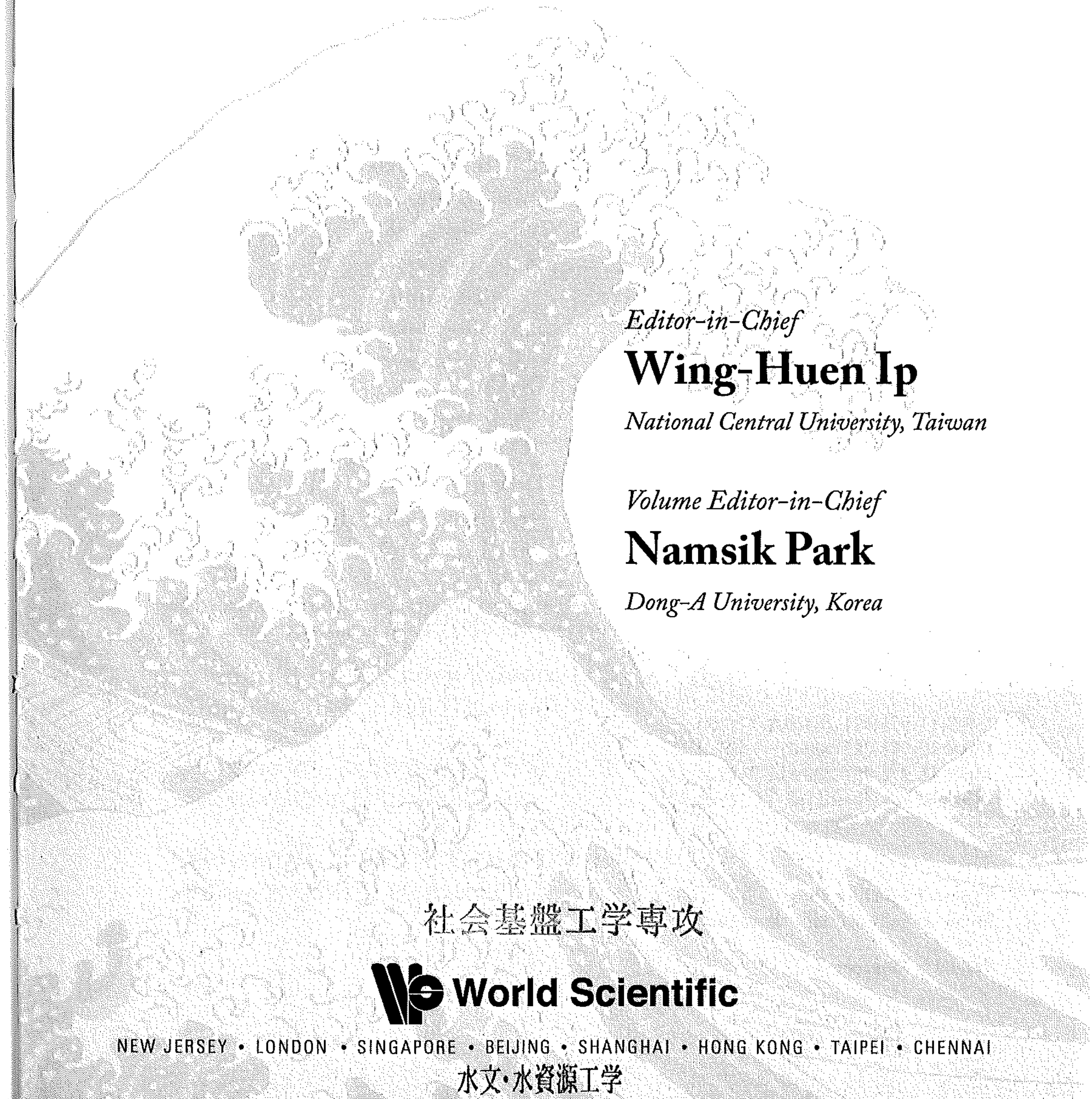
Advances in

Geosciences

Volume 17: Hydrological Science (HS)



Editor-in-Chief

Wing-Huen Ip

National Central University, Taiwan

Volume Editor-in-Chief

Namsik Park

Dong-A University, Korea

World Scientific

NEW JERSEY • LONDON • SINGAPORE • BEIJING • SHANGHAI • HONG KONG • TAIPEI • CHENNAI

Published by

World Scientific Publishing Co. Pte. Ltd.
5 Toh Tuck Link, Singapore 596224
USA office: 27 Warren Street, Suite 401-402, Hackensack, NJ 07601
UK office: 57 Shelton Street, Covent Garden, London WC2H 9HE

British Library Cataloguing-in-Publication Data
A catalogue record for this book is available from the British Library.

