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Entropy-Bayesian Inversion of Hydrological Parameters in the Community Land Model Using Heat Flux and Runoff Data

Z HOU, M HUANG, PNNL; J RAY, L SWILER, SNL

Pacific Northwest National Laboratory; Sandia National Laboratory Mar 31 2014

Outline



Motivation

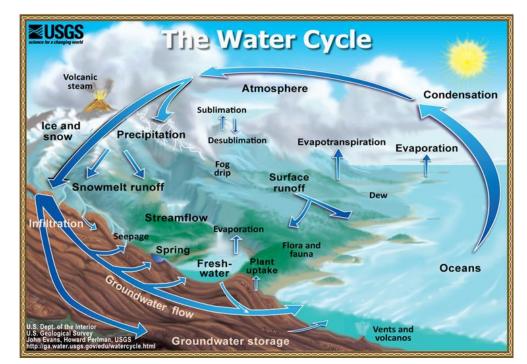
To reduce uncertainty in the Earth system models and improve prediction capability

Background

- Sources of uncertainty
- Uncertainty identification and representation
- Parameter ranking/screening
- Surrogate / ROM development
- System classification
- Stochastic calibration/inversion
 - MCMC-Bayesian using numerical forward models and/or surrogates
 - Multi-chain MCMC
- Entropy (minimum-relative-entropy, MRE) approach for uncertainty quantification (UQ) and Bayesian inversion
 - UQ based on MRE-derived prior probability density functions
 - Bayesian inversion using MRE-priors

Motivations

- Complex physical phenomena are of multi-phase, multi-component, and involve multiple biogeophysical/biogeochemical processes
- Integrated models introduce numerous model and coupling parameters and therefore formidable high-dimensional parameter spaces
- Many model parameter values were assigned without calibration which results in significant modeling errors (e.g., mismatches between observed and simulated flow and energy fluxes in land surface models)



Sources of Uncertainty



Model uncertainty

Simplifications, structural model formulations/structures, extrapolations, resolution, model initial/boundary conditions

Data uncertainty

Instrumental errors, consistency, gaps, resolution, scaling

- Natural uncertainty/variability/heterogeneity
 - Intrinsic quantities vary over time, over space, or across individuals in a population
 - Physical processes/mechanisms/features vary over space, time, and individuals
- Parameter uncertainty
 - Non-measurable, measurement errors, non-uniqueness, inaccurate calibration, mis-classification due to under-sampling...

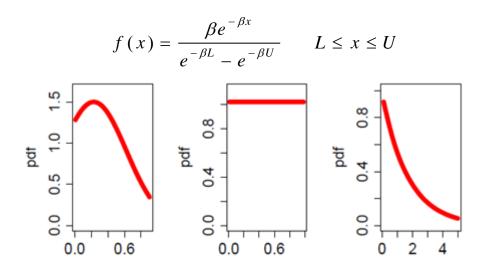


- Sensitivity analyses
- Direct survey data hard information
- Indirect observations for inference soft information
- Classification of systems
- Filtering, gap filling, decomposition, co-kriging
- Surrogates (ROMs) for system predictions and risk analyses
- ► Parameter significances → guidance on conceptual model development and improvement

Uncertainty Representation – MRE priors

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- In practice, measurements are not available, given prior knowledge including databases and experiences, close-form pdfs can be derived using minimum-relative-entropy (MRE) concept (Hou and Rubin 2005):

$$f(x) = \frac{\sqrt{\frac{\gamma}{\pi}} \exp\left[-\gamma \left(x + \frac{\beta}{2\gamma}\right)^2\right]}{\Phi\left[\sqrt{2\gamma} \left(U + \frac{\beta}{2\gamma}\right)\right] - \Phi\left[\sqrt{2\gamma} \left(L + \frac{\beta}{2\gamma}\right)\right]} \qquad L \le x \le U$$



MRE priors for major hydrological parameters in Land Modeling

0.010 0.025

S,



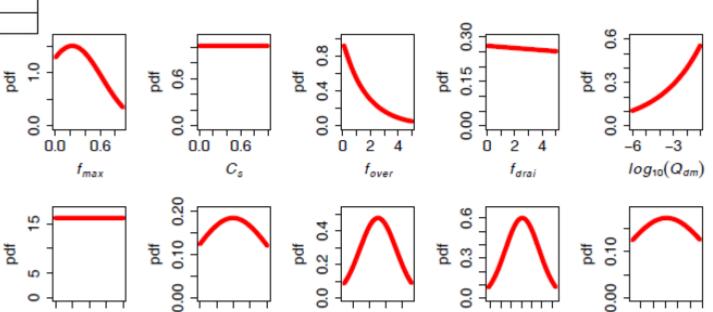
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35

