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BAYESIAN APPROACH FOR UNCERTAINTY ANALYSIS IN HYDROLOGICAL MODEL

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ABSTRACT

Hydrological model prediction is subjected to uncertainty due to uncertainty in data, model parameters and the model structure. This study is aimed at developing a methodology to study the effect of different sources of uncertainty in a lumped hydrological model using a Bayesian framework. Firstly, a Markov chain Monte Carlo (MCMC) simulation technique is applied to implement the concept, where the precipitation uncertainty is dealt with by developing precipitation error model. Next, the Generalized Likelihood Uncertainty Estimation (GLUE) technique is applied. The concept of GLUE is based on the acceptance of multiple sets of parameters rather than a unique optimum set. The likelihood function, which implicitly considers all sources of errors, has been formulated. The result shows that a Bayesian framework provides a useful way to deal with the uncertainty in hydrological models.

Keywords: Uncertainty, Fuji River, Markov chain Monte Carlo, Likelihood function, Confidence interval

1 INTRODUCTION

Hydrological phenomena are complex processes with different space and time variability. Hydrological models are widely used to understand these phenomena. Since a model is representation of reality, it contains numerous approximations, assumptions and simplifications. Due to natural variability and incomplete knowledge about the system, the results obtained from such models do not exactly match observations. This unpredictable difference between the model output and the observed value is referred to as uncertainty or error. Hydrological models are subjected to uncertainty due to the following three sources (Melching, 1995):

- Input data: due to systematic and/or random errors in input data
- Model parameters: due to non-optimal parameter values
- Model structure: due to inability of the model to represent a true process

Uncertainty involves the notion of randomness. In uncertainty modeling, it is not possible to say with certainty what the value of a random variable will be but only the likelihood or probability that it will be within some specified range of values. Probabilistic approach is used predominantly for uncertainty analysis, in which uncertainty is represented by probability distribution.

Collecting additional information on model parameters or using a longer period of data can reduce uncertainty. However, it requires a considerable amount of time and effort and does not seem to be cost effective in most cases. Sometimes, increasing model complexity is considered to reduce model uncertainty. Unfortunately, given a fixed amount of data one can reduce errors in fitting observations in this manner, but may not increase the reliability or accuracy of prediction.

Parameter uncertainty is a major issue in most of the studies related to uncertainty analysis in hydrology. The parameter adjustment, called calibration, is carried out to reduce the errors due to non-optimal parameters. This process also compensates the errors in data and model to some extent. However, the calibrated model lacks the generalization capability for new sets of data as these data sets contain some uncertainty. Therefore, input data uncertainty can not be neglected in uncertainty analysis. In hydrology, research on the combined effect of different sources of uncertainty is still sparse. Therefore, the objective of this research is to develop a methodology to analyze different sources of uncertainty in a hydrological model.

2 STUDY AREA AND HYDROLOGICAL MODEL

The study area for the research is the Fuji River Basin located in Japan. The catchment area of the river is 3570 km^2, and the length of the main stream is 128 km. The Fuji River originates from Mount Nokogiri-dake (2685m). The upper reaches of the main channel lie in the Japanese Southern Alps mountain range, which are over 3000m high. Flat land areas are found only along the middle reach of the channel and near the river mouth. The mean annual precipitation of the basin is about 2100 mm. The dominant land use is forest.

