RECLAMATION
Managing Water in the West

Developing Tool to Assess Model Uncertainty in Sediment Simulation Final Progress Report

Research and Development Office
Science and Technology Program
Final Report ST-2016-8680-1

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10/30/2015

Mission Statements

The U.S. Department of the Interior protects America's natural resources and heritage, honors our cultures and tribal communities, and supplies the energy to power our future.

The mission of the Bureau of Reclamation is to manage, develop, and protect water and related resources in an environmentally and economically sound manner in the interest of the American public.

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The uncertainty in numerical model predictions can result from simplifications in the model's representations of the physical systems (model structure uncertainty), errors in the values assigned to model parameters (parameter uncertainty), and errors in the model inputs (forcing or input uncertainty). It is important to understand the nature of those uncertainties in order to guide data collection and model calibration strategies. The long-term objective of this research is to develop a formal and efficient framework to evaluate uncertainty in predictions from hydrologic, hydraulic, and sediment-transport models. In particular, this project aims to assess the uncertainty associated with parameter, forcing, and model structure using Bayesian uncertainty methods, and reduce the computational cost of the Bayesian method substantially while still providing reliable uncertainty estimates. The new approach for uncertainty will require few enough simulations to be applied to complex model applications, and retain enough formality to reliably evaluate data collection and model calibration strategies. To constrain the scope, this research focuses on applying the framework to a sediment transport model called Sedimentation and River Hydraulics – One Dimension (SRH-1D).

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Contents

Project Objective

The U.S. Bureau of Reclamation (USBR) uses many kinds of computational hydrologic, hydraulic, and sediment-transport models in order to protect and manage water resources. Unfortunately, predictions from such models always possess uncertainty. The uncertainty in model predictions can result from simplifications in the model's representations of the physical systems (model structure uncertainty), errors in the values assigned to model parameters (parameter uncertainty), and errors in the model inputs (forcing or input uncertainty). It is important to understand the nature of those uncertainties in order to guide data collection and model calibration strategies. The long-term objective of this research is to develop a formal and efficient framework to evaluate uncertainty in predictions from hydrologic, hydraulic, and sediment-transport models. In particular, this project aims to assess the uncertainty associated with parameter, forcing, and model structure using Bayesian uncertainty methods, and reduce the computational cost of the Bayesian method substantially while still providing reliable uncertainty estimates. The new approach for uncertainty will require few enough simulations to be applied to complex model applications, and retain enough formality to reliably evaluate data collection and model calibration strategies. To constrain the scope, this research focuses on applying the framework to a sediment transport model called Sedimentation and River Hydraulics – One Dimension (SRH-1D) (Huang and Greimann, 2013), but the methods are transferrable to other types of models. Five major tasks must be completed to achieve the project objective: (1) analyze the application of a previously developed methodologies termed Multi-objective Shuffled Complex Evolution Metropolis algorithms and Bayesian Model Averaging (MSU/BMA) to SRH-1D simulations of flume experiments to assess model weaknesses and data collection strategies; (2) apply MSU/BMA to an SRH-1D model of a real river system and evaluate the method's performance; (3) develop and evaluate a simplified methodology that requires fewer simulations to evaluate uncertainty; (4) implement the method in streamlined software and train USBR staff in its use; and (5) publish project results in refereed journals.

The previous results of the research are documented in Sabatine et al (2015). This report summarizes the more recent results from the research. Final results are expected to be complete at the end of 2016.

The recent results can be categorized into three items:

1. Analysis of the uncertainty in forcing variables, integrate the input error model into MSU algorithm, and test the method.
2. Parallelization of the update process of MSU based on the number of complexes in order to reduce the operating time.

3. Development of a framework for assessing overall uncertainty in SRH-1D by integrating several Bayesian uncertainty methods

Input Uncertainty Estimation

Methodology

There have been a few studies that explicitly account for uncertainty of forcing data within the hydrologic modeling. The studies only deal with input errors related to observed rainfall data. Kavetski et al. (2003) developed an input error model that introduces rainfall depth multipliers as latent variables of the system, allowing the patterns of rainfall as well as the event magnitude to change. However, this approach requires identifying the true rainfall to calculate the likelihood, which is impossible in a real world problem. In addition, the number of latent variables can increase considerably in complex modeling cases, and it will cause dimensionality issues. To avoid these problems, Ajami et al. (2007) proposed the simplified input error model. It describes the uncertainty in rainfall data using random multipliers that corrupt the true rainfall depth at all times from identical normal distributions. They applied a Bayesian method to analyze the input error model and demonstrated that uncertainty in the forcing produces more uncertainty in predictions than parameter uncertainty. Unfortunately, input error models have not been applied in a Bayesian framework in the field of hydraulic and sediment transport modeling. It should be considered because the ignorance of input uncertainty might provide underestimations of overall uncertainty in model predictions.