50

θs

Symbol	Definition
I max	Max fractional saturated area, from
	DEM
C _s	Shape parameter of the topographic
	index distribution
fover	Decay factor (m ⁻¹) for fsat
Ь	Clapp and Homberger exponent
Ks	Hydraulic conductivity (mm s ⁻¹)
θ_{s}	porosity
Ψ_{s}	Saturated soil matrix potential (mm)
f _{drai}	Decay factor (m ⁻¹) drainage
q _{drai,max}	Max drainage (kg m ⁻² s ⁻¹)
S.	Average specific yield



0

2

 $log_{10}(\psi_s)$

20

10

b

0

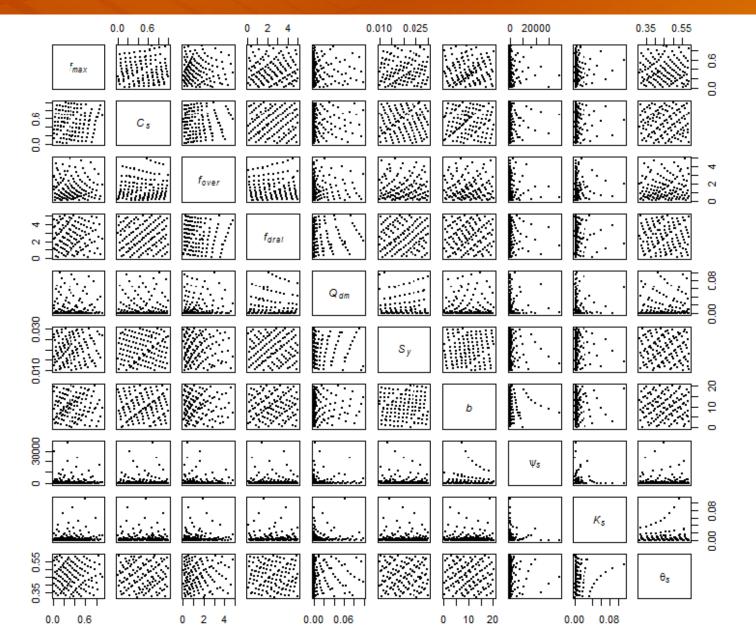
-2.0 0.0

 $log_{10}(K_s)$

MRE-priors for UQ and SA: sampling



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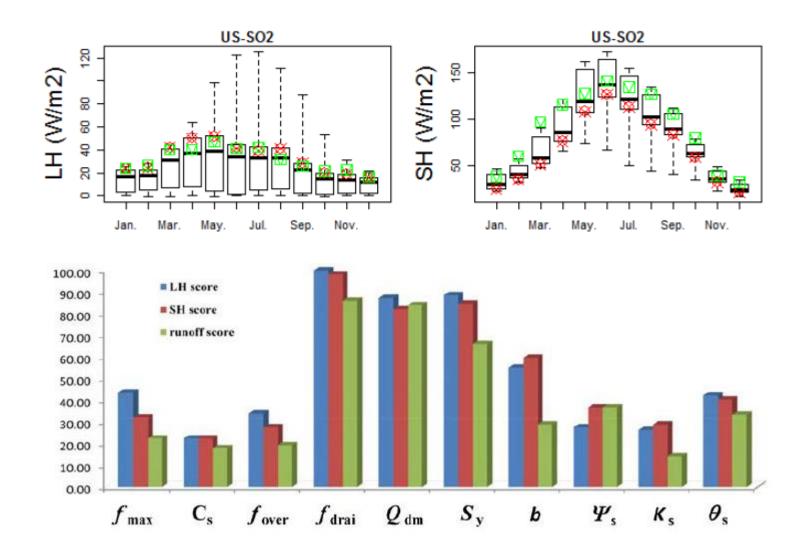


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MRE priors for UQ and SA: response surface and parameter ranking



