uncertainty estimation techniques (GLUE, DREAM).
- * "Beyond the best fit" techniques to assess predictive uncertainties.
- [#] Combining techniques for data assimilation (to improve state estimation), optimization (to improve parameter estimation) and uncertainty modeling (to provide formal characterization of different sources of uncertainty).
- Acknowledgements: We gratefully acknowledge the financial support from the NASA Earth Science Technology Office (ESTO) and the US Air Force Weather Agency (AFWA).