京都大学防災研究所年報　第 49 号 B　平成 18 年 4 月
Annuals of Disas. Prev. Res. Inst., Kyoto Univ., No. 49 B, 2006

# Analysis of Hydrologic Model Parameter Characteristics Using Automatic Global Optimization Method

Giha LEE*, Yasuto TACHIKAWA, and Kaoru TAKARA

*Graduate school of Urban and Environment Engineering, Kyoto University

**Synopsis**

The successful application of hydrologic models depends on how well the models are calibrated. Therefore, the calibration procedure should be performed prudently to improve model accuracy and maximize model reliability before making decision of an intended purpose using a hydrologic model. Despite frequent utilization of manual calibration especially for distributed hydrologic models, much more weakness still remains with respect to the absence of generally accepted objective measures and extreme time consuming. Automatic calibration can overcome these kinds of shortcomings. A global optimization algorithm entitled shuffled complex evolution (SCE) has been proved to be efficient and robust to find optimal parameters of hydrologic models. This study examines the applicability of global optimization scheme, SCE, for calibrating two hydrologic models which have different model structures and indicates variation of optimal parameters according to objective functions. We also analyze parameter transferability under various flood scale. At last, guideline indexes able to assess model stability are introduced to allow modelers to select a more stable and suitable hydrologic model. Above all procedures are applied to Kamishiiba catchment (211km$^2$).

**Keywords:** Automatic calibration, Shuffled complex evolution, Parameter transferability, Model stability

## 1. Introduction

The principal reasons why modeling of rainfall-runoff process is necessary are a limited range of measurement techniques and a temporal and spatial constraint of measurement (Beven, 2001). Manifold hydrologic models have developed mathematically and empirically to describe more closely and accurately the response behavior (transformation) of watershed from rainfall to runoff.

These types of models are conversion and simplification of reality, thus no matter how sophisticated and accurate they may be those models only represent aspects of conceptualization or empiricism of modelers. Accordingly, their outputs are as reliable as hypothesis, structure of models, and quantity and quality of input data, and parameter estimates (Gupta *et al.*, 1999; Muletha and Nicklow, 2005).

In general, one of the useful works to enhance accuracy of model performance is identifying suitable values of model parameters so that model simulations closely match measured behaviors of a study site.

The parameter values are adjusted between each run of the model, either manually by the modelers or by some computer-based optimization algorithm until some optimal parameter set has been found. However, manual calibration has several shortcomings. It requires comprehensive understanding of the catchment runoff behavior and the model structure and can be extremely time consuming. In addition, the termination of calibration process is based on the subjective decision of the hydrologists and therefore, it is difficult to transfer the expertise to another person (Wagener *et al*, 2004). But, methods of automatic calibration can complement these weaknesses. Automatic calibration involves the use of a search algorithm to determine best-fit parameters, and it offers a number of advantages over the manual approach with respect to calibration running time, extensive search of the existing parameter possibilities. There have been many automatic calibration studies dealt with lumped-conceptual models (Sorooshian and Gupta, 1995; Gupta *et al*., 1998) and distributed models (Eckardt and Arnold, 2001; Muletha and Nicklow, 2005).

Nevertheless a remarkable development of automatic calibration, so far, it is not sufficient to interpret parameter tranferability according to a flood scale in a single watershed. It is also difficult to explain parameter transferability according to areas which have same or different geomorphologic characteristics for modeling of ungauged basins since even nearby catchments can be very different with respect to their hydrological behavior.

Furthermore, modelers frequently are faced with of difficulties related to selection of a suitable hydrologic model for analysis of rainfall-runoff process. That is to say, there are no existing benchmark or guideline indexes able to assess the suitability and stability of the model structure for representing the natural system. Gupta *et al.* (1998) pointed out that a subjective selection of objective functions (e.g., SLS, HMLE) for calibration of hydrologic model lead to an overemphasis on a certain aspect of the response (e.g., peak flows), while neglecting the model performance with regard to another aspect (e.g., low flows). They suggested multi-objective optimization method to find the parameter set necessary to fit all aspects of the observed output time series and to identify model structural insufficiencies. Here, it is questionable that hydrologic models, which have totally different mechanism to reflect real rainfall-runoff process, lead to the same simulation results according to the variation of objective functions. If the optimized parameter set vary irregularly according to various objective functions, we are able to conjecture that kinds of model has an unstable model structure. Additionally, such approach makes it possible to allow modelers to distinguish the suitable model among diverse models.

In this paper, the Shuffled Complex Evolution (SCE) optimization method is used to calibrate lumped model, Storage Function Model, and distributed model, KsEdgeFC2D model using five flood events from Kamishiiba catchment located in Kyushu area. Especially, we focus on four main questions as described in following:

(1) Assessment of applicability of automatic global optimization scheme using two visual inspections, goodness-of-fit between the simulated and the observed, minimization progress of objective function values due to number of function evaluations. The outputs from calibrated parameters with SCE method are compared to the simulation results evaluated (manually calibrated) by Tachikawa *et al*. (2004) in their previous literature.

(2) Variation of optimal parameter according to two different objective functions, Simple Least Square (SLS), Heteroscedastic Maximum Likelihood Estimator (HMLE). The performance of each calibration is evaluated by using percent bias (PBIAS) and Nash-Sutcliffe (NS) statistics commonly used in goodness-of-fit measure.

(3) Analysis of parameter transferability including uncertainty of parameters according to a different flood scale through applying calibrated parameters of

four flood events to the rest flood event. Especially, the biggest flood event among flood events occurred in the study site is selected for analyzing the influence due to model parameters optimized by each different flood scale.

(4) Introduction of guideline indexes to analyze the model stability in terms of entire behaviors of predicted hydrographs.

## 2. Applied Hydrologic models

To assess the applicability of global optimization algorithm, Storage Function model (SFM) proposed by Kimura (1975) and KsEdgeFC2D developed by Ichikawa *et al.* (2001) are applied to the Kamishiiba catchment. More detailed description of models is introduced in following subsections.

### 2.1 Storage Function Model (SFM)

This model is known as a reasonable lumped model because of reflection of nonlinear characteristics of hydrologic response behavior and simplification of computational procedures. SFM is also used for the rainfall-runoff simulation in a small watershed less than five hundred square kilometers in Japan. The form of SFM is expressed as:

$$\frac{dS}{dt} = r_e(t - T_l) - q\,, \quad S = kq^p \tag{1}$$

$$r_e = \begin{cases} f \times r, & if \quad \sum r \le R_{SA} \\ r, & if \quad \sum r > R_{SA} \end{cases} \tag{2}$$

where, $S$ = water storage; $r$ = rainfall intensity; $q$ = runoff; $t$ = time step; $k$ = storage coefficient; $p$ = coefficient of nonlinearity; $f$ = primary runoff ratio; $T_l$ = lag time; and $R_{SA}$ = cumulative saturated rainfall.

