Estimating a model discrepancy term for the Community Land Model using latent heat and runoff observations

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Introduction

- Aim: Calibrate the Community Land Model (CLM) using time-series measurements of latent heat and runoff
  - Bayesian calibration of 3 hydrological parameters w/ uncertainty
  - Estimate structural error (model-form error)
  - Compare with calibration done with each data type individually
- Site
  - US-MOz (latent heat) and MOPEX site # 7186000 (runoff)
- Why?
  - Structural error impairs a model's ability to reproduce all observables well
- Challenges
  - CLM is expensive – 45 minutes/invocation per site;
  - No. of model invocation needed for Bayesian calibration = $O(10^4)$

What is CLM?

- A model for biogeochemical & hydrological processes
- Used in Earth system models; coupled to an atmosphere & ocean model
- Can be used in global (gridded) mode or locally for a site ("bucket" mode); can be driven by real meteorology
- Distributed by NCAR; has hard-coded parameters ("nominal values") which are meant to provided good global predictions
- When used in local mode, the parameters have to re-calibrated to be representative of local hydrological and biogenic processes
  - But it is not known whether calibrating to 1 data stream (e.g. latent heat) makes it predictive for all other observables
  - This is a type of structural error

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What is structural error?

- The fundamental inability of a model to reproduce observations
  - Caused by missing physics in the model
- Previous work[1] has shown that calibrating to latent heat (LH) observations makes CLM predictive for LH
  - And it has a modest structural error that can be modeled as i.i.d. Gaussians
  - This does not show if the calibrated model can reproduce other observables like runoff
- This study
  - Calibrate using runoff; see what parameter estimates are like and how well we reproduce runoff
  - Then calibrate jointly on runoff and LH and see whether we still reproduce observations well
  - And how far the parameter estimates are from nominal values

[1]Ray et al, Bayesian calibration of the Community Land Model using surrogates, SIAM J. Unc. Quant., accepted January 2015

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The observations

- Data covers 2004-2007, 48 months
- Latent heat (LH) observations, $Y^{(obs)}_{LH}$
  - Obtained from US-MOz – a site in Missouri Ozark mountains
  - Averaged monthly, and then climatologically averaged to provide a 12-month time-series
- Runoff observations, $Y^{(obs)}_{WPC}$
  - Very noisy and not very useful as-is
  - We take a wavelet transform and use the amplitude-squared (wavelet power) at each time-scale as the observations
    - Called wavelet power curve (WPC)
  - We retain time-scales between 21 days and 4 years for calibration
- Sensitivity analysis showed that LH and WPC are most sensitive to 3 hydrological parameters – $\mathbf{p} = \{F_{drai}, Q_{dm}, S_y\}$
  - These will be our calibration variables

Bayesian inference

- Model paramters p = {F_{drai}, $\log_{10}(Q_{dm})$, S_y} estimated with the model errors
  - $Y^{(obs)}_{LH} = M_{LH}(p) + \varepsilon_{LH}$, $\varepsilon_{LH} \sim N(0, \sigma^2_{LH})$
  - $Y^{(obs)}_{WPC} = M_{WPC}(p) + \varepsilon_{wpc}$, $\varepsilon_{wpc} \sim N(0, \sigma^2_{wpc})$
  - σ^2_i, i ε {LH, WPC} is a crude measure of structural error in CLM
- Our prior beliefs (PDFs) for each parameter in {F_{drai}, $\log_{10}(Q_{dm})$, S_y} are independent, uniform distributions with prescribed upper & lower bounds
- Posterior distribution $P(p, \sigma^2_{LH}, \sigma^2_{WPC} | Y^{(obs)}_{LH}, Y^{(obs)}_{WPC})$

$$P(F_{drai}, \log_{10}(Q_{dm}), S_y \mid Y^{obs}_{LH}, Y^{obs}_{WPC}) \propto \exp\left(-\frac{\left(Y^{obs}_{LH} - M_{LH}(p)\right)^2}{\sigma^2_{LH}} - \frac{\left(Y^{obs}_{WPC} - M_{WPC}(p)\right)^2}{\sigma^2_{WPC}} \right) \pi(p)$$