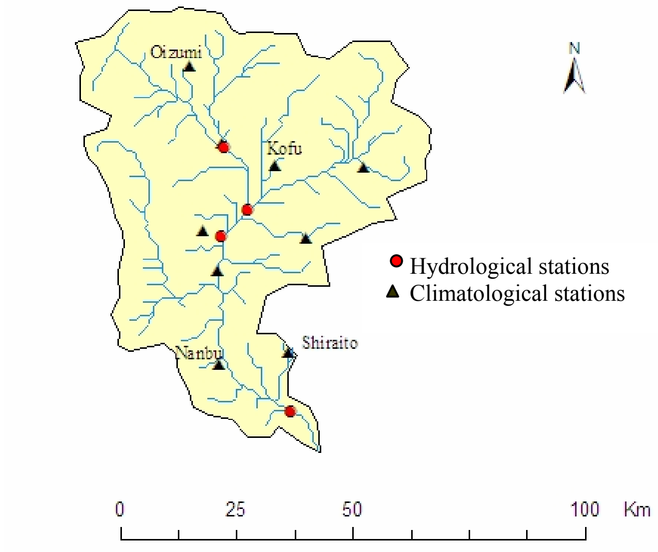

Figure 1: Map of Fuji River Basin

Fig.1 shows the map of the basin with hydrological and climatological stations. The daily data (1992-2001) of precipitation from 9 stations; temperature, wind speed, and sunshine data from 7 stations; and discharges from 4 stations are available for the study. The mean areal precipitation was computed using the Thiessen polygon method. Monthly potential evaporation values for 7 stations were computed using the Priestley-Taylor method. The method is an approximation of the combination equation, which is given by:

$$E = \alpha \frac{\Delta}{\Delta + \gamma} E_r \qquad (1)$$

where α = 1.3, Δ = Slope of saturated vapour pressure curve, γ = Psychrometric constant, E_r = Evaporation by energy balance method.

The hydrological model used in this study is NAM (Fig.2). The full form of NAM is “Nedbor-Afstromnings-Model” in Danish, which means precipitation-runoff model. NAM is a lumped conceptual model, which conceptualizes the rainfall-runoff process by four different and mutually interrelated storages: Snow storage, Surface storage, Lower or Root Zone storage, and Ground water storage. For a detailed description of NAM, refer to DHI (1999). The following is a brief description of the model.

The precipitation is retained in the snow storage only if the temperature is below 0^0C, whereas it is by-passed to the surface storage in situations with higher temperatures. Surface storage represents interception storage, depression storages and storage in the uppermost few centimeters of soil. The amount of water, U, in the surface storage is continuously lost by evaporation and interflow (QIF). When there is maximum surface storage ($U > U_{max}$), some of the excess water , P_N, will enter the streams as overland flow (QOF) and the remaining infiltrates into the lower zone storage representing the root zone. A portion, DL, of the water available for infiltration, is assumed to increase the moisture content, L, in the lower zone storage. The remaining amount of infiltrating moisture, G, is assumed to percolate deeper and recharge the groundwater storage.

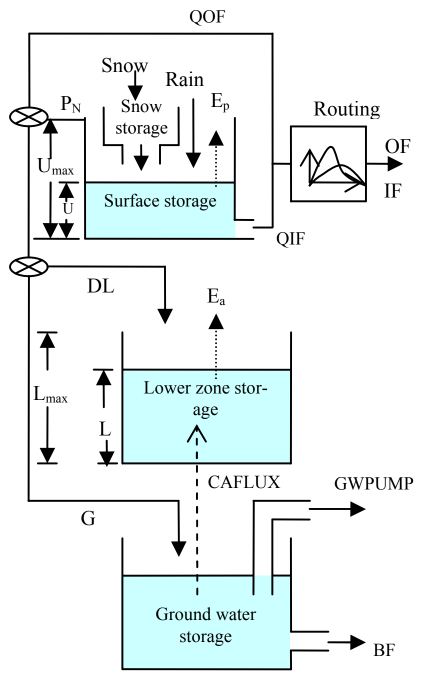

Figure 2: Structure of NAM model

Evapotranspiration demands are first met at the potential rate, E_p, from the surface storage. If the moisture content in the surface storage, U, is less than these requirements, the remaining fraction is assumed to be withdrawn by root activity from the lower zone storage at an actual rate, E_a.

Finally, the overland flow and interflow are routed through two linear reservoirs in series, and the base flow is calculated as the outflow from a linear reservoir. The total runoff is the sum of overland flow (OF), interflow (IF) and base flow (BF). Capillary flux (CAFLUX) and ground water abstraction (GWPUMP) are not included in this version of the model.