### 2.2 KsEdgeFC2D Model

KsEdgeFC2D is a physically based distributed hydrologic model developed by Ichikawa *et al.* (2001) and discharge-stage relationship, which represents the hillslope runoff phenomena, including unsaturated flow is imbedded by Tachikawa *et al.* (2004). The model solves the one-dimensional kinematic wave equation with the discharge-stage equation using the Lax-Wendroff finite difference scheme according to orderly nodes and edges, edge connection along flow direction map. All geomorphologic information are extracted from a 250m based DEM. Channel routing is also carried out by the kinematic routing scheme as well as calculation of slope elements reflecting contributing areas.

The model assumes that permeable soil layers cover the hillslope as illustrated in Figure 1. The soil layers consists of a capillary layer in which unsaturated flow occurs and a non-capillary layer in which saturated flow occurs. According to this mechanism, if the depth of water is higher than the soil depth, then overland flow occurs.

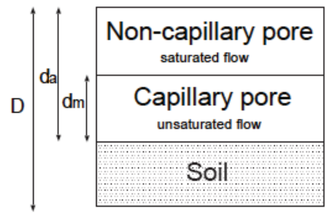



Fig. 1 Model structure for the hillslope soil layer.

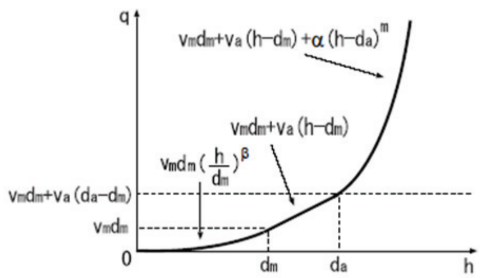



Fig. 2 The discharge-stage relationship.

The discharge-stage relationship is expressed by three equations corresponding to water levels divided into three layers (see Figure 2). This relationship is defined as:

$$q = \begin{cases} v_m d_m (h/d_m)^{\beta}, & 0 \le h \le d_m \\ v_m d_m + v_a (h - d_m), & d_m \le h \le d_a \\ v_m d_m + v_a (h - d_m) + \alpha (h - d_a)^m, & d_a \le h \end{cases} \tag{3}$$

$$\frac{\partial h}{\partial t} + \frac{\partial q}{\partial x} = r(t) \tag{4}$$

Flow rate of each slope segment are calculated by above governing equations combined with the continuity equation like equation (4). where, $v_m = k_m i$; $v_a = k_a i$; $k_m = k_a / \beta$; $\alpha = \sqrt{i} / n$; $i$ is slope gradient, $k_m$ is saturated hydraulic conductivity of the capillary soil layer, $k_a$ is hydraulic conductivity of the non-capillary soil layer, $n$ is roughness coefficient, $d_m$ is the depth of the capillary soil layer and $d_a$ is soil depth. Detailed explanations of model structure appear in Tachikawa *et al.* (2004).

## 3. Study site and storm events

The study site is the Kamishiiba catchment which lies within Kyushu region in Japan and covers an area of 211km$^2$. Topographic data processing is basically performed with 250m DEM (Geographical Survey Institute). Figure 3 shows the study area and drainage outlet, Kaimsiiba Dam described by ExtractNodeEge, one of the geo-processing procedures in Geohymos (http://flood.dpri.kyoto-u.jp/product/geohymos/geohymos.html). Figure 4 describes geomorphologic characteristics of the study site. The maximum elevation is 1724m and average slope of catchment is around 0.52 and hence, the study area is a steep mountainous area. For parameters calibration, and analysis of parameter transferability and model stability, five past storm events are used in this study. Event 1 ~ 4 are gauged on Eshiroyama radar and Event 5 is measured by radar AMeDAS. Rainfall data have 10-min temporal resolutions. Table 1 shows historical storm events for this study.

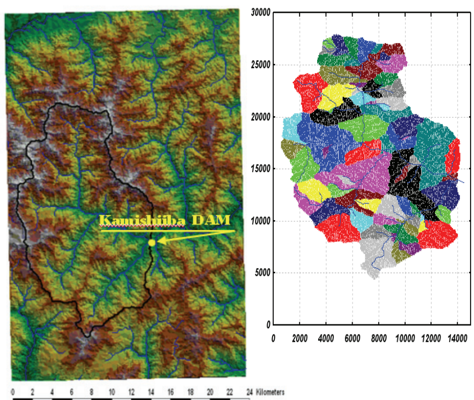



Fig. 3 Channel networks and subcatchments of Kamishiiba.

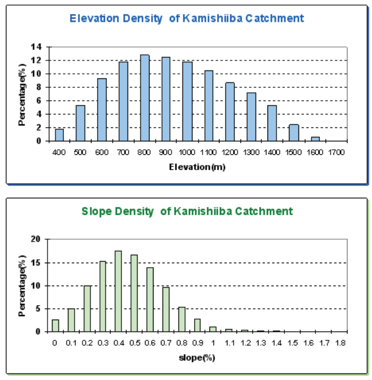



Fig. 4 Elevation and Slope Density graphs of Kamishiiba catchment.

Table 1 Historical storm events.

| *Storm Event* | *Date of occurrence* | *Rainfall duration (hr)* | *Accumulated rainfall (mm)* | *Peak discharge ($m^3$/s)* |
|---|---|---|---|---|
| 1 | 1997 / 09 / 15 | 96 | 495.94 | 1192 |
| 2 | 1999 / 06 / 24 | 168 | 462.56 | 210 |
| 3 | 1999 / 08 / 01 | 168 | 473.63 | 472 |
| 4 | 1999 / 09 / 22 | 120 | 339.62 | 590 |
| 5 | 2005 / 09 / 03 | 144 | 713.93 | 1718 |

In SFM case, a mean areal rainfall data is considered as input data and spatially-distributed two-dimensional rainfall data is applied for simulation of KsEdgeFC2D model. The distributed grid rainfall data which each cell has 1km (Event 1~4) and 2.5km (Event 5) spatial resolutions is shown in Figure 5. Colorful solid lines show the rainfall contour map.

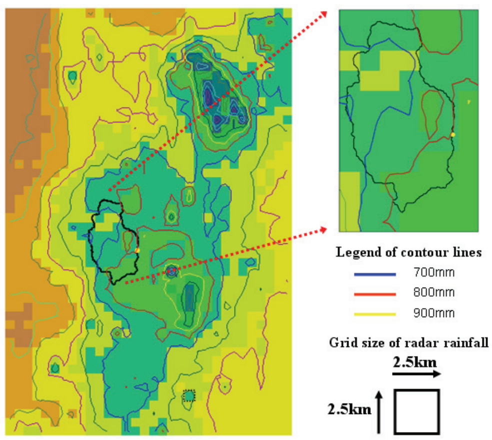



Fig. 5 Spatially distributed 2-D rainfall data (2005) for simulation of KsEdgeFC2D.