- Solved using an adaptive Metropolis algo – DRAM

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Surrogate models

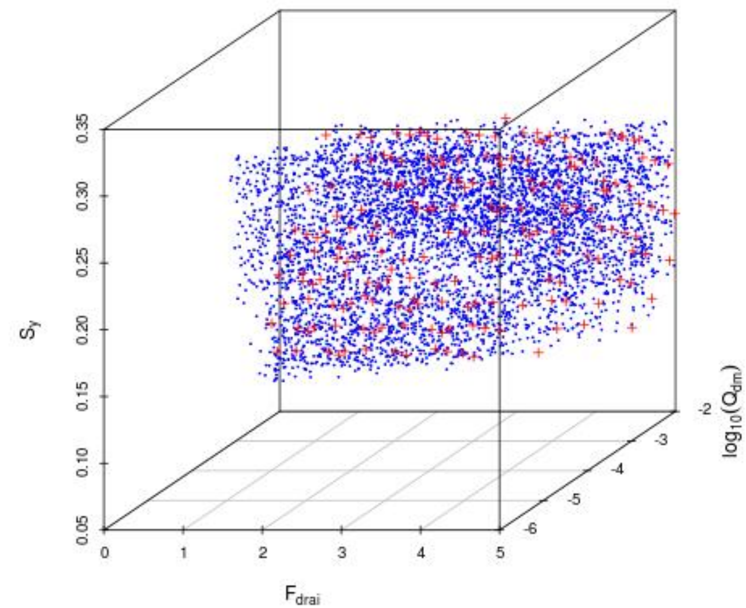
- The inverse problem needs about 50K invocations of CLM
  – Can’t be done today, so we make surrogates
- Surrogate details
  – We sample the (F_{drai}, $\log_{10}(Q_{dm})$, S_y) space with 282 points chosen via a quasi Monte Carlo space-filling method
  – CLM is run at these points; we save climatologically averaged predictions of LH and runoff
  – This is our training set
- Models are curve fits – express Y = *M(p)*
  – You have to pick *M* and fit to data
  – You need some way to check against overfitting - cross-validation, AIC etc.
  – Invariably latent heat or runoff needs to be transformed before being able to fit *M*

Latent heat surrogate models

- Transformations
  - 48 months of LH data is climatologically averaged, then log transformed
- Proposed a 5th order polynomial for $M_{LH}(p)$
  - Used AIC to simplify the model down to quadratic
  - Use randomized subsample validation tests to check for overfitting
  - Separate model for each month
  - The final fitted polynomial model has 10% - 20% errors – not good enough
- Regression kriging
  - Used quadratic as a mean/trend model and stationary Gaussian Process model around it (to combat 10%-20% discrepancy)
  - All models' errors dropped below 10%

Runoff surrogate models

- WPC surrogates
  - Surrogate could only be made for a subspace of (F_{drai}, $\log_{10}(Q_{dm})$, S_y) space
  - Computed the MSE of each training run wrt observations & discarded the worst 25%
  - The retained parameters covered a region $\mathcal{R}$ of the parameter space
  - Within $\mathcal{R}$, $M_{WPC}(p)$ could be modeled using quadratic polynomials
- We redefine our prior
  - $\pi(p) = 1$, $p \in \mathcal{R}$, 0 otherwise