ADVANCES IN GEOSCIENCES
A 6-Volume Set
Volume 17: Hydrological Science (HS)

ISBN-13 978-981-283-808-7 (Set)
ISBN-10 981-283-808-2 (Set)
ISBN-13 978-981-283-811-7 (Vol. 17)
ISBN-10 981-283-811-2 (Vol. 17)

Typeset by Stallion Press
Email: enquiries@stallionpress.com

Printed in Singapore.

Editor-in-Chi

Volume 16:
Editor-in-Ch
Editors:

Volume 17:
Editor-in-Ch
Editors:

Volume 18
Editor-in-Cl
Editors:

Volume 19
Editor-in-Cl

Volume 20
Editor-in-Cl

Volume 21
Editor-in-Cl

EDITORS

Editor-in-Chief: Wing-Huen Ip

Volume 16: Atmospheric Science (AS)
Editor-in-Chief: Jai Ho Oh
Editors: G. P. Singh
C. C. Wu
K.-J. Ha

Volume 17: Hydrological Science (HS)
Editor-in-Chief: Namsik Park
Editors: Ji Chen
Joong-Hoon Kim
Jinping Liu
Young-Il Moon
Sanjay Patil
Ashok Kumar Rastogi
Simon Toze

Volume 18: Ocean Science (OS)
Editor-in-Chief: Jianping Gan
Editors: Minhan Dai
Anne Mueller
Murty Vadiamani

Volume 19: Planetary Science (PS)
Editor-in-Chief: Anil Bhardwaj

Volume 20: Solid Earth (SE)
Editor-in-Chief: Kenji Satake

Volume 21: Solar & Terrestrial Science (ST)
Editor-in-Chief: Marc Duldig

Advances in Geosciences
Vol. 17: Hydrological Science (2008)
Eds. Namsik Park *et al.*

OUTLINE FOR ALTERNATIVE RAINFALL-RUNOFF MODELING FRAMEWORK UNDER UNCERTAINTY

LEE GIHA* and TACHIKAWA YASUTO†
Dept. of Urban and Environmental Engineering,
Kyoto University Kyoto, 615-8540, Japan
**leegiha@flood.dpri.kyoto-u.ac.jp*
†tachikawa@mbox.kudpc.kyoto-u.ac.jp

SAYAMA TAKAHIRO and TAKARA KAORU
Disaster Prevention Research Institute,
Kyoto University Uji, 611-0011, Japan

Model identification is the most fundamental task in rainfall-runoff modeling. However, it is not easy due to various uncertainty sources involved in modeling processes. In spite of their significant effects on prediction results, a current modeling framework fails to fully incorporate them into the modeling process. This paper aims to outline an alternative rainfall-runoff modeling framework under uncertainty. The new modeling framework consists of two conditioning steps. The first step is that a set of possible models is evaluated multi-dimensionally with respect to model performance, model structural stability, and parameter identifiability. Next, the parameter space of the selected model structure in the first stage is conditioned directly or indirectly by adding physical or knowledge-based complementary constraints into the parameter identification procedure. Finally, model predictions are implemented by the filtered model structure and parameter set(s) through the two conditioning steps in the new modeling framework.

1. Introduction

The primary objective of modelers is to identify an appropriate model including its optimal parameter set which is suitable for modeling purpose, catchment characteristics and data.[1] Beven[2] reviewed the basic criteria for model choice. They are summarized as follows: (1) model availability; (2) model predictability for hydrological variables; (3) model reliability; (4) model suitability within the time and cost constraints of modeling objectives. However, he warned that all the available models are easily rejected by these criteria because of inadequate conceptualizations of the models and infeasibility of field data supporting model parameters fully.