## 4. Shuffled Complex Evolution (SCE) Algorithm

The Shuffled Complexes Evolution (SCE), one of the computer-based automatic optimization algorithm developed by Duan *et al*. (1992) is a single-objective optimization method designed to handle high -parameter dimensionality encountered in calibration of a nonlinear hydrologic simulation models. (Duan *et al*, 1992). This evolutionary approach method has been performed by a number of researchers on a variety of models with outstanding positive results (Gupta *et al*., 1999) and has proved to be an efficient, powerful method for the automatic optimization (Duan *et al*, 1992, 1993, 1994; Yu *et al*, 2001; Wagener *et al*, 2004).

Basically, this scheme is synthesized by following three notions: (1) combination of simplex procedure (Nelder and Mead, 1965) with the concepts of controlled random search approaches (Price, 1987); (2) competitive evolution (Holland, 1975); and (3) complex shuffling. The integration of these steps above mentioned makes the SCE method effective and robust, and also flexible and efficient (Duan *et al*., 1994).

The SCE method is initialized by selecting $p$ and $m$, where $p$ is number of complexes and $m$ is number of points in each complex. The population, $s$, is sampled randomly using uniform probability distribution in a feasible parameter space and a objective function value at each point is computed subsequently. Then, the $s$ points are sorted in order of increasing criterion value. Sorted $s$ points are divided into $p$ complexes, each containing $m$ points. Each complex evolves independently according to the competitive complex evolution algorithm based on the Simplex downhill search scheme (Nelder and Mead, 1965). The next step is a shuffling to combine the points in the evolved complexes into a new single population with sharing information came from previous complexes. The evolution and shuffling processes repeat until any of termination criteria are satisfied.

Duan *et al*. (1994) indicated that algorithmic parameters, controlling SCE method, must be selected very carefully because the effectiveness and efficiency of the optimization performance are influenced by the choice of these algorithmic parameters. The necessary algorithmic parameters are explained in Table 2. In this study, all algorithmic parameters are introduced with the recommended values by Duan *et al*. (1994). Those proposed values marked by * are also described in the same Table and $n$ is number of parameters to be optimized in the hydrologic model.

Table 2 Algorithmic parameter in SCE method.

| ***Parameter*** | ***Description*** |
|---|---|
| $m$ | the number of points in a complex<br>$*m = 2n + 1$ |
| $p$ | the number of complexes<br>$*p = 2$ |
| $p_{min}$ | the minimum number of complexes required in the population<br>$* p_{min} = p$ |
| $q$ | the number of points in a subcomplex<br>$*q = n + 1$ |
| $\alpha$ | the number of consecutive offspring generated by each subcomplex<br>$*\alpha = 1$ |
| $\beta$ | the number of evolution steps taken by each complex<br>$*\beta = m = 2n + 1$ |

The purpose of automatic calibration is to find proper values of the model parameters that minimize or maximize the numerical value of the objective function. Two objective functions are used in this study for investigating results due to selection of objective functions. The first is the Simple Least Square estimation criterion (SLS), the most commonly utilized measure in hydrological modeling and the second is the Heteroscedastic Maximum Likelihood Estimator (HMLE) suggested by Sorooshian and Dracup (1980).

These estimation criteria are defined as below forms.

$$\min_{\theta} SLS = \sum_{t=1}^{N} (q_t^{obs} - q_t(\theta))^2 \tag{5}$$

$$\min_{\theta,\lambda} \ HMLE = \frac{1/N \sum_{t=1}^{N} w_t \varepsilon_t}{\prod_{t=1}^{N} w_t} \tag{6}$$

where, $\varepsilon_t = q_t^{obs} - q_t(\theta)$ is the model residual at time

$t$; $q_t^{obs}$ is observed stream flow value at time $t$; $q_t(\theta)$ is model simulated stream flow value at time $t$ using parameter set $\theta$; and $w_t$ is the weight assigned to time $t$.

## 5. Parameter estimation and analysis of results

### 5.1 Identification of parameters to be optimized

Sensitivity analysis is conducted before the calibration process to identify the most important / sensitive parameters, and model components. Insensitive parameters can be fixed to suitable values to decrease the dimensionality of the calibration problem through this process.

In other words, a previous sensitivity analysis shows which parameters should be given priority in the optimization. As a result of this step, four process parameters of SFM are determined for calibration. Five parameters to be optimized are selected in KsEdgeFC2D. Physical parameters, representing physically measurable properties of watershed such as watershed area, channel length, slope gradient and so on, are estimated from geo-processing based on DEM data. Each parameter set of two hydrologic models is optimized using the upper and lower parameter bounds indicated in Table 3.

Table 3 Parameters of two hydrologic models.

| ***Parameters optimized (Storage Function Model)*** | ***Lower bound*** | ***Upper bound*** |
|---|---|---|
| $k$ | 0.0 | 50 |
| $p$ | 0.0 | 1.0 |
| $f$ | 0.0 | 1.0 |
| $R_{SA}$ (mm) | 0.0 | 300 |
| $^*T_l$ (hr) | - | - |
| ***Parameters optimized (KsEdgeFC2D)*** | ***Lower bound*** | ***Upper bound*** |
| $n$ | 0.1 | 0.5 |
| $k_a$ | 0.01 | 0.05 |
| $\beta = k_a / k_m$ | 2 | 10 |
| $d_m$ (mm) | 0.0 | 490 |
| $d_a$ (mm) | 500 | 900 |