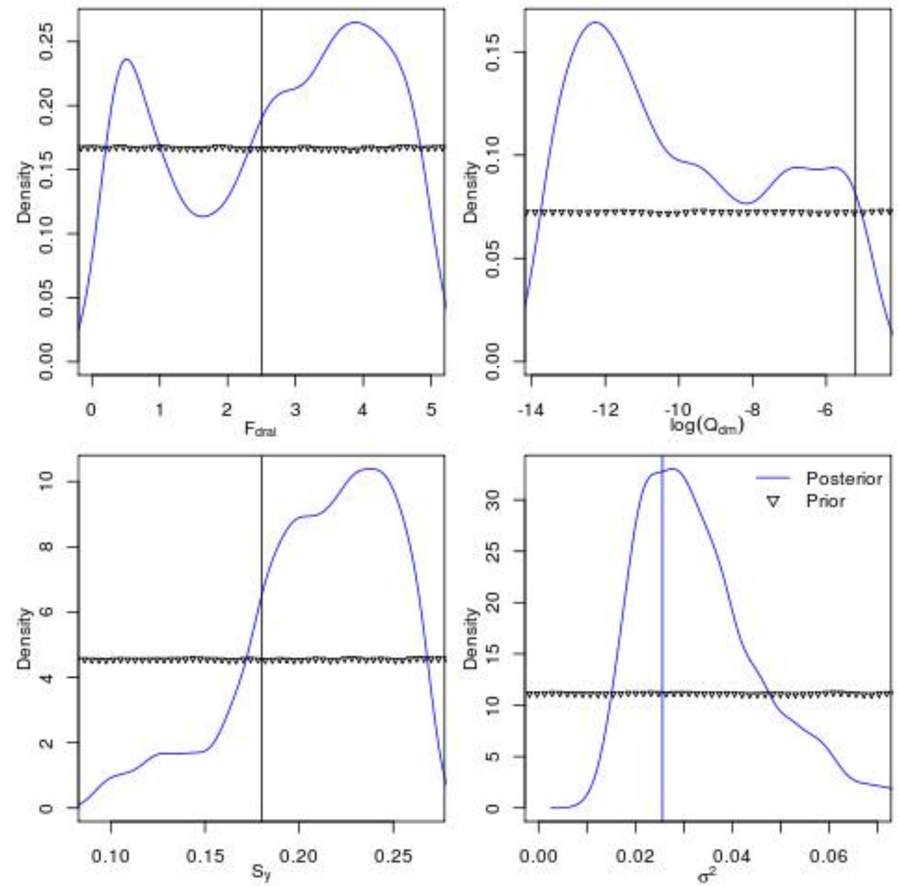


$\mathcal{R}$ defined using a SVM classifier trained on selected & discarded runs in the training set

