Model calibration and uncertainty analysis of runoff in the Zayanderood River basin using generalized likelihood uncertainty estimation (GLUE) method

Majid Mirzaei, Hadi Galavi, Mina Faghih, Yuk Feng Huang, Teang Shui Lee and Ahmed El-Shafie

ABSTRACT

This study is designed to consider the uncertainty in the kinematic runoff and erosion model named KINEROS2. The Generalized Likelihood Uncertainty Estimation (GLUE) method was used for assessing the uncertainty associated with model predictions, which assumes that due to the limitations in model structure, data and calibration scheme, many different parameter sets can make acceptable simulations. GLUE is a Bayesian approach based on the Monte Carlo method for model calibration and uncertainty analysis. The assessment was performed in the Zayanderood River basin located in Central Iran. To make an accurate calibration, five runoff events were selected from three different gauging stations for the purpose. Statistical evaluations for streamflow prediction indicate that there is good agreement between the measured and simulated flows with Nash–Sutcliffe values of efficiency of 0.85 and 0.79 for calibration and validation periods respectively. Uncertainty analysis was carried out on the new distribution of input parameters for model validation.

Key words | GLUE, KINEROS, model calibration, uncertainty analysis

Majid Mirzaei (corresponding author)
Ahmed El-Shafie
Faculty of Engineering and Built Environment,
University Kebangsaan Malaysia,
Selangor DE,
Malaysia
E-mail: *mirzaeii@gmail.com*

Hadi Galavi
Mina Faghih
Teang Shui Lee
Faculty of Engineering,
Universiti Putra Malaysia,
Serdang, Selangor DE,
Malaysia

Yuk Feng Huang
Faculty of Engineering and Science,
Universiti Tunku Abdul Rahman,
Kuala Lumpur,
Malaysia

INTRODUCTION

Reliable predictions of streamflow from watersheds using rainfall-runoff models are important in order to make sure that design criteria such as stability and safety of hydraulic structures, dams and flood retention ponds are kept. Hydrologic simulation models for streamflow have implicit uncertainty in their handling of processes. Uncertainty may occur during data collection, modeling, and analysis of the engineering system and model predictions. A high degree of uncertainty in the model output is associated with calibration when data are limited and the input parameters are highly uncertain. Hassan *et al.* (2008) suggested that in such a case, a more quantitative use of the calibration data and the calibration goodness of fit results become crucial for appropriately quantifying the predictive uncertainty. In recent years, there have been many methods for calculating the margins of uncertainty in model predictions. Methods that represent the parameters of the model state and uncertainty estimation include the classical Bayesian approaches (Kuczera & Parent 1998; Thiemann *et al.* 2001; Vrugt *et al.* 2003a, b; Cheng *et al.* 2007), the pseudo-Bayesian (Beven & Binley 1992), set theory (Keesman 1990; Klepper *et al.* 1991; Van Straten & Keesman 1991; Vrugt *et al.* 2001), multiple criteria (Gupta *et al.* 1998; Yapo *et al.* 1998; Boyle *et al.* 2000; Madsen 2000, 2003; Vrugt *et al.* 2003a, b; Chen & Chau 2006), assimilation sequential data (Madsen *et al.* 2003; Moradkhani *et al.* 2005; Vrugt *et al.* 2005), multi-model method (Georgekakos *et al.* 2004; Ajami *et al.* 2007; Vrugt & Robinson 2007), and artificial neural networks (Chau *et al.* 2005; Muttil & Chau 2006). Blasone *et al.* (2008) remarked that all these methods have their strengths and weaknesses, but differ in their underlying assumptions and how the various sources

doi: 10.2166/aqua.2013.038

of error are discussed and made explicit. For performing a thorough uncertainty analysis, Generalized Likelihood Uncertainty Estimation (GLUE) has a number of advantages over other methods and therefore it has been selected as the uncertainty analysis method for calibration and uncertainty analysis in KINEROS2. The primary advantages of this method are the reduction of the number of simulations required, the ability to use different ways of specifying parameter distributions, the ability to handle very complex models, and the propagation of variability, uncertainty, and parameter dependencies through the model that are reflected in the distributions of model outputs. GLUE is a widely used method, with numerous papers and other publications describing the method and how to apply it (Xu *et al*. 2010). GLUE, developed by Beven & Binley (1992), was subsequently used in many studies (Franks & Beven 1997; Aronica *et al*. 1998; Lamb *et al*. 1998; Cameron *et al*. 1999; Hunter *et al*. 2005; Montanari 2005), and also the formal Bayesian approach (e.g. Gupta *et al*. 1998; Kuczera & Parent 1998; Sohn *et al*. 2000; Feyen *et al.* 2001, 2002, 2003a, b; Vrugt *et al*. 2003a, b).

The GLUE procedure is an extension of the Monte Carlo sampling that randomly integrates the goodness of fit of each simulation. This procedure leads to a form of Bayesian mean different models represented by different conceptualizations or combinations of different parameters and their predictions (Beven & Freer 2001; Hassan *et al.* 2008). The GLUE methodology has been widely used to represent predictive and parametric uncertainty in the Monte Carlo analysis of surface water systems. Uncertainties in a model like KINEROS2 arises from the structural model errors resulting from problems with parameter estimation. A realistic assessment of these various sources of uncertainty is important for scientific-based decision making and helps to direct resources towards improving the model structure and reduce uncertainty.

