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Improving the Efficiency of Monte Carlo Bayesian Calibration of Hydrologic Models via Model Pre-emption

Mahyar Shafii[1], Bryan Tolson[2], L. Shawn Matott[3],

[1] Postdoctoral Fellow, mshafiih@uwaterloo.ca (corresponding author)
[2] Assistant Professor, btolson@uwaterloo.ca
[3] Assistant Professor, lsmatott@buffalo.edu
[1,2] Department of Civil and Environmental Engineering, University of Waterloo, 200 University Avenue West, Waterloo, Ontario, N2L 3G1, Canada
[3] Center for Computational Research, University at Buffalo, 701 Ellicott Street, Buffalo, New York 14203

Abstract

Bayesian inference via Markov Chain Monte Carlo (MCMC) sampling and Sequential Monte Carlo (SMC) sampling are popular methods for uncertainty analysis in hydrological modelling. However, application of these methodologies can incur significant computational costs. This study investigated using model pre-emption for improving the computational efficiency of MCMC and SMC samplers in the context of hydrological modelling. The proposed pre-emption strategy facilitates early termination of low-likelihood simulations and results in reduction of unnecessary simulation time steps. The proposed approach is incorporated into two samplers and applied to the calibration of three rainfall-runoff models. Results show that overall pre-emption savings range from 5% to 21%. Furthermore, results indicate that pre-emption savings are greatest during the pre-convergence “burn-in” period (*i.e.*, between 8% and 39%) and decrease as the algorithms converge towards high likelihood regions of parameter space. The observed savings are achieved with absolutely no change in the posterior set of parameters.

Keywords: calibration, uncertainty analysis, pre-emption, DREAM, SMC, AR

1. Introduction

This paper focuses on improving the computational efficiency of calibration and uncertainty analysis – two essential components of *model assessment*, defined as the use of robust procedures to determine the suitability of a given model for a given purpose *(Matott et al.*, 2009). Investigations of uncertainty in hydrological modelling have emphasized the use of automatic calibration methods, which develop expressions for parameter uncertainty, ranging from simple Monte Carlo simulations such as GLUE *(Beven and Binley*, 1992) to statistical approaches based on Bayesian inference *(Box and Tiao*, 1973; *Kuczera*, 1983). Due to the complexity of large-scale hydrological models, Bayesian inference is facilitated through Markov Chain Monte Carlo (MCMC) sampling from parameters' posterior distributions *(e.g. Haario et al.*, 2001; *Kavetski et al.*, 2006; *Kuczera and Parent*, 1998; *Vrugt et al.*, 2003; *Vrugt et al.*, 2009).

Sequential Monte Carlo (SMC) simulations have also become very attractive in hydrological modelling in recent years *(Hsu et al.*, 2009; *Jeremiah et al.*, 2011; *Moradkhani et al.*, 2005; *Salamon and Feyen*, 2010). SMC samplers combine data assimilation principles with a particle filtering strategy *(e.g., Moradkhani et al.*, 2005; *Smith et al.*, 2008), and generally resemble previous developed Sampling Importance Resampling (SIR) approaches *(e.g., Del Moral et al.*, 2006). More Recently, Jeremiah et al. *(*2011) compared an example SMC sampler with an adaptive MCMC sampler and found that both methods displayed robustness and convergence.

Despite the common use of MCMC and SMC approaches, their application can incur high computational costs. Therefore, strategies for improving the efficiency of such samplers are an ongoing area of research. In MCMC sampling, efforts to improve efficiency include utilizing prior information *(Mertens et al.*, 2004; *Sikorska et al.*, 2012), developing adaptive algorithms (*e.g., Craiu et al.*, 2009; *Haario et al.*, 2001; *Vrugt et al.*, 2003; *Vrugt et al.*, 2009), and using "limited‐memory" sampling (*Kuczera et al.*, 2010). Efforts for overcoming practical SMC issues include using importance sampling (*Cheng and Druzdzel*, 2000) and seeding initial solutions using empirical Bayes (*Chen et al.*, 2004).