Calibration with LH data only

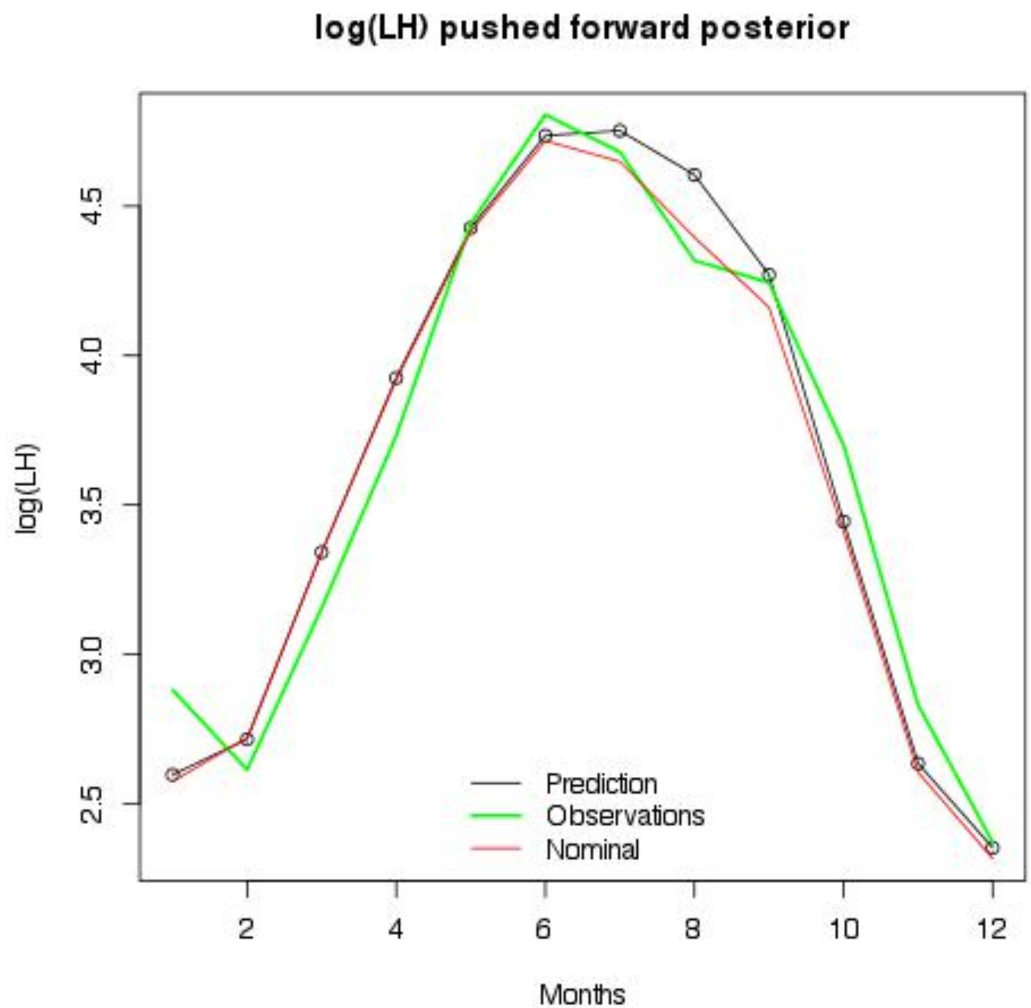
$$P(:|:) \propto \exp\left(-\frac{\left(Y_{LH}^{obs} - M_{LH}(p)\right)^2}{\sigma_{LH}^2} - \cancel{\frac{\left(Y_{WPC}^{obs} - M_{WPC}(p)\right)^2}{\sigma_{WPC}^2}} \right) \pi(p)$$

- The PDFs are not very well defined (bi-modal etc.)
- There is not much support for the nominal values of parameters



Reproducing observations

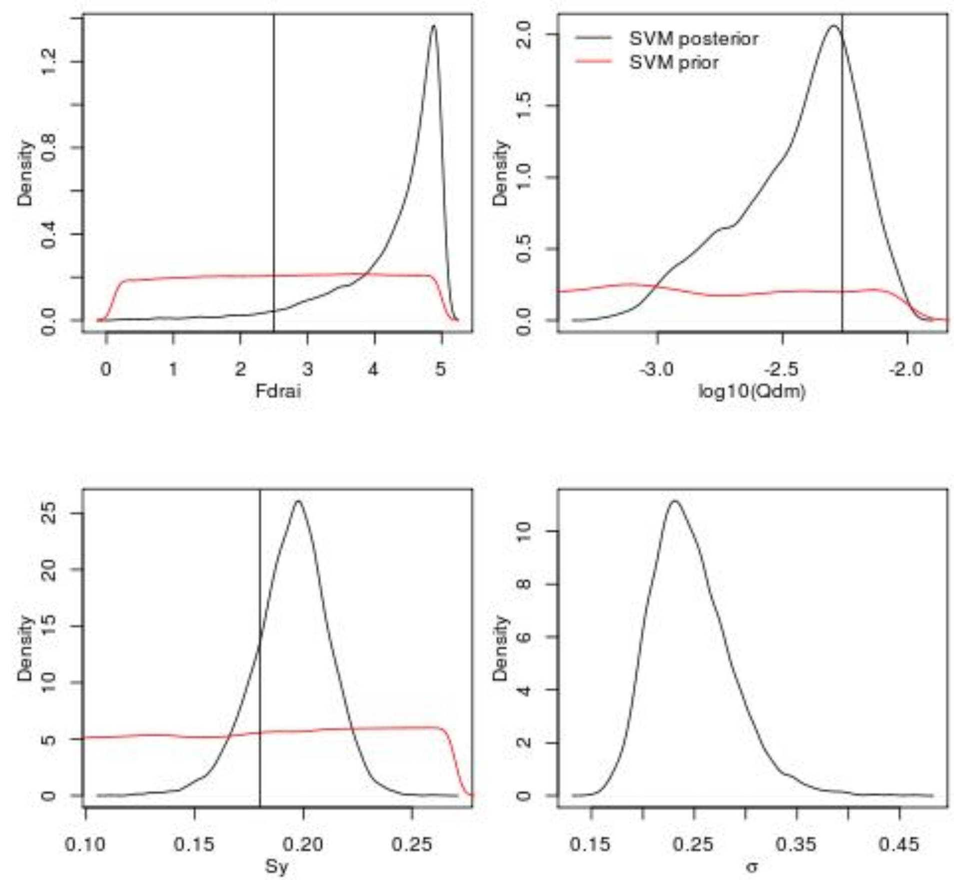
- Pick 100 samples from the posterior density
- Run CLM for each
- Plot ensemble of predictions
- The variation in log(LH) predictions is tiny
  - Can't see the error bars around the circles
  - Explains why it was so difficult to find a sharp posterior distribution