The following are the parameters of simple NAM model:

U_{max}: Maximum water content in the surface storage (mm)
L_{max}: Maximum water content in the lower zone storage (mm)
CQOF: Overland flow runoff coefficient
TOF: Threshold value for overland flow
TIF: Threshold value for interflow

TG: Threshold value for recharge
CKIF: Time constant for interflow (hr)
CK12: Time constant for overland flow and interflow routing (hr)
CKBF: Base flow time constant (hr)

3 METHODOLOGY

3.1 Performance Measure for Sensitivity Analysis

A perturbation approach is applied to show how the different sources of uncertainty affect the output. In this approach, an assumed amount of perturbation is applied to uncertainty source (x) keeping the other sources fixed. Normalized root mean square error (NRMSE) is used as a performance measure (Z), which is given by:

$$Z = \frac{\sqrt{\frac{1}{t}\sum_{i=1}^{t}\left(Q_{obs} - Q_{sim}\right)^2}}{\overline{Q_{obs}}} \tag{2}$$

where Q_{obs} is observed discharge, Q_{sim} is simulated discharge, $\overline{Q_{obs}}$ is the mean of observed discharge, and t is the number of time steps. Sensitivity is computed as the ratio of $(Zx - Z0)/dx$, where Zx is NRMSE after perturbation, $Z0$ is NRMSE of the original input series, and dx is the amount of perturbation.

3.2 Uncertainty Modeling using Bayesian MCMC Simulation

3.2.1 Bayesian Model and MCMC Simulation: an Introduction

Bayesian statistics describe uncertainty using a probability distribution. They combine two sources of information for learning about unknown parameters: prior information based on historical data or expert knowledge and data collected via experimentation and observation. The equation used to estimate uncertainty is given by:

$$P(\theta / D) = \frac{P(D / \theta)P(\theta)}{P(D)} \tag{3}$$

where $P(\theta / D)$ = posterior probability of θ given data D, $P(D/\theta)$ = prior probability of observed data given θ (Likelihood function), $P(\theta)$ = prior probability of θ, $P(D)$= Prior probability of observing data D (Normalizing constant).

The prior probability represents the prior (subjective) belief about the values of parameters. The likelihood function reflects how the uncertainty enters and propagates through the system. The posterior probability represents what is known about the parameters given the prior knowledge and the data.

In most high dimensional and complex model applications like rainfall-runoff modeling, it is impossible to obtain the analytical solution of the Bayesian equation. Therefore, the Markov chain Monte Carlo (MCMC) simulation technique is used to compute the posterior distribution of parameters. It is one of the sampling based techniques that utilize the Bayesian concept. It is a technique for generating random variables with the Markov property, where the outcome of a process at the current time is dependent on immediate past values. In a hydrological context, some of the papers on the application of MCMC technique are: Kuczera and Parent (1998), Bates and Campbell (2001), Engeland and Gottschalk (2002), Kavetski, et al. (2002).

The Metropolis algorithm is one of the commonly used algorithms for MCMC sampling. In this algorithm, the next value of the Markov chain is generated from a proposed density function and then accepted or rejected according to the density at the candidate point relative to the density at the current point.

The algorithm is as follows:

- Initialize θ with arbitrary starting values θ_0.
- For i = 1,2,……..,n
  - Sample $Z \sim u[0,1]$.
  - Sample a candidate θ^* from the proposed distribution. According to Metropolis algorithm, the proposed distribution should be symmetric, i.e.

$$P(A / B) = P(B / A) \tag{4}$$

  - Compute acceptance ratio

$$r = \min\left[1, \frac{\pi\left(\theta^* / D\right)}{\pi\left(\theta^{(i-1)} / D\right)}\right] \tag{5}$$

where $\pi(\theta^* / D)$ is the posterior probability of proposed parameter given data D and $\pi(\theta^{(i-1)} / D)$ is the posterior probability of previous time step's parameter given data D. Both of the posterior probabilities are computed according to the Bayesian equation. As the ratio of two posterior probabilities is required, the normalizing constant in the Bayesian equation need not be calculated.