$^*T_l$ is regarded as a fixed value, 1hr during calibration procedure

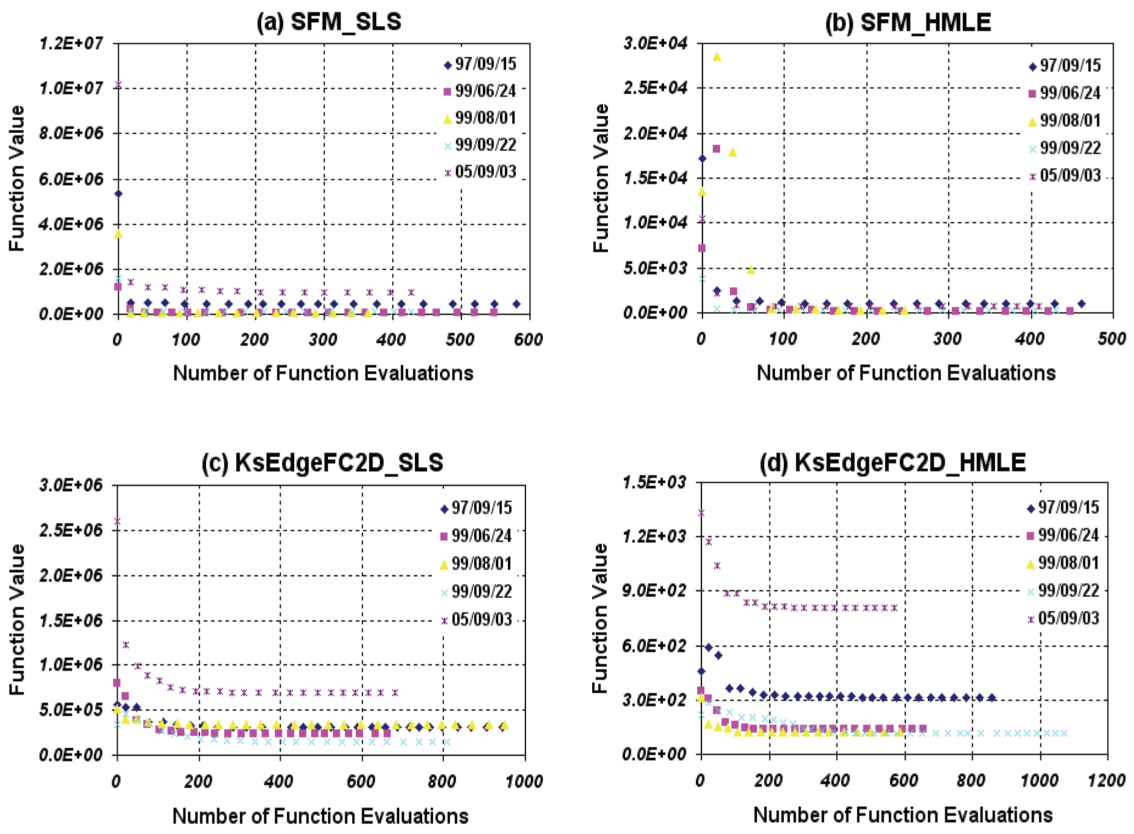



Fig. 6 Minimization progress of objective function value.

### 5.2 Methodology

The five steps for calibration and applicability assessment of global optimization algorithm are carried out as follows.

***Step 1 : Decision of Initial model parameter set of hydrologic models***

Calibration using SCE can be started as we decide initial model parameters within chosen ranges of parameters. The initial SFM parameters selected are $k = 36.3$, $p = 0.6$, $f = 0.6$, $R_{SA} = 230$. The five model parameters in KsEdgeFC2D model are initialized by: $n = 0.3$, $k_a = 0.01$, $d_a = 550$, $d_m = 450$, $\beta = 4.0$.

All initial values selected in this study are the optimal parameters evaluated by Tachikawa *et al.* (2004). The reason we set up these values as initial ones is to compare the best parameter set obtained by manual and automatic calibration more easily. Entire starting points located in vertical axis of Figure 6 indicate initial objective function values and initial parameter values.

Table 4 Algorithmic parameters of SCE used in this study.

| ***Algorithmic parameters*** | ***Storage Function Model*** | ***KsEdgeFC2D Model*** |
|---|---|---|
| $n$ | 4 | 5 |
| $m$ | $m = 2n + 1 = 9$ | $m = 2n + 1 = 11$ |
| $p$ | $p = 2$ | $p = 2$ |
| $p_{min}$ | $p_{min} = p = 2$ | $p_{min} = p = 2$ |
| $q$ | $q = n + 1 = 5$ | $q = n + 1 = 6$ |
| $\alpha$ | $\alpha = 1$ | $\alpha = 1$ |
| $\beta$ | $\beta = m = 2n + 1 = 9$ | $\beta = m = 2n + 1 = 11$ |

***Step 2 : Initialization of SCE algorithmic parameters***

It is essential to select appropriate algorithmic parameter values of SCE strategy for improving calibration procedure more efficiently and robustly. Algorithmic parameters used in this study are initialized as shown in Table 4.

***Step 3 : Selection of objective functions***

The performance of a model is typically judged using objective functions, usually in combination with visual inspection of the calculated hydrograph. A wide range of statistical and hydrological objective functions is available. However, while so many studies have tried to assess the suitability of different measures, it still remains a subjective decision of modelers to select one or more objective functions (Wagener *et al.*, 2004).

Two different measures, Simple Least Squares (SLS) and Heteroscedastic Maximum Likelihood Estimation (HMLE) are used for the model calibration processess. Figure 6 shows that results of iterations gradually approach the minimum objective function value of two rainfall-runoff models. These charts imply that SCE method successfully results in better objective function values than manually optimized ones.

***Step 4 : Analysis of optimized parameters***

Optimized model parameters using the SCE algorithm are compared to optimal values proposed by Tachikawa et al. (2004) for appraising suitability and accuracy of manually optimized parameters. The same parameter set is applied for rainfall-runoff simulation over all storm events in the former research. As shown in Table 5 and 6, pre-specified parameters are compared with newly evaluated parameters using SCE algorithm. In SFM, parameter values of SLS are not similar to the corresponding values of HMLE. In contrast, calibrated parameter values of KsEdgeFC2D have a very small difference between SLS and HMLE. Figure 7, 8 describes parameter values plotted against number of function evaluations. Parameter $k$ of SFM and $k_a$ of KsEdgeFC2D converges into approximate single value, 45 and 0.013 respectively. However, other calibrated parameters are scattered irregularly.

Table 5 Comparison of optimized parameters (SFM).

| Storm Event | Optimized parameters (SFM) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $k$ | | $p$ | | $f$ | | $R_{SA}$ | |
| | SLS | HMLE | SLS | HMLE | SLS | HMLE | SLS | HMLE |
| 1 | 49.61 | 49.64 | 0.52 | 0.64 | 0.63 | 0.57 | 201 | 119 |
| 2 | 34.18 | 37.35 | 1 | 0.97 | 0.84 | 0.86 | 295 | 299 |
| 3 | 49.56 | 49.38 | 0.68 | 0.73 | 0.66 | 0.86 | 5.1 | 7.1 |
| 4 | 49.39 | 49.59 | 0.55 | 0.77 | 0.64 | 0.5 | 226 | 239 |
| 5 | 49.16 | 49.39 | 0.52 | 0.63 | 0.22 | 0.18 | 224 | 193 |
| Manually Optimized | 36.3 | | 0.6 | | 0.6 | | 230 | |

Table 6 Comparison of optimized parameters (KsEdgeFC2D).