Calibration with WPC data only

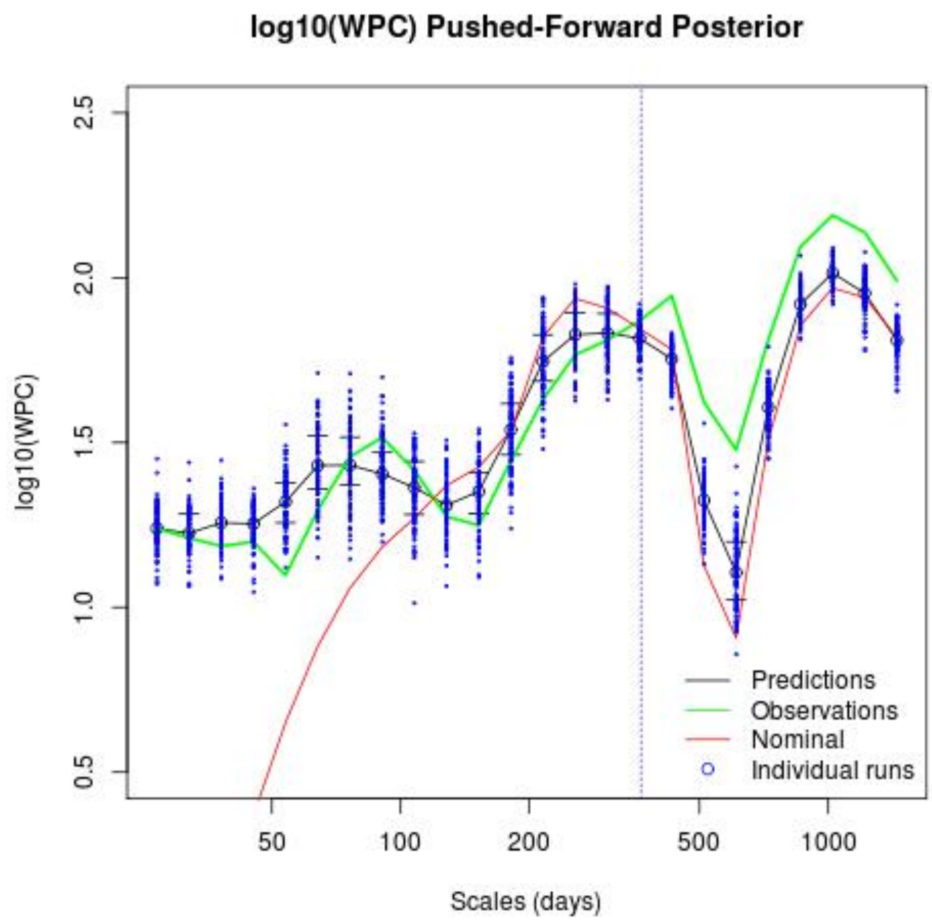
$$P(:|:) \propto \exp\left(- \cancel{\frac{\left(Y_{LH}^{obs} - M_{LH}(p)\right)^2}{\sigma_{LH}^2}} - \frac{\left(Y_{WPC}^{obs} - M_{WPC}(p)\right)^2}{\sigma_{WPC}^2} \right) \pi(p)$$