Therefore, a more effective guideline is necessary to enable modelers to either confirm possible predictor(s) or reject unreliable one(s).

In many hydrologic model applications, the model identification has been conducted by conditioning their predictions to any available observations at the catchment of interest. This procedure is usually called calibration. Then, the calibrated model is verified against different time series or basins not used during calibration. This procedure is called model validation or verification and it commonly follows Klemes's hierarchical validation scheme.[3]

However, many studies[1,2,4] pointed out that this conventional type of model identification is basically required but is insufficient to adequately test the suitability of a model because of its lack of dealing with uncertainty involved in modeling processes. One of the significant problems in the traditional modeling framework is that often, different parameter combinations and even different model structures can become equally good representations of catchment responses.[5] This is entitled 'equifinality'[2,5] and it has become one of the noticeable issues in the hydrological modeling community such as the international working group on Uncertainty Analysis in Hydrologic Modeling, a part of the Predictions in Ungauged Basins (PUB).

Beven[5] outlined the desirable modeling framework considering uncertainty and then Wagener *et al.*[4,6] materialized it by incorporating a parsimonious model with uncertainty analysis tools such as Multi-Objective Complex Evolution Method (MOCOM, Yapo *et al.*[7]) and Dynamic Identifiability Analysis (DYNIA, Wagener *et al.*[8]) They emphasized that for building the advanced modeling framework, uniqueness to figure out the true representation of a hydrological system by calibration and validation steps has to be abandoned, instead, both extended model evaluation and enhanced parameter identification are necessary to confirm reliable predictor(s) or to reject inadequate one(s).

In this regard, this paper proposes an alternative rainfall-runoff modeling framework under uncertainty, which consists of two conditioning processes attempting to identify more reliable model structure(s) with its parameter set(s). This framework is the extended version of the frameworks proposed by Beven[5] and Wagener and Gupta.[4] It may provide a more useful guideline for model identification in practical rainfall-runoff model applications.

2. Description of a New Rainfall-Runoff Modeling Framework under Uncertainty

Figure 1 illustrates the alternative rainfall-runoff modeling framework under uncertainty. It is established by two conditioning processes: enhanced model evaluation and further parameter identification using additional information. Initially, a set of model structures is prepared for model evaluation. Here, it is assumed that all model structures can be potentially useful simulators, unless obvious evidences appear for it to be rejected.

2.1. *First conditioning process: Enhanced model evaluation*

At the first conditioning stage, three different evaluative criteria are applied to the competing models. It allows under-performing models with respect to these evaluative indices to be rejected at this stage. The first measure of model evaluation is Model Performance Index (MPI), which assesses whether the models are able to simulate the observed streamflow accurately or not. Second is Model Structural Stability Index (MSSI) for assessing whether the model structures can represent various local response modes (e.g. low and high flows) with a single parameter set. The last measure is Model Parameter Identifiability Index (MPII) for evaluating whether the model parameters are well identified or not within a predefined feasible parameter space. As a result, the anticipated criteria values will give some objective basis to search for the model with a good balance between prediction accuracy, structural stability, and parameter uncertainty.

Figure 1 includes the schematic model space with respect to the proposed three evaluative criteria. Here, each box indicates the testable model structure and the black box is the best model leading to good model performance, stable model structure and high parameter identifiability while the dark grey box on the bottom left in the three dimensional model space, is referred to as the unideal model.

The new modeling framework emphasizes that one dimensional model evaluation, which is based only on single criterion, results in many possible predictors. It implies that many models can not be rejected by only MPI while they provide different values of both MSSI and MPII. For example, both Model N (the ideal model) and Model $N-1$ can provide equally good model performance measures but Model $N-1$ is worse than Model N