Bayesian uncertainty analysis has, to a certain extent, been used to assess the parameter uncertainty in hydraulic and sediment transport models. Bayesian methods treat the parameters after calibration as random variables having a joint probability density function (pdf). That pdf combines the prior parameter information provided by the modeler and the likelihood information from the calibration data. This paradigm can be written as:

$$p(\theta|y) \propto L(y|\theta)\,p(\theta) \tag{1}$$

where $p(\theta|y)$ is the posterior parameter pdf, $L(y|\theta)$ is the likelihood function, which presents the model's ability to reproduce the observations when θ is used, and $p(\theta)$ is the prior parameter pdf, which summarizes the information about θ before considering any observations. In this paradigm, the posterior distribution of parameter represents the uncertainty in parameter value given the calibration data.

To assess uncertainty in forcing of the sediment transport model SRH-1D, we integrate the input error model into MSU, which is developed for parameter uncertainty estimation. Ajami et al. (2007) presented an input error model as follows,

$$\tilde{r}_t = \phi_t r_t \; ; \qquad \phi \sim N(m, \sigma_m^2) \tag{2}$$

where $\tilde{r}_t$ is true rainfall depth, r_t is observed rainfall depth, and ϕ_t is a random multiplier at time step t with mean m and variance σ_m^2. It is assumed that true rainfall depth is corrupted at all times by random multipliers from the identical distribution with unknown mean and variance. The multiplier ϕ_t helps to maintain the non-homogeneous characteristics of the error in nature which is like higher deviation in higher rainfall depth (Sorooshian and Dracup, 1980). For successful implementation of the input error model, the mean and variance for multiplier distribution need to be calibrated. Including input error parameters, the Bayesian approach of Equation (1) can be modified as,

$$p\left(\theta,m,\sigma_m^2 \middle| y\right) \propto L\left(y \middle| \theta,m,\sigma_m^2\right) p\left(\theta,m,\sigma_m^2\right) \tag{3}$$

We can apply the input error model to express uncertainty in forcing of SRH-1D such as flowrate and sediment discharge at upstream boundary, water surface elevation at downstream boundary, and internal bed level controls. At the same time, this assumes that each type of input data has a different set of input error parameters (mean and variance). Then, MSU can be used to evaluate the uncertainty of input error parameters and model parameters of SRH-1D simultaneously. Later the uncertainty associated with those inputs will be propagated to uncertainty in model predictions for future scenarios.