- The PDFs are simple
  - Not much support for nominal F_{drai}
- PDFs very different from the ones estimated using LH data only
  - First indication that it takes very different estimates of the parameters to match LH and WPC data



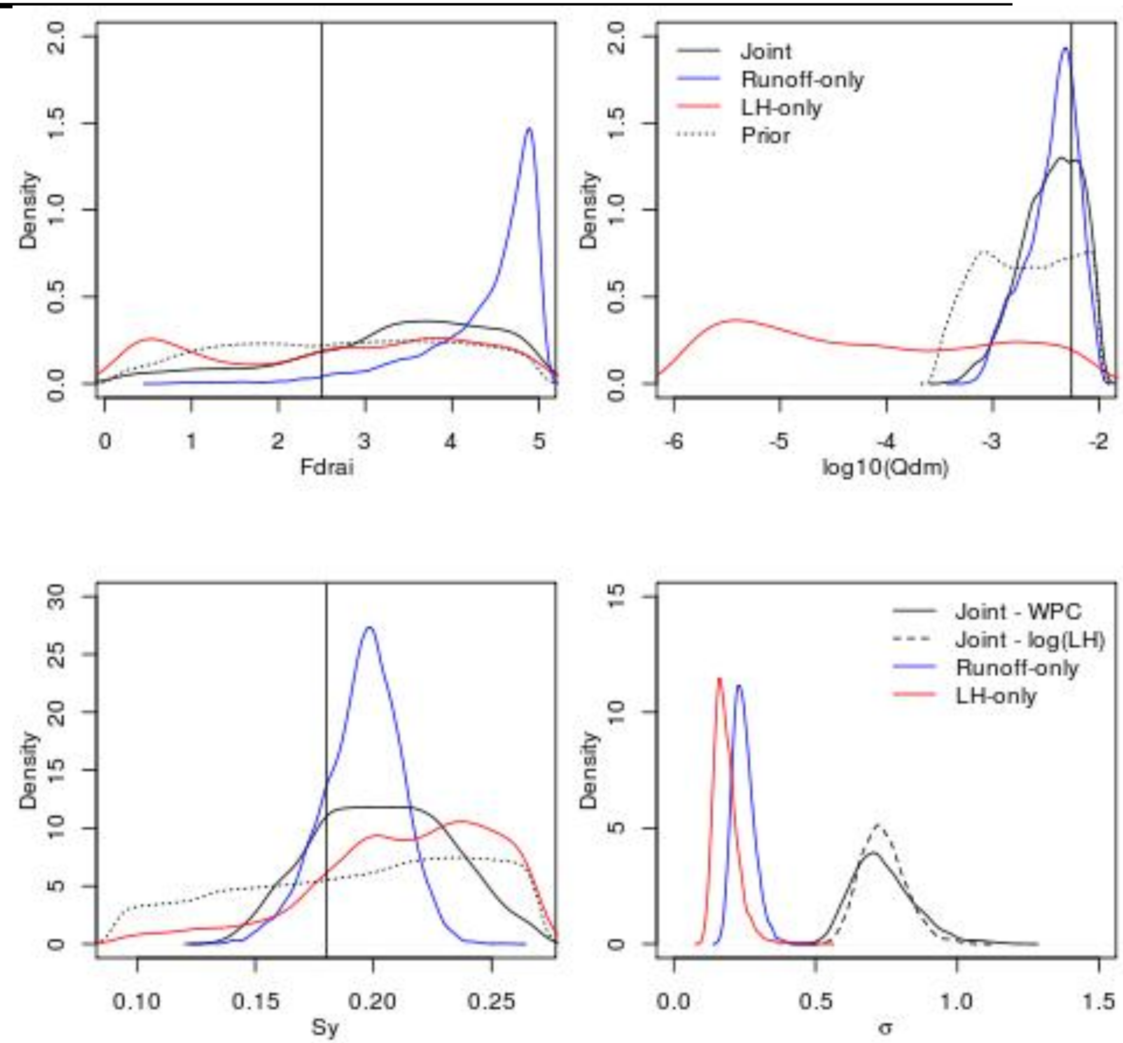
Reproducing observations

- Lots of scatter in predictions at small temporal scales