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▶ Bayesian updating: f(m/d,I) ∝ f(d/m,I)* f(m/I)
▶ Prior pdf

$$f_{\boldsymbol{M}|\boldsymbol{I}(\boldsymbol{m}|\boldsymbol{I})} = \prod_{j=1}^{p} \frac{\sqrt{\frac{\gamma_{j}}{\pi}} \exp\left[-\gamma_{j}(m_{j} + \frac{\beta_{j}}{2\gamma_{j}})^{2}\right]}{\Phi\left[\sqrt{2\gamma_{j}}\left(U_{j} + \frac{\beta_{j}}{2\gamma_{j}}\right)\right] - \Phi\left[\sqrt{2\gamma_{j}}\left(L_{j} + \frac{\beta_{j}}{2\gamma_{j}}\right)\right]}$$

Likelihood function

$$f_{D|\boldsymbol{M},\boldsymbol{\Sigma},\boldsymbol{I}(\boldsymbol{d}^*|\boldsymbol{m},\boldsymbol{\Sigma},\boldsymbol{I})} = \frac{1}{\sqrt{2\pi|\boldsymbol{\Sigma}|}} \left[\exp\{-\frac{1}{2} \left(\boldsymbol{d}^* - \boldsymbol{G}(\boldsymbol{m})\right)\boldsymbol{\Sigma}^{-1} \left(\boldsymbol{d}^* - \boldsymbol{G}(\boldsymbol{m})\right)^T\} \right]$$



- Metropolis-Hasting sampling with community land model simulator as the forward model (Sun et al 2013)
- MCMC inversion using computationally-efficient surrogates (Ray et al 2014, presentation MS29 Apr 1 2014, 9:30-9:55)

Entropy-Bayesian inversion has the following features:

- Honor all the prior knowledge in the form of MRE prior pdfs
- Enables simultaneous ensemble sampling and therefore parallel computing
- Can estimate dependence structure (i.e., Σ) of residuals ε=d-G(m) (differences between observed and simulated responses such as heat fluxes and streamflow rate), and help reduce data redundancy



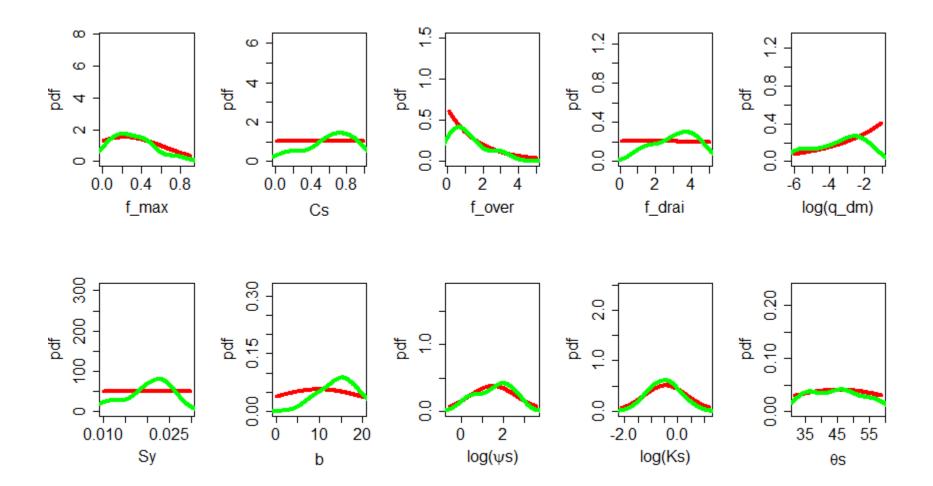
- Derive closed-form prior pdfs using MRE theory, given bounds and statistical moments information about unknown parameters to be calibrated
- 2. Generate the first ensemble of parameter sets and simulate the land models in a task-parallel manner
- 3. Calculate the residuals at each data points for each sample set and then the error covariance matrix and likelihood functions
- 4. Generate a new ensemble of parameter sets from the current intermediate posterior pdfs
- 5. Repeat steps 3 and 4 until convergence of posterior pdfs

Posterior pdfs of hydrological parameters at US-ARM flux tower site

Entropy-Bayesian procedure has been applied to the latent heat flux observation data for calibrating the major hydrological parameters