  - If $Z \le r$ then $\theta^i = \theta^*$
    else $\theta^i = \theta^{(i-1)}$
  - Check convergence. If sufficient sample taken, stop. Otherwise, continue.

In this study, the methodology of Gelman et al. (1997) for assessing convergence of multiple chains is used. The logic of this method is that upon convergence, multiple chains should be statistically equivalent. This method compares between-chain and within-chain dispersion of samples, in an analysis of variance approach. The statistic used for assessing convergence is the scale reduction factor

(R), where convergence of the chain is related to the convergence of R to unity.

3.2.2 Precipitation Error Model

This study focuses on the uncertainty in precipitation data measured by a rain gauge. The form of precipitation error assumed for the study is:

$$P_{cr} = P_{obs} + S + e \tag{6}$$

where P_{cr} = Correct precipitation, P_{obs} = Observed precipitation, S = systematic error, and e = Random error.

Observed precipitation is subjected to both systematic and random errors. Possible sources of errors in precipitation are: reading errors by humans, wind-induced errors, instrumental error, evaporation error, error due to areal mean precipitation from a point observation. The error due to wind and evaporation are both systematic as well as random. This section briefly summarises techniques to analyze some errors.

Reading errors by human: observation errors due to humans are detected by plotting the Double Mass Curve (DMC). As a general rule, if the change in slope of DMC exceeds 10%, corrections need to be applied. The correction formula is:

$$c = \frac{M_c}{M_a} \tag{7}$$

where M_c = Slope of the original line, M_a = Slope of the line after change, c = correction.

$$Corrected\ value = c.Measured\ value \tag{8}$$

Wind-induced errors: The following formulae are used to account for wind error.
For snow (WMO, 1998):

$$k = \frac{1}{1 + 0.14V_g} \tag{9}$$

For rain (Kondo, 1994):

$$k = 1.0 - 0.0151V_g - 0.0021V_g^2 \tag{10}$$

where k = gauge catch deficiency, V_g = wind speed (m/s) at gauge height

$$Corrected\ Precipitation = Measured\ value/k \tag{11}$$

Errors in areal mean precipitation from a point observation: mean areal error in precipitation due to inadequate gauges is analyzed using the following approach:

$$N = \left(\frac{C_v}{E_p}\right)^2 \tag{12}$$

where N = optimal number of stations, C_v = Coefficient of variation, E_p = allowable percentage of error in estimating the mean areal precipitation.

3.2.3 MCMC Implementation steps

The following are the steps in implementing the MCMC method

- Develop precipitation error model.
- Specify range of parameters, prior distribution, proposal distribution and initial values.
- Formulate response error model, and likelihood function.
- Implement MCMC Metropolis algorithm using NAM as a hydrological model as follows.
  - Feed previous time step's parameters and correct precipitation, and other inputs to NAM model. Compute likelihood function.
  - Randomly generate parameters from proposal distribution and do as above.
  - Obtain posterior distribution of parameters as per MCMC Metropolis algorithm.

3.3 Uncertainty Modeling using GLUE concept

3.3.1 Introduction

GLUE is an acronym for Generalized Likelihood Uncertainty Estimation, whose concept was first introduced by Beven and Binley (1992). GLUE is based on the concept that for a physically based hydrological model, no single optimum parameter set exists, but rather a range of different sets of model parameter values may represent the process equally well. This concept is called equifinality of model structures and parameter sets. If there is no unique optimal model, then it is only possible to give different degrees of belief to different models or parameter sets. Some models can certainly be rejected as non-behavioural because they clearly do not give the right sort of response for an application. The 'optimum', given some calibration data has the highest degree of belief associated with it, but there may be many other models that are almost as good.