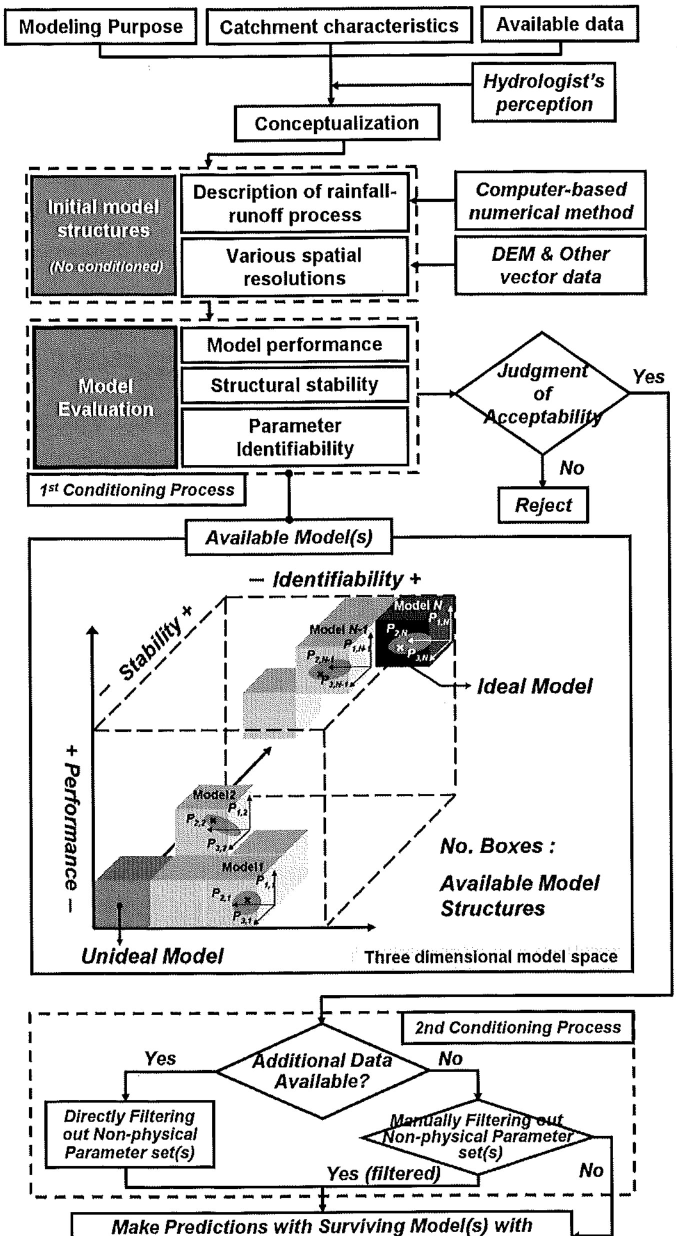


Fig. 1. Schematic stepwise procedure of the alternative rainfall-runoff modeling framework under uncertainty.

in terms of other measures for assessing structural and parameter uncertainties. As a result, additional criteria in the proposed model evaluation procedure can provide richer information enabling modelers to distinguish a balanced model, which lead to accurate and less uncertain prediction result, among a number of possible simulators.

2.2. *Second conditioning process: Further parameter identification*

However, even the best balanced model structure still suffers from the equifinality problem. Plausible parameter combinations that yield similarly good outcomes are widely distributed in the parameter space. In the three dimensional model space of Fig. 1, the light grey elliptical regions of each model (i.e. $P_{i,j}$ is a model parameter where i is the number of parameter to be calibrated and j is the number of available model structure) indicate the constrained parameter space by model calibration with streamflow data and all parameter sets within these regions provide objective function values as good as the global optimal sets marked by a symbol **x**. Note that each model structure has perhaps different parameter dimensions but parameter spaces of all models are represented schematically in three dimensions. In rainfall-runoff modeling, models are usually calibrated based only on streamflow data. However, it is just a basic requirement but insufficient information to identify model parameter(s) reliably. Kuczera and Franks[9] pointed out that a potentially more powerful approach is the use of additional data for further parameter identification.

The second conditioning process is therefore imposing complementary information on the constrained parameter space of the finally-selected model in the first conditioning stage. If additional information on hydrological responses of a catchment are available sufficiently, these constraints are used to directly reject unreliable parameter combination(s). However, despite effectiveness of complementary information, this approach is still limited to the experimental catchments[10] because of insufficient comparable measured data with multiple hydrological variables. If additional data is not available, the alternative approach in the second conditioning process is manual rejection of non-physical parameter set(s). It means that some of behavioral parameter sets, which contain conceptually unrealistic values, can be removed manually by the judgment of hydrologists or well-trained modelers. Although it is likely to receive criticism because of its subjectivity, manual calibration is still used in operational hydrology.[11] At all events, it is sure that the complementary information allows for further rejection or corroboration of model parameters, irrespective of whether it is measurable or not.