Results

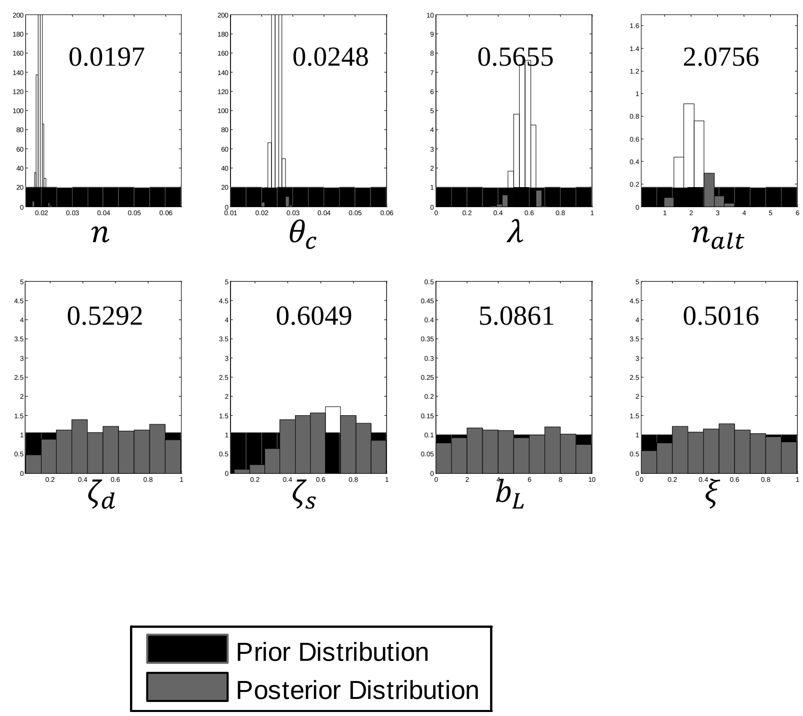
To test this method, we applied Ajami et al.’s input error model (2007) to the two forcing inputs of the Ashida and Michue (1971) case: a clear-water discharge at the upstream boundary and the water surface level at its downstream boundary. Four input error parameters will be added to account for the uncertainties in those two forcing inputs, and Table 1 shows the feasible ranges of these parameters. The ranges are kept as small as possible for computational purposes, but we can widen them if the initial ranges do not capture the full posterior distributions. Then, we apply the MSU to estimate the four input error parameters and the eight model parameters of SRH-1D simultaneously. The eight model parameters of SRH-1D include: Manning’s Roughness (n), critical shear stress (θ_c), hiding/exposure coefficient (λ), active layer thickness (n_{alt}), sediment deposition and erosion parameters (ζ_d, ζ_e), bed load adaptation length (b_l), and bed mixing coefficient (ξ).

Figure 1 presents the marginal posterior distributions of the parameters obtained from MSU in cases where only eight model parameters are considered in MSU. The posterior distributions of the parameters of the probability distributions of the values of these parameters after the MSU simulation has been performed. Figure 2 presents the case where the eight model parameters and four input error parameters are considered in MSU at the same time. Comparing the posterior distributions from both cases, we can see two results. One is that considering input error parameters, the estimated posterior distributions for the model parameters moved and assigned the mode of the probability distribution to different parameter values, for critical shear stress, hiding factor, and active layer thickness multiplier. The other is that the mean of each input error model has a mode different than one, for both the input discharge and the downstream water surface elevation. If the forcing input was correct, the mean of the input error would concentrate around one, and the distribution of the model parameters would be the same as if we did not account for input uncertainty.

Table 1 Initial bounds for input error parameters

Parameters		Minimum	Maximum
m_1	Mean of input error model for flowrate	0.8	1.2
σ_1^2	Variance of input error model for flowrate	1×10^{-5}	1×10^{-3}
m_2	Mean of input error model for water level	0.8	1.2
σ_2^2	Variance of input error model for water level	1×10^{-5}	1×10^{-3}

(a) Original MSU



Numbers: mean of posterior distribution

Figure 1 Marginal posterior distributions from MSU not including input model error.