GLUE is a technique of Monte Carlo simulation based on the Bayesian concept, in which the likelihood function is interpreted as degree of belief or acceptability. Therefore, the definition of likelihood used in GLUE is rather different from the traditional statistical definition. In GLUE, the likelihood is a function of the model performance expressed in terms of the objective function chosen. Prior distributions of models and predictions are assessed in terms of likelihood measure relative to the available observation and a posterior distribution calculated that can be used in prediction. The likelihood measure will reflect the performance of particular model, given the errors in model structure, inputs, and observations. Since the likelihood measure value is associated with a parameter set, it will reflect all these sources of error implicitly. Equifinality in model performance will be reflected directly by different models having similar values of the chosen likelihood measure.

3.3.2 Analysis Procedure using GLUE concept

Prior to uncertainty modeling using GLUE, the things to specify are: prior distribution, range of parameters, likelihood function and acceptance criteria. Based on the prior distribution, parameters are generated randomly. The model is run for each set of parameters, and the likelihood measure for each run is evaluated. Parameters with likelihood below a threshold are rejected. The likelihood weights associated with the retained models are rescaled to give a cumulative sum of 1.0. Next, at each time step, the predicted outputs are weighted by the likelihoods, from which uncertainty bounds can be calculated to represent the uncertainty. Likelihood values from different types of data may be combined in different ways or updated as more data are collected.

4 CASE STUDY

4.1 Case Study Conditions

4.1.1 For assessing Precipitation Error

Wetting error: Wetting loss can be taken as 0.25 mm per precipitation (Patra, 2000).
Evaporation error: As the data come from an automatic gauge, error due to evaporation is not significant. Therefore, evaporation error is neglected in this study.
Random error: Random error is assumed to be normally distributed with mean = 0 mm and variance = 0.05 mm^2.

4.1.2 For MCMC simulation

Parameter ranges: The ranges of parameters are shown in Table 1.

Table 1: Parameter ranges

Parameters	Ranges
U_{max}	10-40
L_{max}	100-400
CQOF	0.1-0.9
CKIF	500-1000
CK12	5-40
TOF	0.01-0.9
TIF	0.01-0.9
CKBF	500-5000
TG	0.01-0.9
Lambda	0.6-1.1

Prior distribution: Uniform within the ranges specified above
Proposed distribution: Uniform within the ranges specified above
Response error model: The form of response error model is additive as shown below:

$$Q_{obs} = Q_{pred} + \varepsilon \qquad (13)$$

where Q_{obs} is observed discharge, Q_{pred} is predicted discharge and ε is response error, which is assumed normally distributed with mean = 0 and variance = σ_e^2.
Likelihood function: The form of the likelihood function is:

$$L(\theta / Data) = (2\pi\sigma_e)^{-n/2} \exp\left[-\frac{1}{2\sigma_e^2}\sum_{t=1}^{n}\left(Q_{obs} - Q_{pred}\right)^2\right] \qquad (14)$$

Simulation: Five parallel chains, each of 10,000 samples with different starting points, are generated using MCMC-Metropolis algorithm. The convergence of the parameters is monitored by computing R statistics for different sample sizes and initial samples before convergence are discarded.

4.1.3 For GLUE

Parameter ranges: Same as MCMC simulation.
Prior distribution: Uniform within the specified ranges
Likelihood function: Aggregated function of Normalized mean absolute error ($L1$) and Normalized root mean square error ($L2$) is used as a likelihood measure.

$$L1 = \frac{\left|\frac{1}{n}\sum_{i=1}^{n}\left(Q_{obs} - Q_{sim}\right)\right|}{\overline{Q_{obs}}} \qquad (15)$$

$$L2 = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Q_{obs} - Q_{sim}\right)^2}}{\overline{Q_{obs}}} \qquad (16)$$

where Q_{obs} is observed discharge, Q_{sim} is simulated discharge, and $\overline{Q_{obs}}$ is mean of observed discharge.
The aggregated form of likelihood function (L) is:

$$L = \left((L1)^2 + (L2)^2\right)^{1/2} \qquad (17)$$

Acceptance criteria: All the parameters having likelihood function value below 2.0 are accepted.
Number of simulations: 30000

4.2 Computations

4.2.1 Calibration of NAM model

Besides 9 model parameters, one more stochastic parameter, λ , is introduced to account for any error due to model structure deficiencies. The form of model is:

$$Y = \lambda f(x, \theta) \qquad (18)$$

Where Y is predicted discharge, x is input data and θ is parameter.