2.3. *Model prediction*

Finally, the surviving model with its behavior parameter sets should be retained until those that violate new evaluative criteria are found and then they are used for runoff prediction. In other words, the prediction result of the new modeling framework is not a single output sequence but a set of hydrographs.

3. Details of Evaluative Criteria Used in the First Conditioning Step

The purpose of the extended model evaluation is fundamentally to understand characteristics of each model structure and establish a preference between competing model structures with respect to three different criteria, model performance, structural stability and parameter identifiability. The ideal model may have a perfect (or stable) structure, which provides accurate and reliable prediction results. In addition, its response surface to parameters may be very convex or concave so that the global optimum can be easily found out using effective automatic optimization algorithms. One dimensional model evaluation based only on model performance, which is usually adopted in traditional model testing, is replaced by a three-dimensional one in order to provide a more extensive guideline with respect to selecting an adequate model.

3.1. *Model performance index (MPI)*

Model performance is a basic benchmark to support not only model selection but it is also used when discussing results with other hydrologists or stakeholders. It is typically judged by using an objective function which is to be minimized or maximized according to the modeling purposes. A wide range of statistical and hydrological objective functions is available. In general, these objective functions contain a summation of the error term and the summation of the squared errors, which is often used to avoid the canceling of errors of opposite sign. Boyle *et al.*[12] pointed out that global behavior could be described by overall measure like Root Mean Square Error (RMSE) but this aggregation of error was likely to decrease the amount of information in data. They recommended a separation of runoff time series into specific response periods to investigate the influence of individual model parameter on both global and local behaviors. Indeed, some models can reproduce the specific local behaviors (e.g. peak or rising/recession flows) very well while their overall model performances are not acceptable. For assessing model performance in the new modeling framework, the hydrograph is simply divided into two components (i.e. high and low flow periods) by the threshold, defined as the mean value of observed discharge data. The performances of each model structure are evaluated by Nash-Sutcliffe Coefficient (NSC) for two periods and then the average of the two measures is referred to as MPI, which is defined as:

$$\mathrm{NSC_{High}} = 1 - \frac{\sum_{t=1}^{N_{High}} (q_{obs}(t) - q_{sim}(t))^2}{\sum_{t=1}^{N_{high}} (q_{obs}(t) - \bar{q}_{obs}^{High})^2} \tag{1}$$

$$\mathrm{NSC_{Low}} = 1 - \frac{\sum_{t=1}^{N_{Low}} (q_{obs}(t) - q_{sim}(t))^2}{\sum_{t=1}^{N_{Low}} (q_{obs}(t) - \bar{q}_{obs}^{Low})^2} \tag{2}$$

$$\mathrm{MPI} = 0.5(\mathrm{NSC_{High}} + \mathrm{NSC_{Low}}) \tag{3}$$

where $q_{obs}(t)$ is the observed discharge at time step t; $q_{sim}(t)$ is the simulated discharge; $\bar{q}_{obs}^{High}$ and $\bar{q}_{obs}^{Low}$ are the mean observed discharge over the simulation periods, N_{High} and N_{Low}, respectively.

3.2. *Model structural stability index (MSSI)*

Structure error is an unavoidable problem in hydrological modeling since a hydrologic model is just a conversion and simplification of reality, thus those models only represent aspects of conceptualization or empiricism of modelers. In consequence, output time series of hydrologic models are as reliable as hypothesis, structure of models, quantity and quality of available data, and parameter estimates. Gupta *et al.*[13] demonstrated that one parameter set might be insufficient to represent the entire behavior of the catchment due to the imperfection of model structures. In other words, a subjective selection of objective functions for calibration of conceptual hydrologic models results in an overemphasis on different response modes. Therefore, the dependency of model performance on objective functions can be used to account for model structural stability. Two objective functions, Simple Least Squares (SLS) and Heteroscedastic Maximum Likelihood Estimator (HMLE) are recommended for evaluation of model structural stability. SLS is expressed as:

$$\mathrm{SLS} = \sum_{t=1}^{N} (q_t^{obs} - q_t(\theta))^2 \tag{4}$$

where q_t^{obs} is observed streamflow value at time t; $q_t^{(\theta)}$ is simulated streamflow value at time t using a parameter set θ and N is the number of flow values available. It has a feature that residuals between observed and simulated discharge are evenly weighed throughout a event, thus a parameter set, which matches well around peak discharge, will be obtained.