- But calibrated model's predictive skill better than nominal values of the parameters



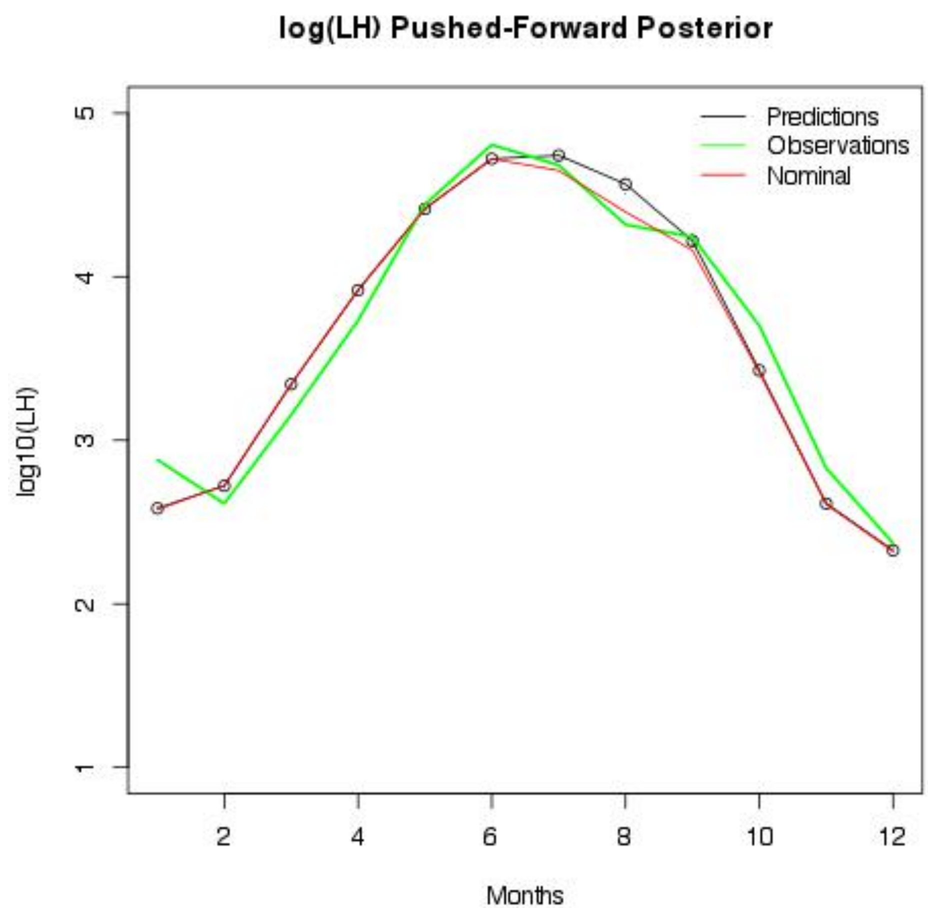
Joint calibration to LH and WPC data

- Huge change in PDFs
  - F_{drai} affects LH much, so joint and LH-only calibration are similar
  - Qdm affects WPC much, and so joint and WPC-only calibration similar
  - S_y – well, your pick
- And the structural error is 6x larger
  - We simply can't be very predictive