NAM was calibrated at the beginning of the modeling study as a base model for the sensitivity analysis. The data required for NAM are: precipitation, evaporation, temperature (if snow module included), and discharge. In this study, 10 parameters (including λ) are found by manual calibration. 7 years of data (1992-1998) are used for calibration and the remaining 3 years for validation. The performance of the model is evaluated by using Nash-Sutcliffe efficiency coefficient (COE), which is given by:

$$COE = 1 - \frac{\sum_{i=1}^{n}\left(Q_{obs} - Q_{sim}\right)^2}{\sum_{i=1}^{n}\left(Q_{obs} - \overline{Q_{obs}}\right)^2} \tag{19}$$

where Q_{obs} is observed discharge, Q_{sim} is simulated discharge, $\overline{Q_{obs}}$ is the mean of observed discharge, and n is the number of time steps.

The calibrated parameter values are: U_{max}=30, L_{max}=30, CQOF=0.6, CKIF=500, TOF=0.3, TIF=0.1, TG=0.3, CK12=20, CKBF=1000, λ =0.7. The Nash-Sutcliffe efficiency coefficients for calibration and validation are 0.66 and 0.73 respectively.

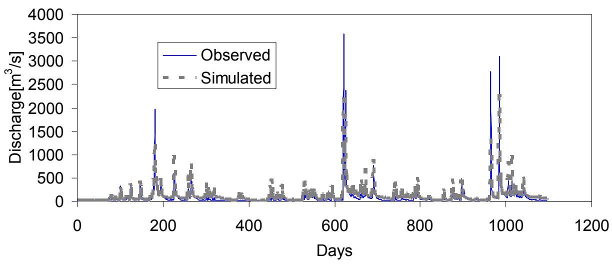

Figure 3: Validation

Comparison of observed and predicted discharges for validation (Fig.3) shows the performance of the model is good for most parts of the hydrograph except the very high peaks, which are under predicted by the model.

4.2.2 Preliminary comparison of precipitation and parameter uncertainties

To make a crude estimate of the effect of precipitation uncertainty and parameter uncertainty in the preliminary stage, a simple sensitivity approach as discussed in section 3.1 is performed. The following cases are considered for analysis:

Case0: Base model with observed precipitation and optimized parameters

Case1: Only precipitation is considered as uncertain while other two inputs are fixed at the observed values. Observed precipitation is increased by 10%, 20%, 30% respectively keeping the parameters fixed at their optimized value.

Case 2: All parameters are increased by 10%, 20%, 30%, the precipitation is fixed at the observed value.

Table 2: Sensitivity analysis

Error (%)	Sensitivity index	
	Case 1	Case 2
10	1.69	1.06
20	2.06	1.38
30	2.34	1.65

The results of the sensitivity analysis are presented in Table 2. They show that the sensitivity index for precipitation uncertainty is higher than that for parameter uncertainty. Therefore, precipitation uncertainty should be analyzed along with the parameter uncertainty in the hydrological model.

4.2.3 Precipitation Error Analysis

Precipitation error analysis is done according to equation 6, where the reading error, wind-induced error and wetting error are considered as systematic errors. Among systematic errors, reading errors are analyzed using DMC as discussed in section 3.2.2, wind errors are computed from equations (9), (10), and (11), and wetting error as specified in section 4.1.1. Random error is computed according to the normal distribution assumption as specified in section 4.1.1.

The result of reading errors by human is as follows.