HMLE is the most successful form of the Maximum Likelihood criteria, which properly accounts for non-stationary variance in streamflow measurement errors[14]. This new measure containing weight provides more balanced performance across the entire flow range and it is calculated as:

$$\mathrm{HMLE} = \frac{1}{N} \frac{\sum_{t=1}^{N} w_t \varepsilon_t}{\left(\prod_{t=1}^{N} w_t\right)^{\frac{1}{N}}} \tag{5}$$

where $\varepsilon_t = q_t^{obs} - q_t(\theta)$ is the model residual at time t; w_t is the weight assigned to time t computed as $w_t = f_t^{2(\lambda-1)}$; f_t=q_t^{true} is the expected true flow at time t; λ is the transformation parameter which stabilizes the variance. Yapo *et al.*[7] recommended the use of f_t as observed flow for more stable estimator.

Finally, the MSSI is formulated as:

$$\mathrm{MSSI} = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (q_{SLS}(t) - q_{HMLE}(t))^2} \tag{6}$$

where N is total number of simulation time step; $q_{SLS}(t)$ and $q_{HMLE}(t)$ are the simulated discharges by each optimal parameter of SLS and HMLE, respectively. Here, the lower value of MSSI indicates the more stable model structure.

3.3. *Model parameter identifiability index (MPII)*

Parameter identifiability implies the level of "uniqueness" of parameters. It means that a well-identified model has a certain (or global optimal) parameter value while a poorly-identified model accepts many behavioral parameter values, which can provide model performance measures as good as the value estimated by the best-performing parameter. Wagener *et al.*[8] proposed a simple measure of parameter identifiability based on Regional Sensitivity Analysis (RSA, Spear and Hornberger[15]). The uniform random sampling method used in their research (Wagener *et al.*[8]) is able to extrapolate the parameter space easily but is computationally inefficient since a large number of samples are necessary to protect misleading results (Feyen *et al.*[16]). On the other hand, Markov Chain Monte Carlo (MCMC) methods generate samples from a Markov chain in an attempt to estimate a stationary posterior parameter distribution and it can be useful for high dimensional optimization problems (Kuczera and Parent[17]). The Shuffled Complex Evolution Metropolis (SCEM) algorithm is an effective and efficient evolutionary MCMC sampler which has enhanced search capability and operates by merging the strengths of the Metropolis algorithm, controlled random search, competitive evolution, and complex shuffling (Vrugt *et al.*[18]).

This algorithm can provide not only optimal parameter set but also its underlying stationary posterior distribution within a single optimization run. In these posterior distributions of individual parameters, the parameter value corresponding to the highest density indicates the optimal parameter value while other parameter values within these distributions are referred to as behavioral parameters. Therefore, SCEM can be used to estimate posterior distributions of individual parameters and then investigate the uniqueness of calibrated parameters. Here, the highest density value of each distribution is used as the indicator of parameter identifiability. Then, the mean of these maximum identifiability values of each parameter is regarded as MPII. Moreover, the uncertainty associated with parameters from the estimated posterior distributions is quantified and it gives the basis for making probabilistic predictions associated with parameter uncertainty. Figure 2(a) shows the example of posterior parameter distribution. In this figure, the value, marked by open circle, is the indicator of parameter

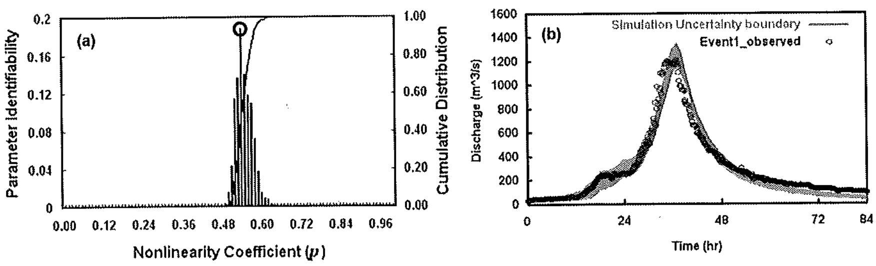


Fig. 2. (a) Example of estimation of parameter identifiability and (b) simulation uncertainty boundary associated with the behavior parameter sets within the posterior distribution.