As a complementary approach to the aforementioned efforts, this study explores the use of model 'pre-emption' to improve the computational efficiency of MCMC and SMC samplers in the context of hydrological modelling. Model pre-emption is a relatively simple strategy for identifying low-quality simulations and terminating them early before the entire simulation run time completes. Previous research by Razavi et al. (2010) establishes that model pre-emption can yield substantial computational savings when applied to various optimization-based calibration strategies (DDS and PSO) and various *informal* uncertainty-based calibration strategies (*e.g.*, GLUE (*Beven and Binley*, 1992) and DDS-AU (*Tolson and Shoemaker*, 2007)). In contrast, this study investigated model pre-emption for use within *formal* likelihood functions embedded within the MCMC and SMC sampling algorithms. These pre-emption enabled formal samplers were then applied to the calibration and uncertainty analysis of three rainfall-runoff models. To the best of our knowledge, such an implementation has not been considered in previous studies on the use of MCMC and SMC sampling in hydrological modelling.

2. Methods

Model pre-emption was applied to two algorithms, *i.e.* an MCMC implementation known as DiffeRential Evolution Adaptive Metropolis or DREAM (*Vrugt et al.*, 2009) and an SMC implementation described by Jeremiah et al. (2011) and referred to herein as JSMC. DREAM runs multiple Markov chains simultaneously to facilitate efficient global exploration of the parameter space and its convergence is monitored using the Gelman-Rubin metric ($\hat{R}$) (*Gelman* *and Rubin*, 1992), *i.e.*, values less than 1.2 indicate convergence. The JSMC sampling process propagates a population of parameter vectors (or particles) of size N from an initial sampling distribution to the desired posterior distribution. For more information on the JSMC sampler refer to Jeremiah et al. *(*2011).

Both DREAM and JSMC are designed to take samples from the Bayesian posterior distributions of model parameters. Two Bayesian formulations were investigated in this study, as described below. Consider a time series of N streamflow observations, $Y_t \; t=1,..,N$ (or $\mathbf{Y}$ in vector notation) used to calibrate hydrologic model $h(\boldsymbol{\theta})$ given its parameter vector ($\boldsymbol{\theta}$). Assuming the model errors are uncorrelated and Gaussian distributed with zero mean and variance σ_ε^2, the posterior probability density function $p(\boldsymbol{\theta}\,|\,\mathbf{Y})$ has the following form (after integrating out σ_ε^2):

$$p(\boldsymbol{\theta}\,|\,\mathbf{Y}) \propto \left(\sum_{t=1}^{N} \varepsilon_t^{\,2}\right)^{-\frac{N}{2}} \qquad (1)$$

where $\boldsymbol{\varepsilon}_t = Y_t - h(\boldsymbol{\theta})$ is a vector of residuals. Equation (1) assumes that errors are uncorrelated, but this is not a very realistic assumption in the context of hydrologic modelling. One approach to account for auto-correlation is to use a first-order Auto-Regressive (AR) scheme for the error series *(Sorooshian and Dracup*, 1980):

$$\varepsilon_t = \rho\varepsilon_{t-1} + \nu_t \qquad t=1,...,N \qquad (2)$$

where $\varepsilon_0 = 0$, ρ is the first-order correlation coefficient, and ν_t is the remaining error prescribed to have a zero mean and constant variance σ_ν^2. The resulting joint posterior distribution of $\boldsymbol{\theta}$ and ρ in this case would be:

$$p(\boldsymbol{\theta},\rho|\mathbf{Y}) \propto \left(\varepsilon_1^2(1-\rho^2)+\sum_{t=2}^{N}\delta_t^2\right)^{-\frac{N}{2}} \qquad (3)$$

where $\delta_t(\boldsymbol{\theta},\rho\,|\,\mathbf{Y}) = \varepsilon_t(\boldsymbol{\theta}\,|\,\mathbf{Y}) - \rho\varepsilon_{t-1}(\boldsymbol{\theta}\,|\,\mathbf{Y}) \quad t=1,...,N$. It is observed in both Equations (1) and (3) that the posterior density will monotonically decrease when residuals are incorporated time step by time step into the equations. Since the posterior densities calculated with Equation (1) and (3) monotonically degrade as the simulation proceeds through time, both formulations are suitable for adopting a model pre-emption approach *(Razavi et al.*, 2010).