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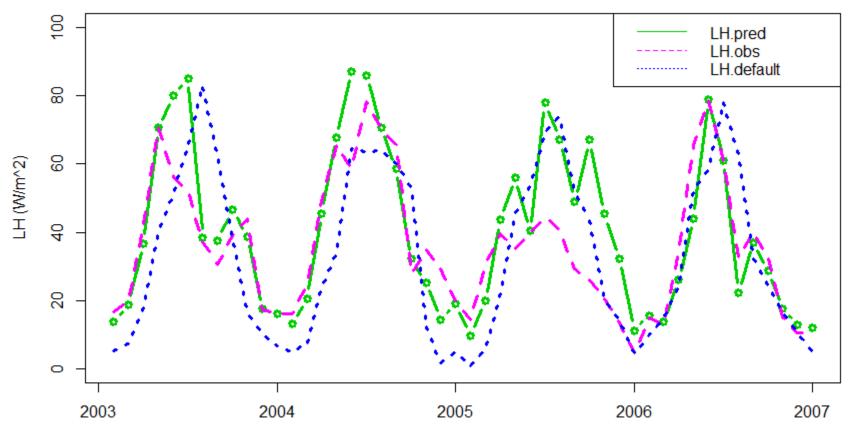
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Posterior pdfs of hydrological parameters at US-ARM flux tower site



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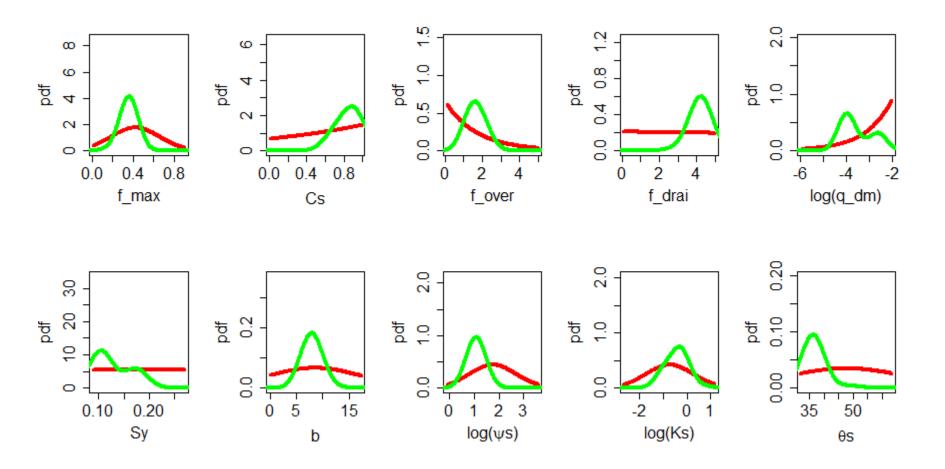
year

Posterior pdfs of hydrological parameters at a MOPEX basin (id 07147800)

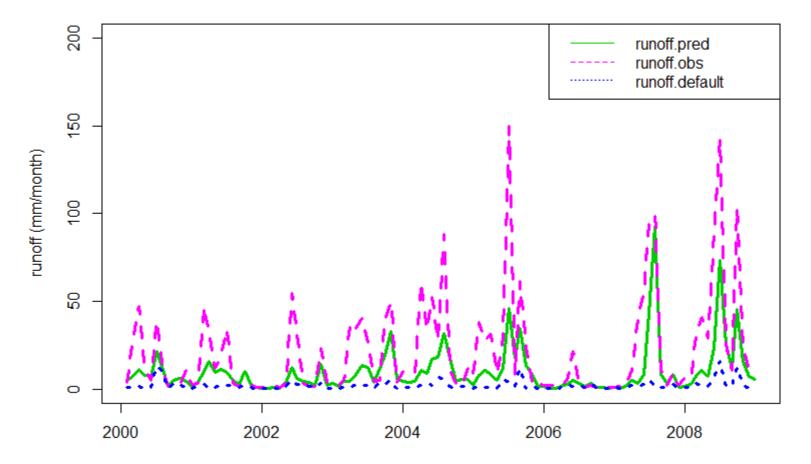
Entropy-Bayesian procedure has been applied to the runoff (streamflow) data for calibrating the major hydrological parameters

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Posterior pdfs of hydrological parameters at US-ARM flux tower site



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year

Summary



- Entropy (MRE) concept can be used to derive prior probability density functions that serves as the basis for further sensitivity analyses, parameter screening, uncertainty propagation, and surrogate development
- Integrated Entropy-Bayesian inversion enables ensemble sampling and task parallel computing, which helps reduce the computational time to achieve posterior estimates of unknown parameters
- Entropy-based UQ and Bayesian calibration have been applied to various flux tower sites and US MOPEX basins, for improving the Community Land Model (CLM) –
 - significant improvement in the modeling accuracy can be achieved using the calibrated parameters than using the existing hard-coded values