identifiability and the parameter value corresponding to this is the best-performing parameter value. The distribution containing the sharper peak indicates that the model parameter is identified better within the feasible parameter space. Figure 2(b) presents the hydrograph simulation uncertainty estimated by the parameter sets within posterior parameter distributions.

4. Need of Complementary Constraints for Further Parameter Identification (Direct Rejection of Non-Physical Parameter Set)

A complex rainfall-runoff model due to over-parameterization can permit multiple alternative flow pathways leading to equally good hydrological outputs. Such a model usually has the poor parameter identifiability showing the uniform posterior parameter distribution. Furthermore, the commonly used streamflow data to evaluate such a model does not contain sufficient information on these possible flow pathways and thus, in spite of our deep faith in the computer-based automatic optimization tools, the model still has numerous plausible parameter combinations (Franks *et al.*[19]). Therefore, additional information is needed to offer a step forward to identifying the minimum reliable parameter sets. It can be done by further constraining the feasible parameter space.

Figures 3(a) and (b) show the parameter identification processes based on streamflow and multi-response data, respectively (Mroczkowski *et al.*[20]). The strategy shown in Fig. 3(a) only uses hydrological response A for both calibration and validation while response B is totally disregarded. This kind of framework represents the traditional split-sample test using streamflow

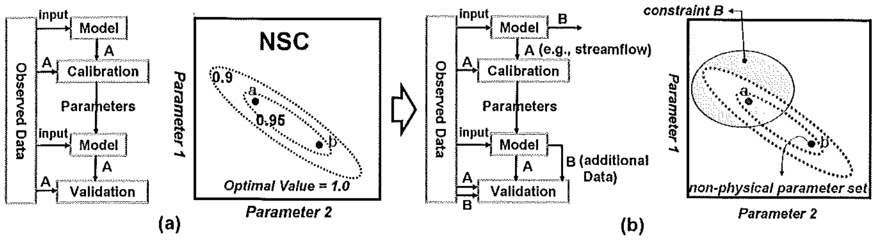


Fig. 3. Schematic diagrams of parameter identification based on (a) streamflow data and (b) multi-response data.

data alone. It is conceivable that many models cannot be rejected with regard to response A. The parameter space constrained by only response A contains numerous plausible parameter sets. For example, two parameter sets, *a* and *b* have the same model performance measure value, 0.95 because they are inside the same contourline of NSC. On the other hand, the alternative strategy illustrated in Fig. 3(b) uses response A for calibration but both responses are used for validation. This strategy provides much greater opportunity to select reliable parameter set(s) or reject unreliable one(s) because it imposes greater constraint on the parameter space. The previous parameter space based only on response A has the intersection, which comes from the additional response B. It means that parameter set *b* can be regarded as a non-physical parameter set not satisfying both physical constraints (i.e. outside the intersection) such that this parameter set will be rejected and not used for model prediction (i.e. reduction of parameter uncertainty).

Experimental methods such as isotope tracers, isotopic hydrograph separations and stream water residence time have been used as additional physical constraints for reducing parameter uncertainty in water quantity and quality modeling. However, these approaches that attempt to yield multiple output variables usually require the reformulation of models by adding another conceptual parameters. Ultimately, it again results in the decline of parameter identifiability. Therefore, to avoid over-parameterization, the desirable features of the enhanced parameter identification using multi-response data are as follows: (1) provide the evidence capable of rejecting unreliable parameter sets; (2) do not cause over-complexity due to numerous parameters that has to be calibrated.

Finally, statistical error estimation will be used to evaluate the improvement of simulated variables through the enhanced conditioning processes and demonstrate superiority of the proposed method to currently-available model identification methods. Therefore, filtered behavioral parameters in the second conditioning process are more physically-sound and also they can provide more reliable prediction results than the modeling case without additional constraints.