| Storm Event | Optimized parameters (KsEdgeFC2D) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $n$ | | $d_m$ | | $d_a$ | | $k_a$ | | $\beta$ | |
| | SLS | HMLE | SLS | HMLE | SLS | HMLE | SLS | HMLE | SLS | HMLE |
| 1 | 0.196 | 0.256 | 489.995 | 489.998 | 576.904 | 561.785 | 0.017 | 0.016 | 3.839 | 4.054 |
| 2 | 0.135 | 0.157 | 10.006 | 10.039 | 899.984 | 895.274 | 0.01 | 0.01 | 7.425 | 7.929 |
| 3 | 0.102 | 0.103 | 203.71 | 130.145 | 639.218 | 713.858 | 0.016 | 0.014 | 7.091 | 7.573 |
| 4 | 0.332 | 0.475 | 489.992 | 489.961 | 529.731 | 500 | 0.011 | 0.01 | 4.417 | 4.213 |
| 5 | 0.1 | 0.1 | 191.655 | 176.937 | 500.001 | 500.023 | 0.016 | 0.011 | 7.997 | 7.999 |
| Manually Optimized | 0.25 | | 450 | | 550 | | 0.01 | | 4.0 | |

Table 7 Model performance of each calibration.

| Method | Storm Event | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1997.9.15 | | 1999.6.24 | | 1999.8.1 | | 1999.9.22 | | 2005.9.3 | |
| | SFM | KsEdgeFC2D | SFM | KsEdgeFC2D | SFM | KsEdgeFC2D | SFM | KsEdgeFC2D | SFM | KsEdgeFC2D |
| SLS_PBIAS | 4.11 | -1.16 | 3.14 | -4.73 | 3.68 | 3.18 | 0.31 | -2.57 | 9.09 | 7.77 |
| HMLE_PBIAS | 1.18 | -1.55 | 2.06 | -4.71 | 5.07 | 4.42 | 16.11 | -2.07 | 9.27 | 9.31 |
| *Previous_PBIAS | 6.80 | -0.73 | 11.78 | -10.39 | 18.11 | 2.05 | 2.33 | -0.70 | 8.48 | 16.20 |
| SLS_NS | 0.94 | 0.99 | 0.88 | 0.90 | 0.95 | 0.96 | 0.93 | 0.99 | 0.96 | 0.98 |
| HMLE_NS | 0.88 | 0.98 | 0.88 | 0.90 | 0.94 | 0.99 | 0.68 | 0.97 | 0.91 | 0.97 |
| *Previous_NS | 0.93 | 0.98 | 0.42 | 0.65 | 0.69 | 0.94 | 0.92 | 0.96 | 0.95 | 0.92 |

***Step 5 : Assessment of model performance of each calibration***

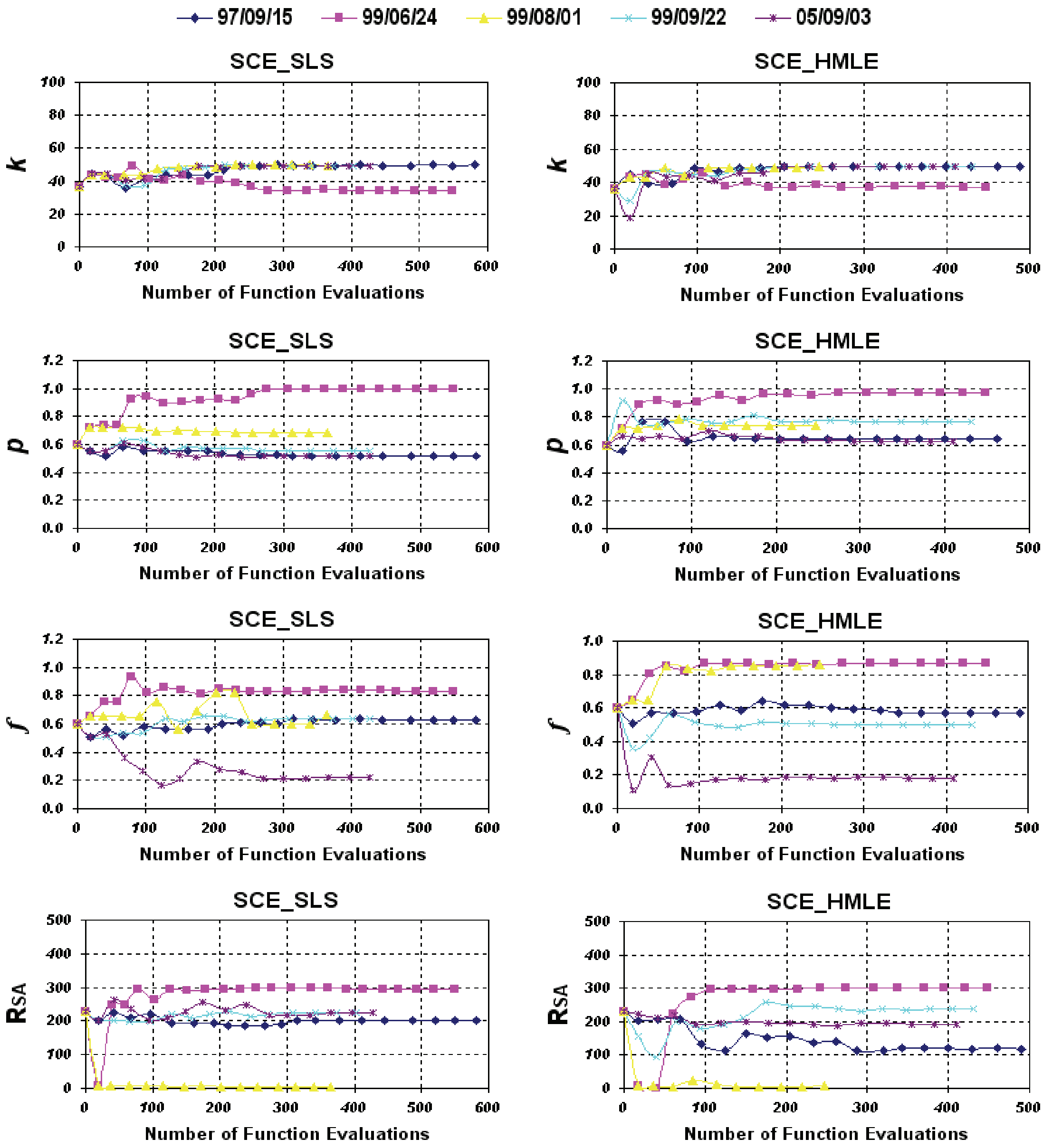
The success of automatic calibration is measured by how much improvement in model performance is achieved in this step compared with results from the former study using manual calibration.

