

第 II 部門 **Methodology for Hydrologic Model Quantitative Comparison-An Example by Using SFM and TOPMODEL**

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1. Introduction

For many years hydrologists have been interested in the effects of various uncertainties on the accuracy and reliability of the estimation of catchment hydrological variables such as peak flow and flood volume¹⁾. Among early contributions, some of them focus on the rainfall uncertainty and its influence to the runoff (e.g., Storm *et al.*²⁾); some of them focus on the sensitivity of model structure due to the input error (e.g., Singh and Woolhiser³⁾). Recent researches relating to hydrologic model uncertainty most refer to parameter uncertainty identification, the procedure of parameter calibration, and their impact to simulation result^{4,5)}. Among them, Generalized Likelihood Uncertainty Estimation (GLUE) Methodology⁶⁾ offers a path of identifying parameter uncertainty. Nevertheless, parameter equifinality became the conclusion of GLUE; uncertainty related to input data and other factors are excluded. Even it is said that they could also be included in GLUE but this has not normally been done⁶⁾.

The performance of hydrologic models is profoundly affected by the sources of uncertainty, briefly they are:

- (a) Observed data,
- (b) Data for model calibration,
- (c) Parameter space, and
- (d) Model structure.

Among those, data uncertainty occupies the most and contaminates other sources of uncertainty.

In this study, a methodology is proposed to recognize and quantify the different uncertainty sources. Firstly, Monte Carlo simulation method is applied to add bias item in model input data series (rainfall), then rainfall realizations, parameter space, and model outcomes (outflow discharge) under different bias level are acquired. Secondly, by examining the counter relationship between model simulation outcomes, calibration outcomes and observed watershed response series (discharge), an uncertainty structure is recognized. Finally, parameter uncertainty, calibration uncertainty, and model structure uncertainty caused by input data uncertainty are recognized, separated, and quantified through the methodology.

Nash coefficient is used as a measure of uncertainty, also an index which originated from Nash coefficient named Model Structure Indicating Index (MSII) is proposed to quantify model structure uncertainty which can be used as a tool for implementing model quantitative comparison. For the demonstration of the proposed method, a conceptual hydrologic model named Storage Function Method⁷⁾ (SFM) and a semi-distributed hydrologic model TOPMODEL⁸⁾ are employed. Through fixing the value of one parameter of SFM, a poorest

structure model is formed as a contradistinction in performing model comparison. The results show that a larger value of MSII indicating a poorer structure of hydrologic model in a dynamic manner, that is, incorporating the MSII to the input uncertainty.

2. Uncertainty recognition in hydrological modeling

In this study, prediction uncertainty which came from the four kinds of sources mentioned previously is classified into four categories: system uncertainty, entire uncertainty, inherent uncertainty, and structure uncertainty. The definition and the procedure to recognize them are described below.

System Uncertainty: The system uncertainty can be recognized by evaluating the discrepancy between observed watershed response series and the model outcome during the process of model parameter calibration.

Entire Uncertainty: After calibrating the model parameter, the calibrated parameter space will reflect its uncertainty through the model structure and propagates to the model outcome. This uncertainty can be recognized by examining the discrepancy between observed watershed response data and model outcome by using input data and parameter sets.

Inherent Uncertainty: Inherent uncertainty represents the sensitivity of parameter space which determined according to the input uncertainty and reflects to model outcomes. This can be examined by the discrepancy among model outcomes derived from different best fit parameter sets. Watershed response data is not used here, which indicates the model structure uncertainty is eliminated as much as possible.

The goodness of model structure can be evaluated by the distance between entire uncertainty and inherent uncertainty. The smaller the distance is, the better the quality of the prediction result.

3. Algorithm for uncertainty recognition and quantification

Instead of sampling the parameter space directly like what GLUE did, the study here generates the parameter set space by introducing noise item into input data with specified probability distribution. Here Normal distribution with mean equals to zero and standard deviation from 1.0 to 5.0 (mm/hr) is used to acquire model parameter space and outcomes under different input uncertainty. For each iteration, 10000 model outcomes for each specified input uncertainty were derived from the combination of rainfall series and parameter set generate output series through the model. The system uncertainty and the

prediction ability were identified and recognized by corresponding parameter set.