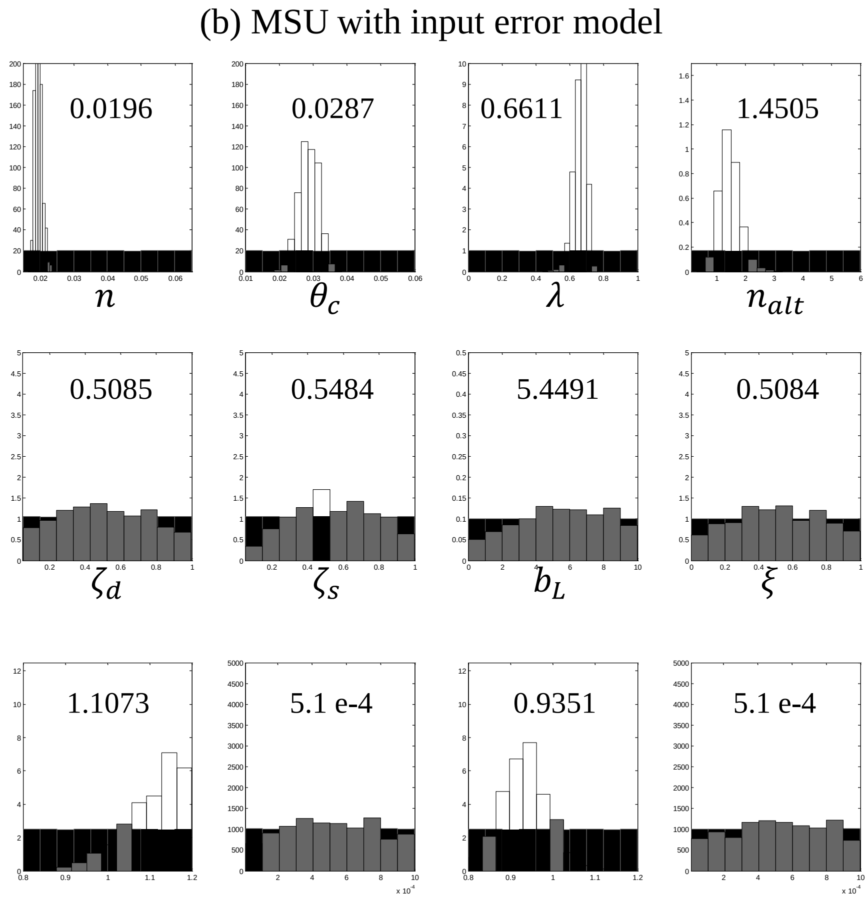


Figure 2 Marginal posterior distributions from MSU including model error

In addition, we produced the predictive distributions of model outputs to present the uncertainty in model predictions resulting from both input and parameter uncertainties. To evaluate the input uncertainty impacts, we compared the 95% credible intervals (CI) of estimated uncertainty in model predictions. Figure 3 shows that the 95% CI are wider with input uncertainty considering compared with the original case (only considering uncertainty in model parameters). This result reveals that the estimated uncertainty bounds are substantially affected by input uncertainty. In addition, it can be inferred that the input error model is compensating for the existing model structural deficiencies. Only the bed profile and D16 are shown, but other representative diameters were also compared against measured results and the same generally conclusions are valid.