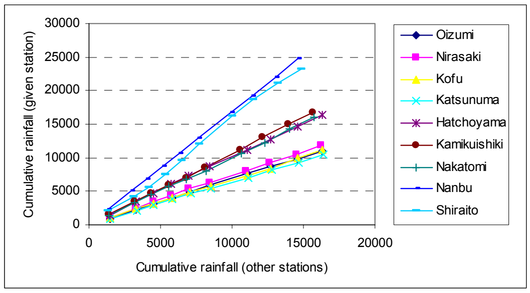

Figure 4: Double mass curve

The plot of DMC of all stations for period of 1992-2001 (Fig.4) shows that there is not any observational error for the 8 stations. In the case of only one station called Shiraito, it is found that there is significant change in slope (>10%) of DMC after 1996. Therefore, correction is applied for the station from 1997.

Error in areal mean precipitation from a point observation is computed from equation (12).

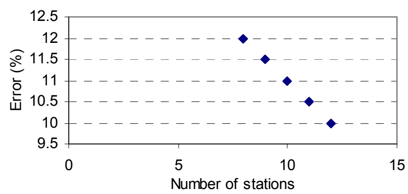

Figure 5: Error in mean areal precipitation

From Fig.5, it is seen that the error in mean areal precipitation with 9 gauges used in the study is about 11.5%. The error in mean areal data can never be eliminated. Normally 10% error is taken as the standard value in designing gauge network, using equation (12).

4.2.4 MCMC Simulation Results

Given the various conditions specified in section 4.1.2, MCMC simulation of the Fuji River Basin is performed using Metropolis algorithm. During convergence monitoring, it is found that R values are close to 1 for all parameters after 500 iterations. Therefore, the first 500 samples are discarded for each chain for further analysis. Therefore, the remaining number of simulations for each chain is 9500, and the total number of simulations left from five chains is 47500.

Table 3: Posterior distribution of parameters for MCMC based simulation

Parameters	Mean	Standard deviation	Median	First Quartile	Third Quartile
U_{max}	25.04	8.68	25.11	17.45	32.58
L_{max}	250.39	86.80	250.84	175.04	325.68
CQOF	0.50	0.23	0.50	0.30	0.70
CKIF	748.74	143.93	746.18	624.78	873.03
CK12	22.38	10.13	22.25	13.55	31.19
TOF	0.45	0.26	0.45	0.23	0.68
TIF	0.45	0.26	0.45	0.23	0.67
CKBF	2752.5	1301.38	2770.7	1616.5	3876.18
TG	0.45	0.26	0.45	0.23	0.67
Lambda	0.85	0.14	0.85	0.73	0.98

The posterior distributions of parameters from 47500 simulations are shown in Table 3.

Next, the 95% confidence interval for discharge is calculated using the 47500 set parameters. Each parameter set is passed to NAM, and discharge is computed for each set. 95% confidence interval about mean for each time step, i is given by:

$$CI = \overline{Q_{sim,i}} \pm 1.96 S_i \;/\sqrt{n} \qquad (20)$$

where CI is confidence interval, $\overline{Q_{sim,i}}$ is average simulated discharge, S_i is standard deviation of simulated discharge and n is number of samples.

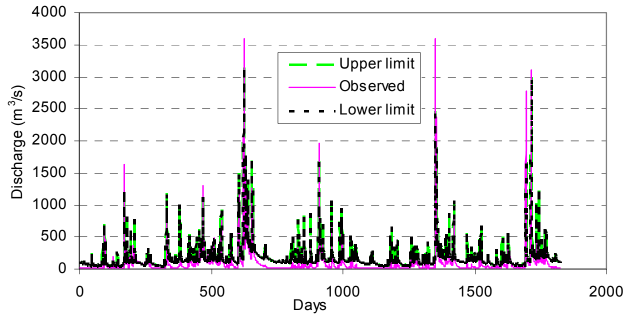

Figure 6: Confidence interval of discharge (1997-2001) from MCMC results

The 95% confidence interval for discharge for the period of 1997-2001 is plotted in Fig.6. The plot shows that most of the observed values of discharge are close to the confidence bound, but not contained within the bound.