The performance of each calibration is evaluated by using percent bias (PBIAS) and Nash-Sutcliffe (NS) statistics of the residuals, commonly used goodness-of-fit measure between the simulated time series and the observed time series, defined as:

$$PBIAS = \frac{\sum_{t=1}^{N} q_t^{obs} - q_t(\theta)}{\sum_{t=1}^{N} q_t^{obs}} \times 100\% \tag{7}$$

$$NS = 1 - \frac{\sum_{t=1}^{N} (q_t^{obs} - q_t(\theta))^2}{\sum_{t=1}^{N} (q_t^{obs} - q^{mean})^2} \tag{8}$$

where, $q^{mean}$ is the average flow rate of observed data.



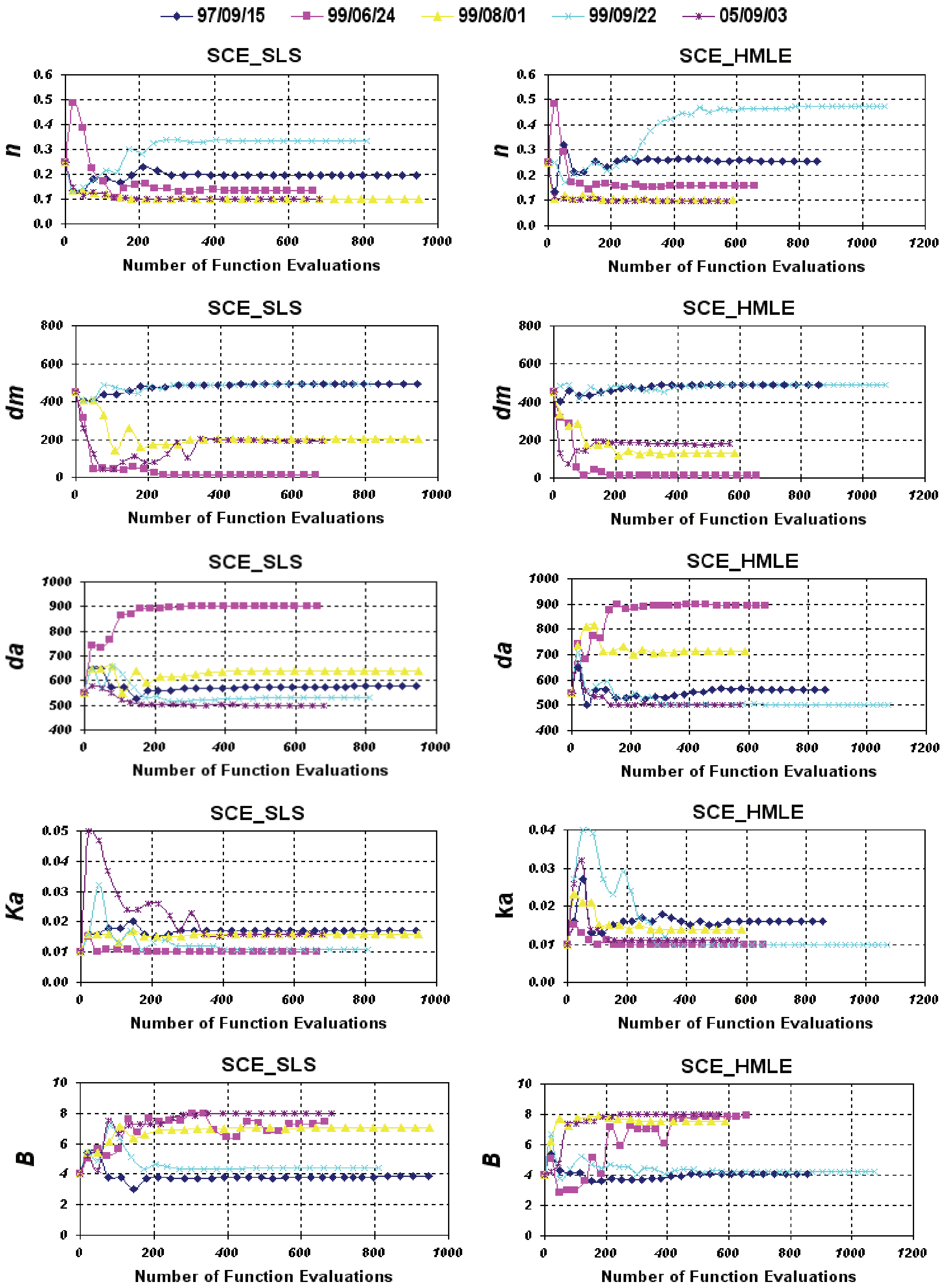

(a) SLS (b) HMLE

Fig. 7 Parameter value plotted against number of function evaluations by SCE algorithm (SFM).

As shown in Table 7, the overall model performance with parameters calibrated by SCE method lead to a better improved simulation results. The distributed model, KsEdgeFC2D tends to reproduce hydrograph more closely to measured streamflow data when compared with SFM. The simulation results due to two different objective functions bring on similar hydrologic responses, except for several cases (Event 1, 4, 5) carried out using SFM. The calibrated SFM based on HMLE doesn't emphasize minimization of peak flow error in these unusual cases. The reproduced and observed hydrographs are displayed in Figure 9.

## 6. Analysis of parameter transferability according to flood scale

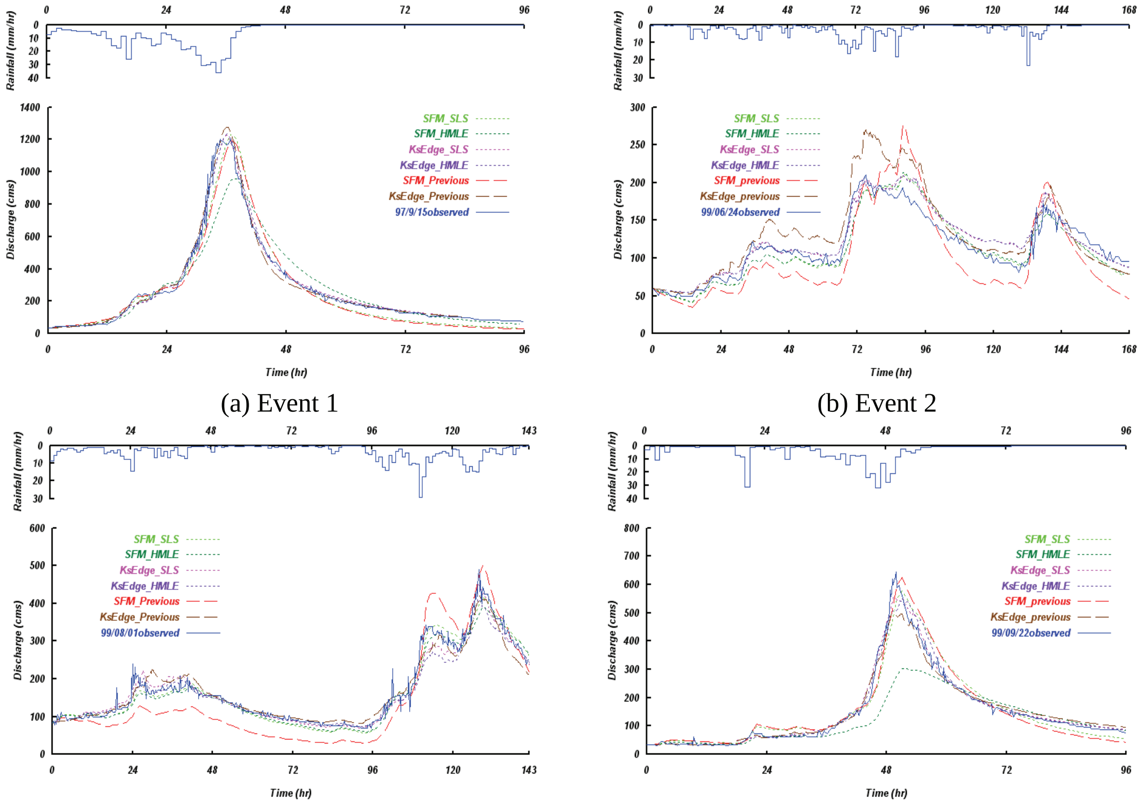
Parameter transferability is a one of the issue that a number of hydrologist and engineers has studied recently. This issue is very important for Predictions for Ungauged Basins (PUBs). It is not clear how model parameters according to variation of geomorphologic characteristics and flood scale affect the accuracy and reproducibility of hydrographs. In