4. Results and conclusions

Fig.1, Fig.2 and Fig.3 show the Nash coefficient of different categorized uncertainty of the different hydrologic model. It is expected that Inherent Uncertainty occupied the highest area, System Uncertainty is located in the middle and Entire Uncertainty is located on the lowest area. The reason for this allocation is that Entire Uncertainty denotes the outmost prediction uncertainty; consequently, within increasing input uncertainty, it located at the lowest area. System uncertainty denotes the uncertainty of the model calibration process, so it will smaller than Entire Uncertainty. While Inherent Uncertainty representing the possible bias range caused by the process of model calibration, it should be the smallest, hence it located in the highest area. Model structure can be evaluated by manipulating MSII. The smaller the MSII indicates the better of the process of model calibration and the smaller of the different between Entire Uncertainty and Inherent Uncertainty, which representing the goodness of model structure. In **Fig.4** we can see that parameter-constrained SFM is the highest, which represents the worst model structure among the three; TOPMODEL is the lowest, which indicates the best model structure. The results show that a larger value of MSII indicates a poorer structure of hydrologic model, within increasing input uncertainty the tendency becomes more apparently. The index can be used as a tool for implementing model quantitative comparison among ungauged or poor record watershed.

5. Reference

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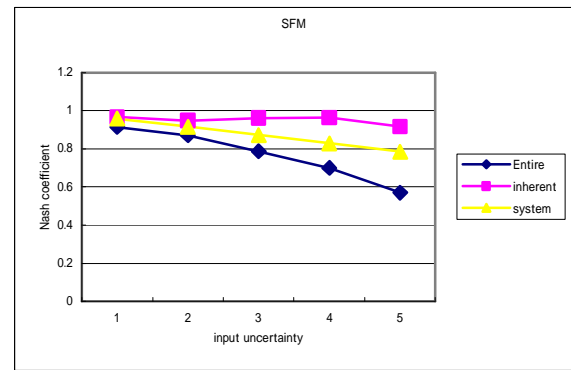


Fig.1 Nash Coefficient of SFM

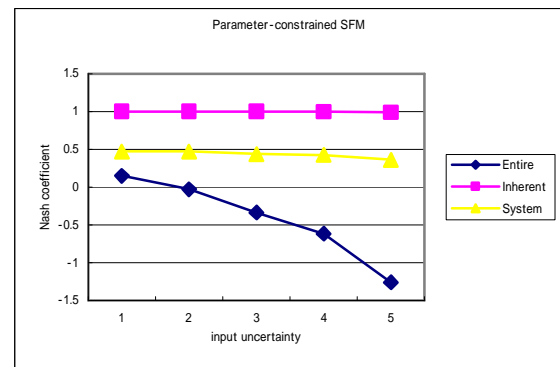


Fig.2 Nash Coefficient of parameter-constrained SFM

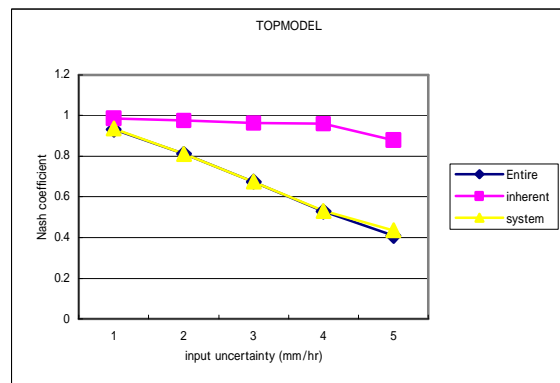


Fig.3 Nash Coefficient of TOPMODEL

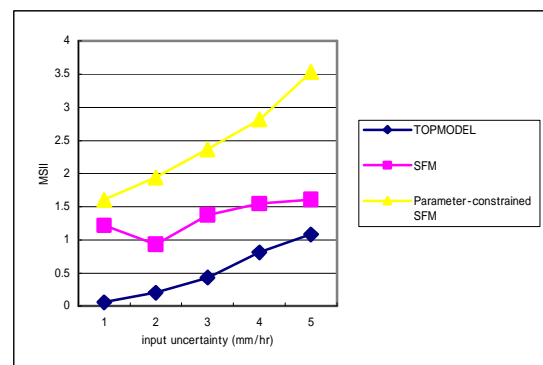


Fig.4 MSII of SFM, parameter constrained SFM and TOPMODEL

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