Pre-emption-enabled DREAM and JSMC sampling was applied to the calibration and uncertainty analysis of three different rainfall-runoff models. Table 1 provides summary information on these case-studies and lists corresponding case study reference papers containing complete descriptions.

[Table 1 goes here]

2.1. Model pre-emption

In deterministic model pre-emption *(Razavi et al.*, 2010), model performance (in terms of some monotonically degrading calibration objective function) is monitored during simulation, and a given simulation is terminated early if it is recognized to be so poor that it will not contribute to guiding the search strategy. In the present study, the DREAM and JSMC sampling algorithms were modified to support deterministic model pre-emption. The first step in implementing pre-emption is to select an appropriate objective function. As noted previously, both Equations (1) and (3) are suitable choices for model pre-emption *(Razavi et al.*, 2010).

Another important factor in pre-emption implementation is the pre-emption threshold, *i.e.*, a likelihood value where the solutions resulting in likelihood values worse than this threshold would be rejected even if the simulation is carried out completely. Both DREAM and JSMC decide to jump from a current state ($\boldsymbol{\theta}_{\mathbf{n}}$) to a candidate state ($\boldsymbol{\theta}^{*}$) based on the ratio of the posterior densities of the two states, *i.e.*, $p(\boldsymbol{\theta}^{*} \mid \mathbf{Y}) / p(\boldsymbol{\theta}_{\mathbf{n}} \mid \mathbf{Y})$. $\boldsymbol{\theta}^{*}$ is accepted if $p(\boldsymbol{\theta}^{*} \mid \mathbf{Y}) / p(\boldsymbol{\theta}_{\mathbf{n}} \mid \mathbf{Y}) > Z$, where Z is a random number uniformly distributed between 0 and 1; otherwise the sampler remains at $\boldsymbol{\theta}_{\mathbf{n}}$. A move to $\boldsymbol{\theta}^{*}$ is accepted only if $p(\boldsymbol{\theta}^{*} \mid \mathbf{Y}) > Z \times p(\boldsymbol{\theta}_{\mathbf{n}} \mid \mathbf{Y})$. Thus, the posterior density value of $p(\boldsymbol{\theta}^{*} \mid \mathbf{Y})_{\min} = Z \times p(\boldsymbol{\theta}_{\mathbf{n}} \mid \mathbf{Y})$ can be considered as the pre-emption threshold so long as the random number Z is generated *prior* to evaluating a given candidate solution. Algorithms can then determine, a priori, the minimum acceptable value of the candidate posterior density ($p(\boldsymbol{\theta}^{*} \mid \mathbf{Y})_{\min}$ as the pre-emption threshold.

Defining a pre-emption enabled version of DREAM and JSMC requires slight adjustment of the acceptance/rejection step in the Metropolis-Hastings algorithm, as illustrated in Figure 1. When a given parameter set $\boldsymbol{\theta}_{\mathbf{n}}$ is evaluated (box 1 in Figure 1), Z is generated and the pre-emption threshold for candidate $\boldsymbol{\theta}^{*}$ or $p(\boldsymbol{\theta}^{*} \mid \mathbf{Y})_{\min}$ is identified (box 2). At any time step (t) of the model simulation, the likelihood can be calculated as $p_t(\boldsymbol{\theta}^{*} \mid \mathbf{Y})$ and evaluated against $p(\boldsymbol{\theta}^{*} \mid \mathbf{Y})_{\min}$ (boxes 3-6). If the evaluated density of any candidate solution becomes lower than $p(\boldsymbol{\theta}^{*} \mid \mathbf{Y})_{\min}$ at any point through the simulation, it is pre-empted (box 7); otherwise, the evaluation of $\boldsymbol{\theta}^{*}$ terminates without any time saving (box 8). Note that a pre-empted candidate would never be accepted by the Metropolis-Hastings algorithm, even if the simulation had not been pre-empted. As such, the pre-emption strategy employed here is deterministic in that it has absolutely no influence, other than computational savings, on the behaviour of the algorithm.