(a) SLS (b) HMLE

Fig. 8 Parameter value plotted against number of function evaluations by SCE algorithm (KsEdgeFC2D).

this study, we analyze effect of parameter uncertainty according to flood scale. The biggest flood event, Event 5 among the flood events occurred in the study cathment is particularly selected for analyzing the affection due to model parameters optimized by each different flood scale. The simulated results of parameters transferability are displayed in Figure 10. If we focus on just peak flow, the interesting finding is that the best parameter set of Event 1 results in the better prediction results than when we apply another




(a) Event 1 (b) Event 2

(c) Event 3 (d) Event 4

Fig. 9 Comparison of Simulation results according to hydrologic models and objective functions.

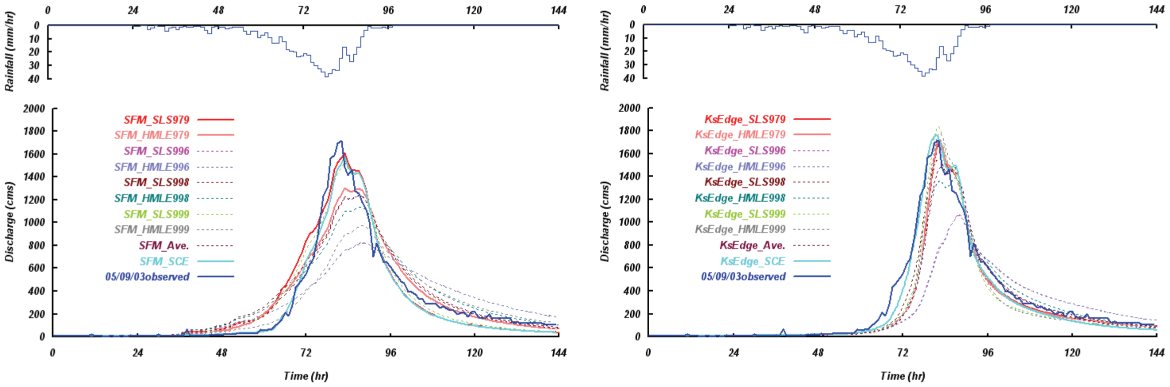
Table 8 The evaluation of model performance according to flood scale : Each calibrated model parameter from Event 1~4 are applied to Event 5 for analysis of parameter transferability.

| *Model* | *Storage Function Model* | | | | | | | | *KsEdgeFC2D* | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Applied parameter set* | 97/9/15 | | 99/6/24 | | 99/8/1 | | 99/9/22 | | 97/9/15 | | 99/6/24 | | 99/8/1 | | 99/9/22 | |
| | SLS | HMLE | SLS | HMLE | SLS | HMLE | SLS | HMLE | SLS | HMLE | SLS | HMLE | SLS | HMLE | SLS | HMLE |
| **RMSE** | 9.27 | 10.5 | 20.8 | 20.7 | 12.5 | 14.3 | 8.5 | 17.4 | 11.3 | 11.3 | 21.9 | 22.2 | 8.4 | 11.9 | 10.1 | 10.9 |
| **NS** | 0.93 | 0.91 | 0.65 | 0.65 | 0.87 | 0.83 | 0.94 | 0.75 | 0.9 | 0.9 | 0.61 | 0.6 | 0.94 | 0.88 | 0.92 | 0.9 |
| **PD** | 103 | 413 | 896 | 891 | 493 | 580 | 180 | 744 | 38 | 0.8 | 648 | 658 | 166 | 328 | 119 | 59 |

parameter set calibrated from Event 2, 3, 4. In other words, it implies that the unknown parameters can be replaced by pre-specified (pre-classified) parameters from the various past events for flood prediction. Furthermore, it may be the useful information for parameter transfer if the calibrated model parameters from the similar flood scale successfully reproduce more reliable output to the target event in the single study watershed. The parameter transferability is evaluated by Root Mean Square Error (RMSE) estimator and absolute Peak Difference (PD) between the computed and the observed. The evaluated results using these estimators are shown in Table 8.

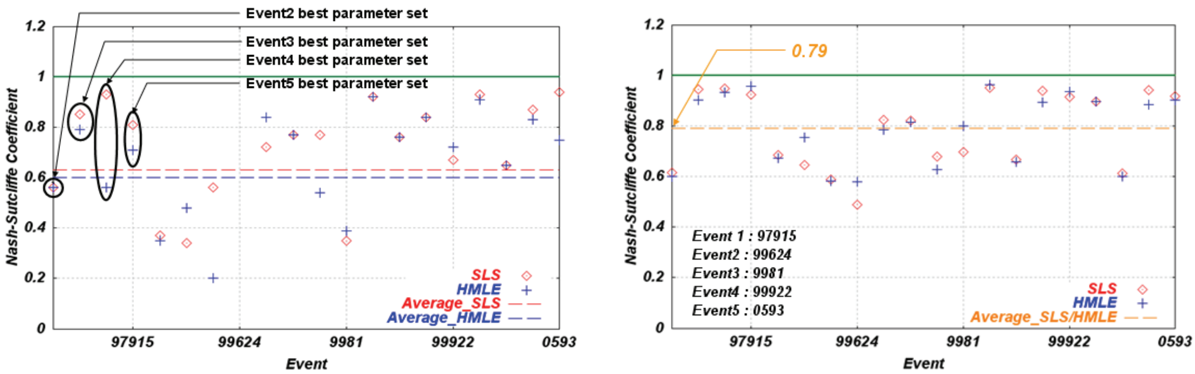
## 7. Analysis of model stability

As we pointed out in subchapter 5.2, the hydrographs simulated by the distributed model overlap closely real ones without regard of objective functions while the simulated results of SFM vary according to objective functions. In addition, the range of fluctuation due to parameter transfer in SFM