4.2.5 GLUE simulation Results

GLUE based simulation of the Fuji River Basin is performed according to the various conditions specified in section 4.1.3. Initially 30000 Monte Carlo simulations were performed, and then 11379 simulations were retained after applying the threshold of acceptance. Next, likelihood weighted discharge is computed for each time step using the linear weighting, which is given by :

$$W_i = \frac{LH_i - LH_{\min}}{LH_{\max} - LH_{\min}} \qquad (21)$$

where W_i is weight for realization i, LH_i is likelihood for realization i, $LH_{\min}$ is minimum likelihood of all realizations, and $LH_{\max}$ is maximum likelihood of all realizations. Finally, the uncertainty is described by computing the 95% confidence interval according to equation (20).

Table 4: Posterior distribution of parameters for GLUE based simulation

Parameters	Mean	Standard deviation	Median	First Quartile	Third Quartile
U_{max}	25.29	8.66	25.53	17.85	32.83
L_{max}	251.53	86.64	252.06	175.88	327.42
CQOF	0.53	0.19	0.52	0.38	0.68
CKIF	748.33	143.67	748.05	624.38	872.77
CK12	24.78	8.55	24.84	18.20	31.77
TOF	0.44	0.25	0.44	0.23	0.66
TIF	0.46	0.26	0.46	0.23	0.68
CKBF	2675.3	1306.9	2645.12	1528.76	3802.26
TG	0.46	0.25	0.46	0.24	0.68
Lambda	0.74	0.09	0.73	0.66	0.81

The posterior distributions of parameters from GLUE based simulations are shown in Table 4. Comparing the result of MCMC simulation from Table 3 and GLUE simulation from Table 4, it is seen that the posterior distribution of parameters from both the methods are closer.

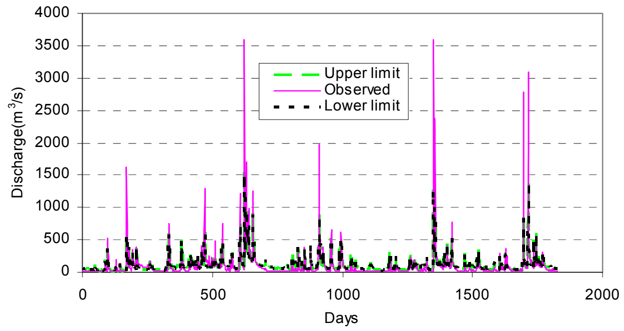

Figure 7: Confidence interval of discharge (1997-2001) from GLUE results

The plot of the 95% confidence interval for discharge for the period of 1997-2001 obtained from the GLUE results is shown in Fig. 7. As can be seen in the figure, the observed discharge for low flows and medium flows are close to the confidence bounds, while the observed high peaks seem to be far from the bound.

5 CONCLUSIONS

This study focused on the uncertainty analysis of a lumped conceptual model using NAM model as an example. A stochastic term is added as an adjustment factor for model structural inadequacy, which is treated as parameter. Initially, a simple comparison is done between precipitation and parameter uncertainty using a perturbation approach. The result of the analysis shows that precipitation uncertainty plays a more significant role in the uncertainty in discharge prediction. Therefore, input uncertainty could not be neglected in hydrological model simulation.

In this study, two methods: Markov chain Monte Carlo (MCMC) simulation and Generalized Likelihood Uncertainty Estimation (GLUE) are implemented for uncertainty analysis. Both of these methods are based on the concept of Bayesian analysis. For MCMC simulation, additive type precipitation error model is developed to include systematic as well as random error. For each realization of MCMC simulation of NAM model, parameters are sampled randomly according to the Metropolis algorithm. For GLUE, an aggregated objective function is applied as a likelihood function.

The result of the study summarized by 95% confidence interval of discharge shows that the observed values of discharge in both cases are close to the confidence bounds except for high peaks. The deficiency in the uncertainty bounds to capture the observed discharges reflects the errors in input data and model structure.

Finally, this study concludes that the use of MCMC and GLUE can serve as a methodology to incorporate input and parameter uncertainty in any hydrological model. The future study should be aimed at analyzing different sources of errors in ground observed precipitation as well as precipitation obtained from remote sensing, errors in evaporation data and discharge data.

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