[Figure 1 goes here]

Assuming computational cost is the same for all model time steps (*i.e.*, the simulation model takes identical amount of time during different time steps), the associated computational savings for a given application of DREAM or JSMC can be estimated as follows *(Razavi et al.*, 2010):

$$\mathrm{S} = 100 \times \left[\frac{n - n_p}{n} \right] \tag{4}$$

where S is the computation savings (in percent), n is the total number of time steps in the calibration period, and n_p is the number of time steps simulated before the simulation is terminated by pre-emption. Note that the pre-emption approach outlined in this section is applicable to any other MCMC or SMC samplers that utilize the Metropolis-Hastings acceptance/rejection approach for evaluating candidate moves.

3. Results

3.1. Non-pre-emptive experiments

A “standard” (*i.e.*, non-pre-emptive) DREAM implementation was applied to three case studies, thereby establishing baseline computational costs for the algorithm. Preliminary investigation of model residuals indicated the standard Bayesian formulation of Equation (1) was sufficient for calibrating the HYMOD case study. Conversely, the AR-based formulation of Equation (3) was required for the WetSpa and SWAT case studies to accommodate correlation among the residuals. The Gelman-Rubin convergence metric ($\hat{R}$-statistic) indicated that DREAM converged after 7800, 4000, and 161000 simulations of the in HYMOD, WetSpa, and SWAT case studies, respectively. After convergence, 10000 more samples were taken to form the posterior distribution.

A baseline set of non-pre-emptive JSMC sampling experiments were also applied to the three case studies. Although JSMC convergence and model residuals are treated differently, the same likelihood formulations as the DREAM experiments were used, and the same computational budgets were considered. Note that the relative efficiencies of DREAM and JSMC were compared previously by Jeremiah et al., (2011) and such inter-algorithm comparisons were not pursued in the present study. Instead, the numerical experiments focused on the application of pre-emption to reduce the computational burden of these methods.

3.2. Application of model pre-emption

Pre-emption-enabled versions of DREAM and JSMC were applied to the same calibration problems as mentioned in Section 3.1. The pre-emptive DREAM and JSMC experiments were performed using the same sequence of random numbers (generated by a random number generator) applied in previous experiments. Moreover, the same computational budgets were considered for corresponding pre-emptive and baseline experiments. These identical settings ensured that a given samplers' search behaviour was the same with and without pre-emption. As expected, the pre-emption-based DREAM and JSMC samplers yielded the same sets of posterior parameter values as those obtained in the corresponding baseline (*i.e.*, non-pre-emptive) experiments. In other words, use of model pre-emption did not change the calibration results, and the only effect of using pre-emption was a reduction in the required amount of computation.

Table 2 provides average computational savings (in percent) for the pre-emption-based DREAM and JSMC experiments. The total average savings ranged from 5% to 21% in DREAM, and from 16% to 18% in JSMC. Extrapolating based on average simulation model runtimes and the percentage savings yields estimated wall-clock savings of up to 38 hours for our case studies.

For more computationally demanding hydrologic models, such as fully distributed models requiring hours of simulation time, the wall-time savings afforded by pre-emption would be even more significant.

For the selected algorithms (*i.e.*, DREAM and JSMC), most of the pre-emption savings occurred during the initial sampling or "*burn-in" period*, defined as the period before the Gelman-Rubin metric indicates convergence. As the samplers converge, candidate parameter sets ($\boldsymbol{\theta}^*$) decreasingly differ from the current parameter sets ($\boldsymbol{\theta}_\mathbf{n}$). This in turn increases the likelihood ratio acceptance criteria, $p(\boldsymbol{\theta}^* \mid \mathbf{Y}) / p(\boldsymbol{\theta}_\mathbf{n} \mid \mathbf{Y})$, and reduces the probability of pre-emption. To quantify this behaviour, the DREAM pre-emption savings were separated into burn-in and post-burn-in periods, and the JSMC results were likewise divided into two halves. The results are shown in brackets in Table 2.

[Table 2 goes here]

Figure 2 illustrates the empirical cumulative distribution function of the simulation time at which model pre-emption terminated a given simulation. For DREAM in the post-burn-in period, almost all pre-emption occurred after 85% of the simulation was completed. This explains why the overall cumulative savings reported for DREAM in Table 2 are relatively low. However, unacceptable simulations were terminated much earlier during the burn-in period and there was considerable computational savings in this stage. Fairly similar pre-emption behaviour was observed for the JSMC sampler (lower panel in Figure 2).