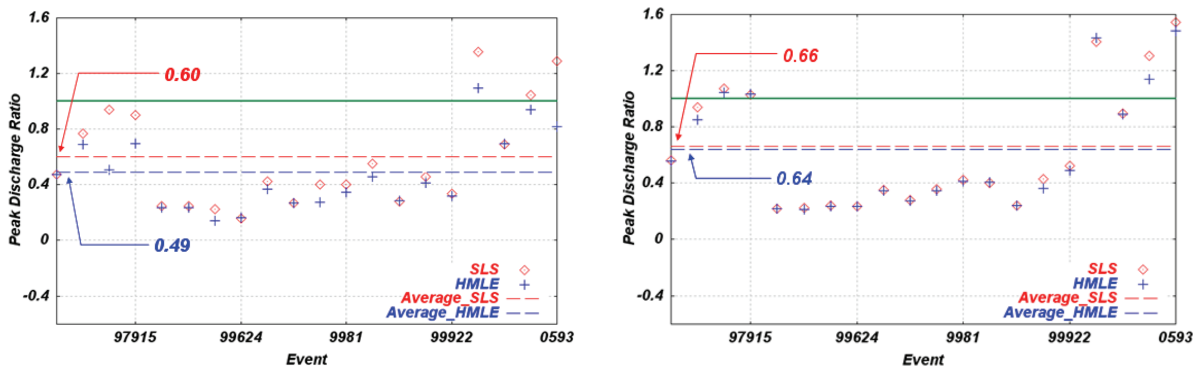

(a) SFM (b) KsEdgeFC2D

Fig. 10 Analysis of parameter transferability (Event 5).




(a) SFM (b) KsEdgeFC2D

Fig. 11 Evaluation of model stability using NNS; Dashed lines are Normalized Nash-Sutcliffe coefficient.




(a) SFM (b) KsEdgeFC2D

Fig. 12 Evaluation of model stability using NPR; Dashed lines are Normalized peak discharge ratio.

cases is bigger and more irregular than those of KsEdgeFC2D cases. These kinds of behaviors of model response are intimately associated with model stability and hence it is strongly requested to propose some guideline indexes able to allow the engineers and hydrologists to select a suitable and secure hydrologic model in terms of model structure. In this study, we evaluate model stability through normalization of the prediction uncertainty in terms of entire behaviors of predicted hydrographs. Two types of indexes, Normalized Nash-Sutcliff coefficient (NNS) and Normalized Peak discharge ratio (NPR) are suggested for analyzing the model stability. NNS and NPR are defined as following expressions.

$$NNS_M^j = \frac{1}{N}\sum_{i=1}^{N} NS_i^j(\theta_k) \tag{9}$$

$$NPR_M^j = \frac{1}{N}\sum_{i=1}^{N} \frac{P_{sim}^j(\theta_k)}{P_{obs,i}} \tag{10}$$

where, $j$ is the objective function; $M$ is the hydrologic model; accordingly $NNS_M^j$, $NPR_M^j$ are the normalized Nash-Sutcliffe coefficient and peak discharge ratio values under $j$, $M$ respectively; $i$ is the target event for analysis; $\theta_k$ is the calibrated model parameters at event $k$; $k$ is the rest events excluding event $i$; $N$ is the total number of combination. As illustrated in Figure 11(a), 12(a), each evaluated result of SFM under the different objective functions tends to fluctuate irregularly. In other words, there are large intervals in the calibrated values based on between SLS (red diamond symbols) and HMLE (blue cross symbols). Furthermore, Figure 11 reveals that the distribution of evaluated NS in KsEdgeFC2D has more constant variance. It implies that KsEdgeFC2D has more stable model structure than SFM and hence KsEdgeFC2D is less influenced by objective functions and flood scale. The results of NNS and NPR are summarized in Table 9.

Table 9 Analysis of model stability.

| *Hydrologic Model* | *NPR* | | *NNS* | |
|---|---|---|---|---|
| | SLS | HMLE | SLS | HMLE |
| **SFM** | 0.60 | 0.49 | 0.63 | 0.60 |
| **KsEdgeFC2D** | 0.66 | 0.64 | 0.79 | 0.79 |

## 8. Conclusions

In this paper, SCE global optimization algorithm is successfully applied for calibration of two rainfall-runoff models. The simulated hydrographs by using automatic calibration are closer to the measured ones than hydrographs reproduced by manually calibrated parameters. In addition, analysis of parameter variation according to objective functions and flood scale is performed. As results of these works, we can find out that parameter set of the conceptual and lumped model is strongly connected with objective functions and flood size. In contrast, the distributed model structure is very stable regardless of objective functions and the variance of model performance from different flood scale is considerably constant. However, it is hard to explain the model stability and parameter transferability because while an amount of data from a wide range of climatic and geomorphologic conditions should be used for studying this issue, a few different types of storm events are used in this study. Hence, it is absolutely necessary to investigate tendency of those two issues under various flood scale and spatial conditions. Also more general and acceptable methods are requested to prove the stability of models used for rainfall-runoff modeling.

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## 自動広域最適化手法を用いた水文モデルのパラメータ特性の分析

Giha LEE*・立川康人・宝　馨

＊京都大学大学院工学研究科都市環境工学専攻

### 要　旨

水文モデルの精度を向上させ，信頼性を高めるためにはモデル同定の過程が重要となる。分布型流出モデルの場合は，試行錯誤的にパラメータを決定することが多いが，客観性を欠き，モデル同定に多くの時間を要する。これに対して，自動キャリブレーションはそれらの欠点を克服し，そうした手法の一つであるshuffled complex evolution (SCE)は広域のパラメータ同定のための最適化アルゴリズムを実現している。本研究では，構造の異なる2つの水文モデルのパラメータ同定にSCEを適用し，異なる目的関数ごとに同定されるパラメータがどのような値を取るかを分析する。また，規模の異なる洪水によって求められたパラメータ値の持つ不確実性が，流出予測シミュレーション結果に及ぼす影響を分析する。さらに流出モデルの安定性を評価する指標を示し，その指標を用いて流出モデルの性能を分析する．上椎葉流域(211km$^2$)を対象にこれらの分析を実施した。

キーワード：自動キャリブレーション，Shuffled complex evolution，流出モデルの安定性