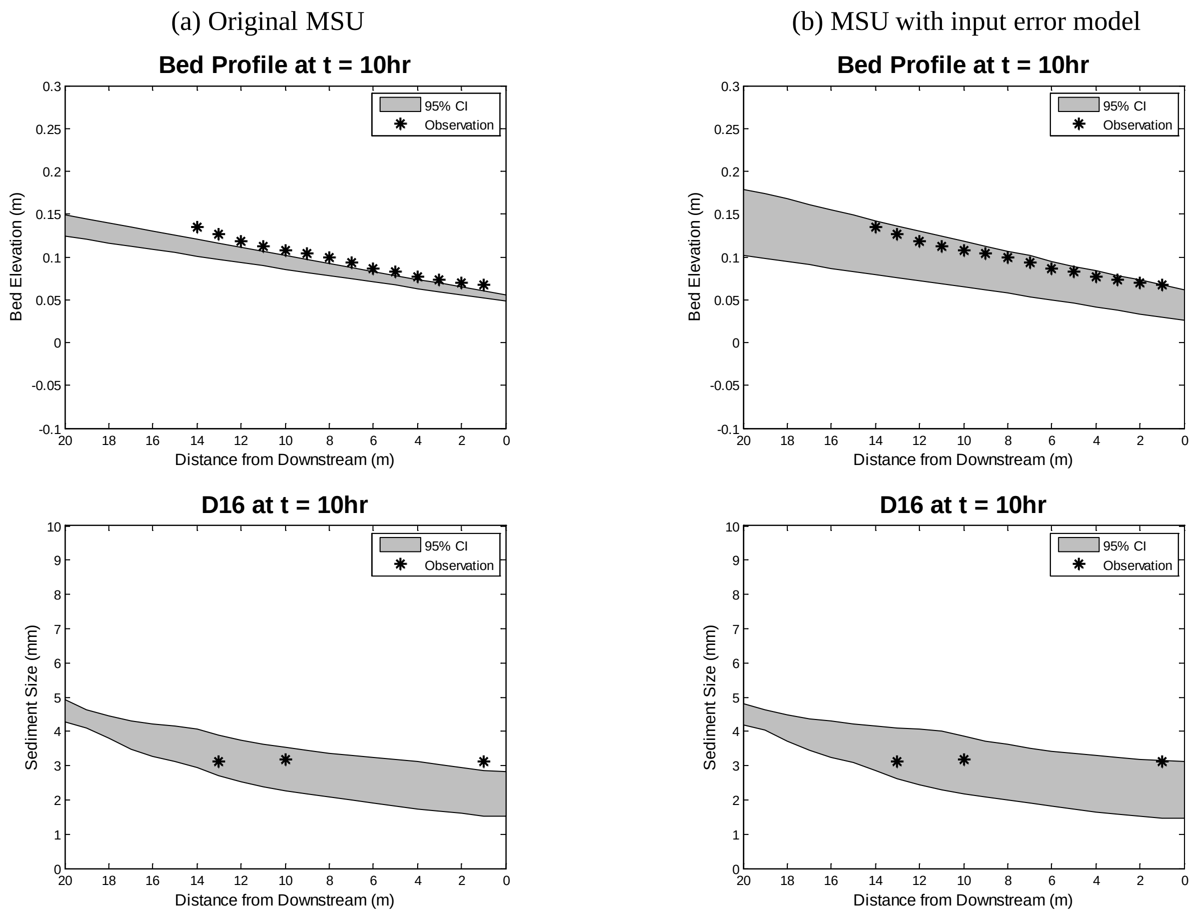


Figure 3 Confidence intervals for the forecast period.

Parallelize Update Process

We parallelized the MSU algorithms to reduce the computational cost. One of the easiest ways to reduce operating time of massive computations is to parallelize the computing process. Unfortunately, one cannot easily parallelize the MCMC sampling process because the Bayesian implementation with MCMC is sequential computing such that a realized posterior distribution becomes a prior for next step (Foglia et al., 2009). To overcome this limitation, we parallelize the MCMC sampling process based on the number of updating sequences. For example, MSU computes likelihoods of initial parameter sets and partitions them into a pre-defined number of complexes. The parameter sets are then updated sequential within each complex. After a few iterations of updating, MSU combines the parameter sets into a single list, which is shuffled and re-divided into complexes. The updating sequences of multiple complexes can thus proceed in parallel. We modified the source code of MSU to perform parallel computing for the updating sequences using the number of computing cores same as the number of complexes q. By parallelizing the MSU updating process, we reduced the operating time of MSU implementation by a factor of $1/q$ of the original without any change in results of uncertainty estimates.

Overall Uncertainty Framework

In this period, we also developed an outline of the Bayesian framework for estimating the overall uncertainty in SRH-1D modeling. The framework includes the several methods, which have been developed through this project, and it will be in streamlined software as a final product of this project. The uncertainty assessment procedure of the developing Bayesian framework is as below:

1. Define application case. Identify the system configuration (e.g., geomorphic characteristics, sediment size range, flow conditions, sediment load type), the quantity of interest to forecast, available observations, and forecast time period.
2. Determine sediment transport models to consider. Decide among the available sediment transport models for a given case based on the system configuration.
3. Select a sediment transport equation (others will be considered later). To perform uncertainty methods, select a single sediment transport model from a class of the available models.
4. Determine model parameters to consider. Identify the parameters contained in the sediment transport model, and decide which parameters will be analyzed.
5. Define input error models. Determine forcing inputs to consider as uncertain. Develop the input error models, and define the input error parameters for each forcing input.
6. Perform a parameter screening. Conduct the Latin Hypercube - One at a Time sampling (LH-OAT) method to quantify the importance of model parameters and input error parameters on the model simulations, and determine which parameters can be neglected in uncertainty analysis.
7. Organize variables for MSU. Based on the physical characteristics, organize the calibration data into multiple variables for MSU implementation.
8. Implement MSU. Perform the uncertainty method MSU to estimate the model parameters and input error parameters, which are treated as important from the screening result.
9. Repeat Steps 3 to 7 for all sediment transport models.
10. Simulate the calibration period. Obtain the model outputs from the all considered models using optimized parameter sets for the calibration period.
11. Organize variables for BMA. Based on the physical characteristics, organize the calibration data into multiple variables for BMA implementation.
12. Run BMA. Estimate the model weights and standard deviations with their underlying probability distributions.
13. Simulate the forecast period. Obtain the model outputs from the all considered models using optimized parameter sets for the forecast period.

14. Generate BMA predictions. Applying the weights and standard deviations to the forecast model outputs, produce the deterministic and probabilistic BMA predictions.

This approach will be implemented and evaluated in the final deliverable.

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