[Figure 2 goes here]

3.3. Sensitivity of pre-emption savings to calibration period

The effectiveness of model pre-emption can be sensitive to the location of large storms within the calibration period *(Razavi et al.*, 2010). For example, inferior parameter sets will generally trigger early exceedance of the pre-emption threshold if major events happen early in the calibration period. However, pre-emption will not help as much if a major storm occurs at the end of a calibration period. This is because the simulation will need to cover most of the calibration period before a pre-emption judgment can be made.

To explore the sensitivity of model pre-emption to the calibration period, the HYMOD case-study was calibrated using pre-emption-enabled DREAM considering four different years from the observation period. Results showed the pre-emption savings varied according to the selected calibration period, and in some cases considerable savings were achieved. Overall pre-emption savings in these experiments ranged from 8% to 35% during the entire simulation and 10% to 39% during the burn-in period.

4. Discussion and Conclusions

In view of the computational burden associated with samplers employed for Bayesian inference (*e.g.* DREAM or JSMC), a model pre-emption approach was investigated for saving computational time. The proposed approach (*i.e.*, avoiding unnecessary simulations) yielded on average between 5 and 21% computational savings in the three selected case studies. In one of the case studies, it was shown that savings could reach as high as 39% depending on the selected calibration period. The time savings were larger during the initial stage of sampling, and ranged from 8% to 39%. Such savings are considerable for simulation models that require several minutes or hours to complete. Moreover, the pre-emption savings varied according to the selected calibration period, and in some cases considerable savings were achieved. Implementing pre-emption did not change the calibration results compared to when calibrating without pre-emption. Moreover, implementation was straightforward and our approach is generally applicable to any samplers that utilize the Metropolis-Hastings acceptance/rejection approach for evaluating candidate moves in the search space.

The case-study results presented here provide strong empirical evidence that a model pre-emption approach is a good choice for application to other case studies involving formal Bayesian calibration. Pre-emption will be most useful in calibration problems where it is very hard to find good solutions and a lot of time is wasted fully evaluating bad solutions long after it is known that they will contribute no new information to the sampling algorithm. Moreover, our results suggest that pre-emption savings are most significant in cases where Bayesian samplers do not converge. In practice, convergence failure is relatively common during the initial phases of calibrating complex hydrological models where multiple applications of a Bayesian sampler can be required. For example, refinement of the model, model input forcings and/or likelihood function is often required before a satisfactory calibration result is obtained. The burn-in period of the selected case-studies are representative of these no-converged situations and corresponding results suggest that savings of up to 39% can be achieved. In this way, pre-emption can accelerate model development by helping modellers more quickly determine when there is an issue preventing MCMC or SMC algorithm convergence.

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References

Beven, K., and A. Binley (1992), The future of distributed models: model calibration and uncertainty prediction, *Hydrological Processes*, *6*(3), 279-298.

Box, G. E. P., and G. C. Tiao (1973), *Bayesian Inference in Statistical Analysis*, Addison-Wesley, Boston, MA.

Boyle, D. P. (2000), Multicriteria calibration of hydrological models, Ph.D. Dissertation thesis, Univ. of Ariz.

Chen, W., B. R. Bakshi, P. K. Goel, and S. Ungarala (2004), Bayesian Estimation via Sequential Monte Carlo Sampling: Unconstrained Nonlinear Dynamic Systems, *Ind. Eng. Chem. Res.*, *43*, 4012-4025.

Cheng, J., and M. J. Druzdzel (2000), AIS-BN: An Adaptive Importance Sampling Algorithm for Evidential Reasoning in Large Bayesian Networks, *Journal of Artificial Intelligence Research*, *13*, 155-188.

Craiu, R., J. Rosenthal, and C. Yang (2009), Learn From Thy Neighbor: Parallel-Chain and Regional Adaptive MCMC, *Journal of the American Statistical Association*, *104*(488), 1454-1466.

Del Moral, P., A. Doucet, and A. Jasra (2006), Sequential Monte Carlo samplers, *J. R. Stat. Soc., Ser. C Appl. Stat. Ser. B*, *68*, 411-436.