Reproducing LH observation with CLM

- Hardly any variability
  - LH predictions not at all sensitive to posterior
  - No wonder we could not get useful PDFs our of LH-only calibration



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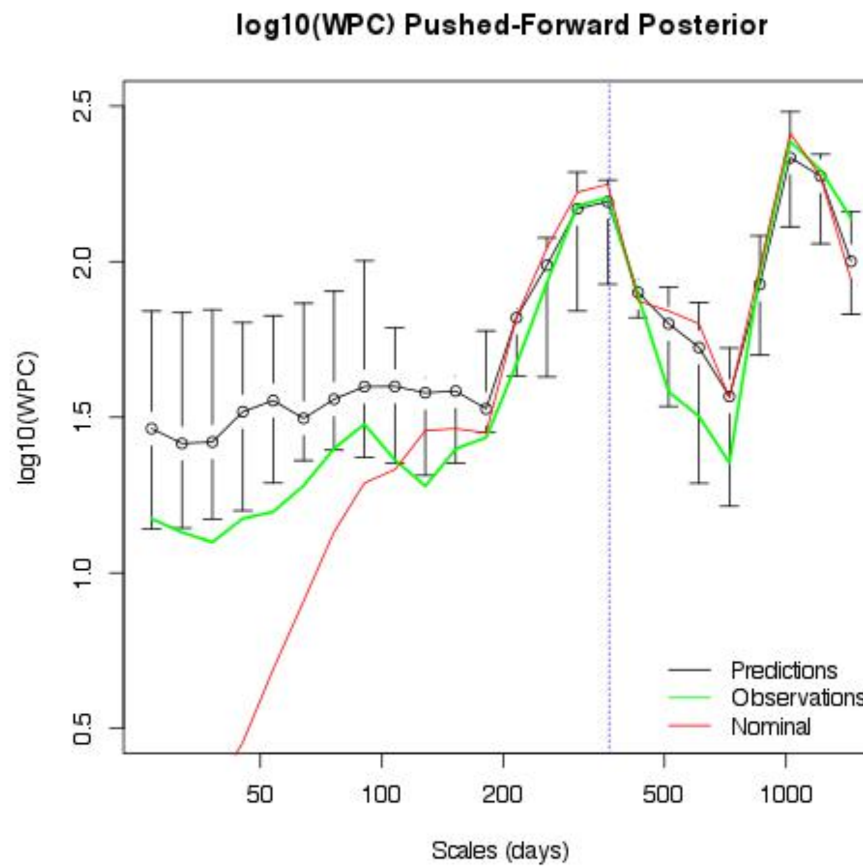
Reproducing WPC observation with CLM

- Good variability
  - Observations contained in inter-quartile “error bars”
- Big improvement in predictions at monthly timescales
  - Should be enough to resolve seasonal variations



Conclusions

- CLM can be calibrated to reproduce a given datastream well
  - The model form error so obtained is too optimistic
  - And the parameters estimates are wrong
- Joint calibration with 2 types of data uncovers a second type of structural error
  - Its inability to reproduce multiple observations stream accurately
  - The parameter estimates obtained from 2 data streams have some resemblance to their nominal values
- Related talks
  - L. Swiler, MS 164, Room 251, Monday, 2:20pm – 2:50pm *[On the perils of parameter estimation using surrogates of CLM]*
  - Z. Hou, CP 16, Room 254B, Wednesday, 9:25am – 9:35am *[On the applicability of parameter estimated from one site, to other similar sites; called "transferability"]*

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