5. Conclusions

This paper has discussed the alternative rainfall-runoff modeling framework under uncertainty. Two conditioning processes incorporated into the new modeling framework was introduced. In the first step of the framework, a set of possible model structures was evaluated multi-dimensionally with respect to model performance, model structural stability, and parameter identifiability. The mean value of NSCs for low and high flow periods was proposed as MPI to assess the model predictability. The discrepancy between hydrographs reproduced by two different objective functions, SLS and HMLE was referred to as MSSI to assess the model structural uncertainty. In addition, the highest value of posterior parameter distribution was estimated by the stochastic optimization algorithm, SCEM and then it was adopted as MPII to evaluate the parameter identifiability. In the second conditioning process of the new modeling framework, the parameter space of the selected model structure in the first stage was conditioned directly or indirectly by adding physical or knowledge-based complementary constraints into parameter estimation procedure. The further parameter identification using observable multi-response data (i.e. direct filtering of non-physical parameter set) basically requires the capability providing apparent evidences to reject the unreliable parameter combination(s). Also, it should not cause over-parameterization because of over-complexity by either revision or reformulation of the model with additional parameters that is likely to worsen parameter identifiability and in turn, cause the equifinality problem.

References

1. T. Wagener, H. S. Wheater and H. V. Gupta, *Rainfall-runoff Modeling in Gauged and Ungauged Catchment* (Imperial College Press, London, 2004).
2. K. Beven, *Rainfall-runoff Modeling: The Primer* (John Wiley and Sons, Chichester, 2001).
3. V. Klemes, *Hydro. Sci. Journal* **31**(1) (1986) 13–24.

4. T. Wagener and H. V. Gupta, *Stoch. Environ. Res. and Risk Assess.* **19** (2005) 378–387.
5. K. Beven, *Hydro. Processes* **16**, 2 (2002) 189–206.
6. T. Wagener, D. P. Boyle, M. J. Leeds, H. S. Wheater, H. V. Gupta and S. Sorooshian, *Hydrol. and Earth Sys. Sci.* **5** (2001) 13–26.
7. P. O. Yapo, H. V. Gupta and S. Sorooshian, *J. Hydrol.* **204** (1998) 83–97.
8. T. Wagener, M. J. Leeds, H. S. Wheater and H. V. Gupta, *Hydrol. Processes* **17**(2) (2003) 455–476.
9. G. Kuczera and S. W. Franks, in *Mathematical models of large watershed hydrology*, eds. V. P. Singh and D. Frevert (Water Resources Publisher, Highland, 2002).
10. J. Seibert and J. J. McDonnell, *Water Resour. Res.* **38**(11) (2002) 1241.
11. T. S. Hogue, S. Sorooshian, V. K. Gupta, A. Holz and D. Braatz, *J. Hydrometeorology* **1** (2000) 524–542.
12. D. P. Boyle, H. V. Gupta and S. Sorooshian, *Water Resour. Res.* **36**(12) (2000) 3663–3674.
13. H. V. Gupta, S. Sorooshian and P. O. Yapo, *Water Resour. Res.* **134**(4) (1998) 751–763.
14. S. Sorooshian and J. A. Dracup, *Water Resour. Res.* **16**(2) (1980) 430–442.
15. R. C. Spear and G. M. Hornberger, *Water Research* **14** (1980) 43–49.
16. L. Feyen, J. A. Vrugt, B.Ó. Nualláin, J. Knijff and A. D. Roo, *J. Hydrol.* **332** (2007) 276–289.
17. G. Kuczera and E. Parent, *J. Hydrol.* **211** (1998) 69–85.
18. J. A. Vrugt, H. V. Gupta, W. Bouten and S. Sorooshian, *Water Resour. Res.* **39**(8) (2003) 1–14.
19. S. W. Franks, S. Uhlenbrook and P. Etchevers, in *Hydrology 2020: An integrating Science to Meet World Water Challenges*, eds. T. Oki, C. Valeo and K. Heal (IAHS Press, Wallingford, 2006).
20. M. Mroczkowski, G. P. Raper and G. Kuczera, *Water Resour. Res.* **33**(10) (1997) 2325–2336.