Gelman, A., and D. B. Rubin (1992), Inference from Iterative Simulation Using Multiple Sequences, *Statistical Science*, *7*(4), 457-472.

Haario, H., E. Saksman, and J. Tamminen (2001), An adaptive Metropolis algorithm, *Bernoulli*, *7*(2), 223-242.

Hsu, K., H. Moradkhani, and S. Sorooshian (2009), A sequential Bayesian approach for hydrologic model selection and prediction, *Water Resour. Res.*, *45*, W00B12.

Jeremiah, E., S. Sisson, L. Marshall, R. Mehrotra, and A. Sharma (2011), Bayesian calibration and uncertainty analysis of hydrological models: A comparison of adaptive Metropolis and sequential Monte Carlo samplers, *Water Resour. Res.*, *47*(W07547).

Kavetski, D., G. Kuczera, and S. W. Franks (2006), Bayesian analysis of input uncertainty in hydrological modeling: 1. Theory, *Water Resour. Res., 42, W03407, doi: 10.1029/2005WR004368*.

Kuczera, G. (1983), Improved parameter inference in catchment models: 1. Evaluating parameter uncertainty, *Water Resour. Res.*, *19*(5), 1151-1162.

Kuczera, G., and E. Parent (1998), Monte Carlo assessment of parameter uncertainty in conceptual catchment models: the Metropolis algorithm, *Journal of Hydrology*, *211*(1-4), 69-85.

Kuczera, G., D. Kavetski, B. Renard, and M. Thyer (2010), A limited-memory acceleration strategy for MCMC sampling in hierarchical Bayesian calibration of hydrological models, *Water Resour. Res.*, *46*(7), W07602.

Matott, L. S., J. E. Babendreier, and S. T. Purucker (2009), Evaluating uncertainty in integrated environmental models: A review of concepts and tools, *Water Resour. Res.*, *45*.

Mertens, J., H. Madsen, L. Feyen, D. Jacques, and J. Feyen (2004), Including prior information in the estimation of effective soil parameters in unsaturated zone modelling, *Journal of Hydrology*, *294*(4), 251-269.

Moradkhani, H., K.-L. Hsu, H. Gupta, and S. Sorooshian (2005), Uncertainty assessment of hydrologic model states and parameters: Sequential data assimilation using the particle filter, *Water Resour. Res.*, *41*, W05012.

Razavi, S., B. Tolson, L. S. Matott, N. Thomson, A. MacLean, and F. Seglinieks (2010), Reducing the Computational Cost of Automatic Calibration through Model Pre-Emption, *Water Resour. Res.*, *46*(11), W11523.

Safari, A., F. De Smedt, and F. Moreda (2009), WetSpa model application in the Distributed Model Intercomparison Project (DMIP2), *J. Hydrology*.

Salamon, P., and L. Feyen (2010), Disentangling uncertainties in distributed hydrological modeling using multiplicative error models and sequential data assimilation, *Water Resour. Res.*, *46*, W12501.

Sikorska, A. E., A. Scheidegger, K. Banasik, and J. Rieckermann (2012), Bayesian uncertainty assessment of flood predictions in ungauged urban basins for conceptual rainfall-runoff models, *Hydrol. Earth Syst. Sci.*, *16*, 1221-1236.

Smith, P. J., K. J. Beven, and J. A. Tawn (2008), Detection of structural inadequacy in process-based hydrological models: A particle-filtering approach, *Water Resour. Res.*, *44*, W01410.

Sorooshian, S., and J. A. Dracup (1980), Stochastic parameter estimation procedures for hydrologie rainfall-runoff models: Correlated and heteroscedastic error cases, *Water Resour. Res.*, *16*(2), 430-442.

Tolson, B. A. (2005), Automatic calibration, management and uncertainty analysis: Phosphorus transport in the Cannonsville watershed, Cornell Univ., Ithaca, N. Y.

Tolson, B. A., and C. A. Shoemaker (2007), Dynamically dimensioned search algorithm for computationally efficient watershed model calibration, *Water Resour. Res.*, *43*, *W01413*, *doi:10.1029/2005WR004723*.

Vrugt, J. A., H. V. Gupta, W. Bouten, and S. Sorooshian (2003), A Shuffled Complex Evolution Metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters, *Water Resour. Res.*, *39*(8), 1201, doi:1210.1029/2002WR001642.

Vrugt, J. A., C. J. F. ter Braak, C. G. H. Diks, D. Higdon, B. A. Robinson, and J. A. Hyman (2009), Accelerating Markov chain Monte Carlo simulation by differential evolution with self-adaptive randomized subspace sampling, *International Journal of Nonlinear Sciences and Numerical Simulation*, *10*(3), 273-290.

Table 1. Three rainfall-runoff models and the catchments studied in this paper

<table>
<tr><th>Simulation Model
(Type)</th><th># of
Para.</th><th>Catchment
(Area km^2)</th><th>Forcing data</th><th>Calibration
Period</th><th>Refs. for more info</th></tr>
<tr><td>HYMOD
(lumped)</td><td>5</td><td>Leaf
(1994)</td><td rowspan="2">Precipitation
Temperature
PET*</td><td>1953-1954</td><td>Boyle (2000);
Vrugt et al. (2003)</td></tr>
<tr><td>WetSpa
(semi-distributed)</td><td>6</td><td>Baron
(965)</td><td>1995-2000</td><td>Safari et al. (2009)</td></tr>
<tr><td>SWAT
(semi-distributed)</td><td>26</td><td>Cannonsville
(37)</td><td>Precipitation
Temperature
PET*
Sol. radiation
Rel. humidity</td><td>1996-1998</td><td>Tolson (2005);
Tolson and Shoemaker (2007)</td></tr>
</table>

* Potential Evapotranspiration

Table 2 New

Table 2. Average computation saving (in percent) obtained from model pre-emption in different calibration problems

Method	Case Study		
	HYMOD	WetSpa	SWAT
MCMC	14* [17**]	21 [39]	5 [8]
JSMC	16 [21]	18 [28]	17 [25]

* During entire simulations

** During initial sampling stage (burn-in period in MCMC, and first half of JSMC simulations.

Figure 1 New

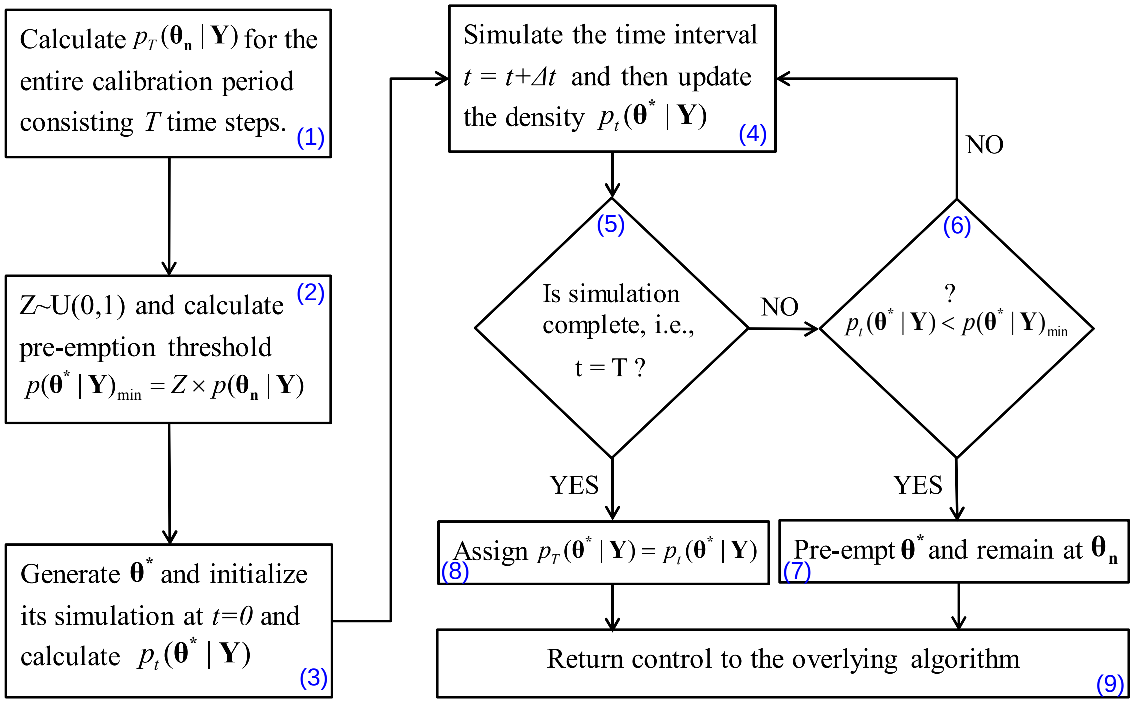

Figure 1. Modified acceptance/rejection step in Metropolis-Hastings component implemented in pre-emption

Figure 2

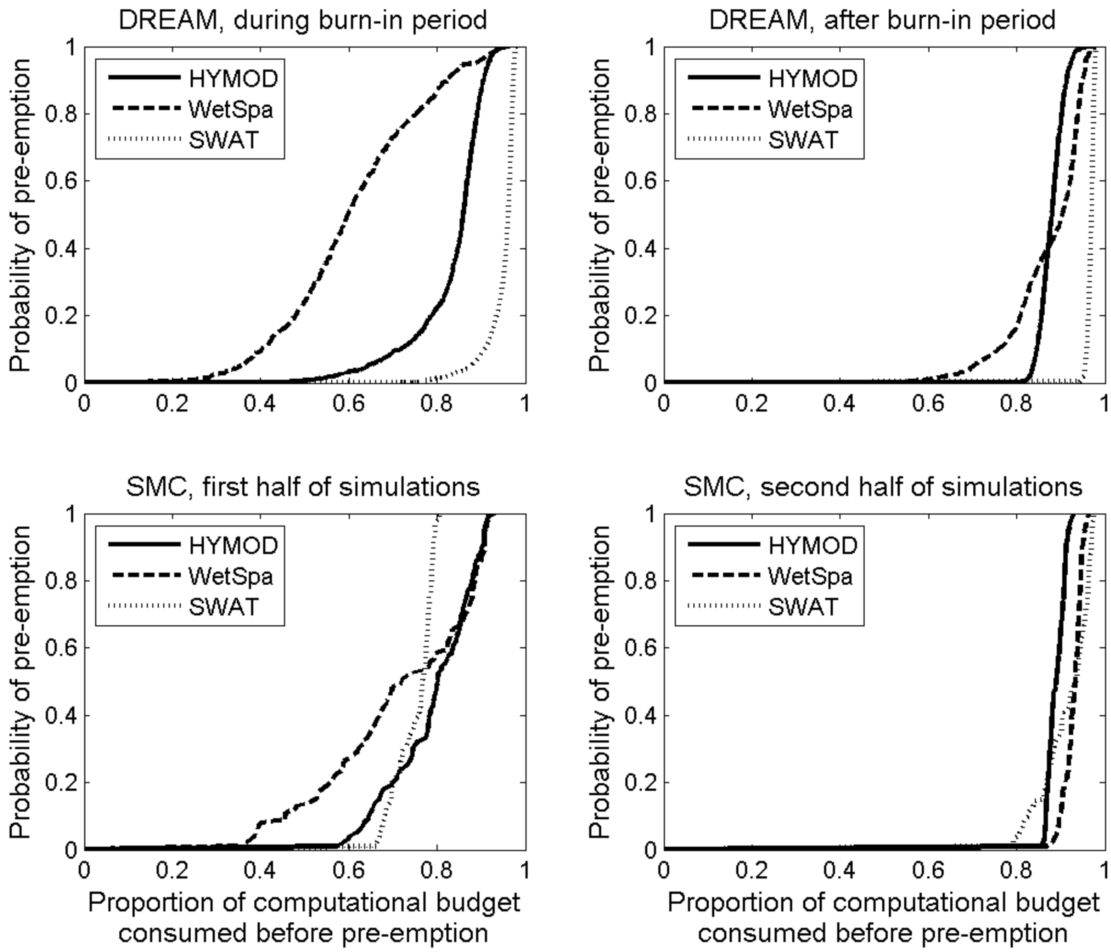

Figure 2. Empirical cumulative distribution function of the simulation time at which model pre-emption is applied in different calibration problems