The focus of this paper is on the calibration of the distributed, physically based, and event based KINEROS2 model. Given the differences in soil, land use, topography, and climate, the KINEROS2 model is spatially distributed. Schuol & Abbaspour (2006) further added that KINEROS2 offers the possibility to extend the model's hydrological erosion sub-models. The specific objectives of this study are: (1) to assess the uncertainty of the parameters of a physically based water balance model, specifically KINEROS2 with GLUE; and (2) to calibrate and validate KINEROS2.

CASE STUDY

The catchment of the Zayanderood River is situated in Central Iran. In this study, a specific part of the catchment between the longitudes of 32°17′10″ N and 33°12′49″ N, and the latitudes of 50°1′36″ E and 50°46′26″ E was selected (Figure 1). This area was selected partly because it covers the main source of streamflow of the Zayanderood River, but more importantly the region is relatively well covered by a reasonably dense network of rain gauge stations. The climate is semi-arid, with an annual average precipitation of 611 mm and annual average temperature of 11 °C. Precipitation data show a seasonal distribution with wet season, autumn, winter and spring, and dry season in summer.

KINEROS2

KINEROS2 is a distributed system and a physical event-based model that describes the processes of interception, infiltration dynamics, runoff, and erosion of a watershed characterized mainly by surface runoff. The watershed is conceptualized (as a cascade and channels of which the stream is fed into in a top-down approach) using a finite difference solution of the equations of one-dimensional kinematic wave (Semmens *et al.* 2005). Excessive rainfall, which leads to flow, is defined as the difference between the amount of rainfall and the depth of interception and infiltration. The speed at which infiltration occurs is not constant but depends on the intensity of rainfall and on the amount of accumulated infiltration or the state of available soil moisture. The Automated Geospatial Watershed Assessment (AGWA) tool is a versatile system of hydrological analysis that is addressed to: (1) provide a simple, direct and repeatable method for hydrological modeling; (2) make the use of the Geographic Information System (GIS) database achievable; (3) be compatible with other geospatial basin analysis software environment; and (4) be useful for the development of alternative scenarios and future simulation works at multiple scales (Miller *et al*. 2002). AGWA provides the functionality to carry out the processes of

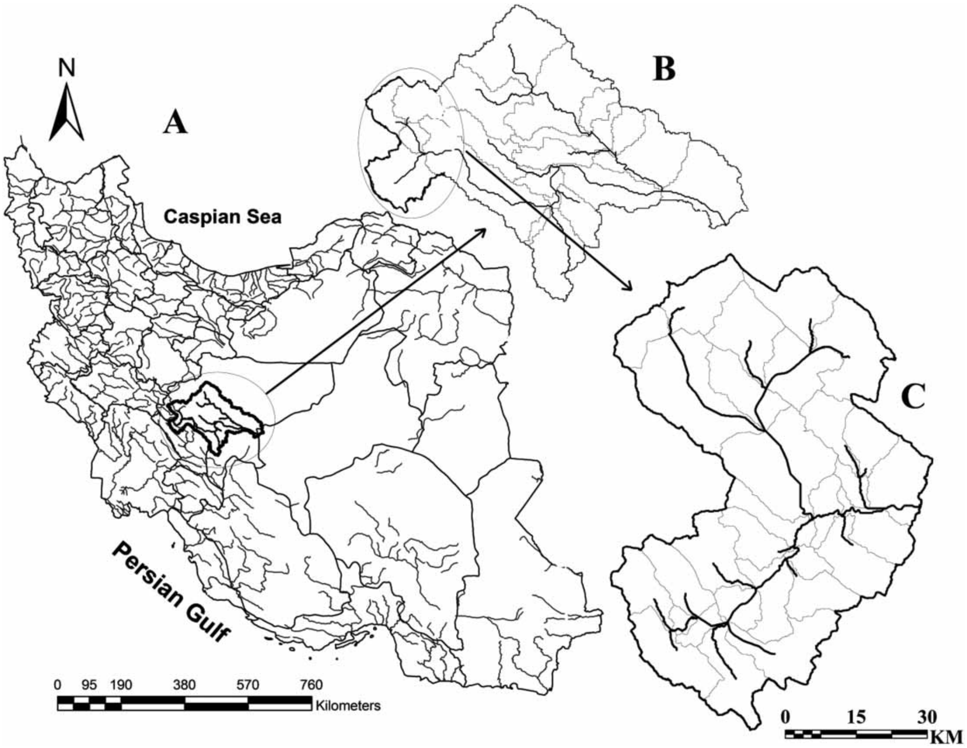

Figure 1 | (A) Location map of Zayanderood basin in Iran, (B) location map of study area in Zayanderood basin and (C) map of study area.

modeling and evaluation for the Soil And Water Assessment Tool (SWAT) and KINEROS2. Nedkov & Burkhard (2011) reiterated the modeling process in the AGWA GIS environment consisting of the five main steps including watershed delineation and discretization, vegetation cover and soil parameters, precipitation writing files, running the model, and finally the visualization of results.

Database

The use of hydrologic models, and KINEROS2 in particular, necessitates the availability of an appropriate data set including a digital elevation model (DEM), land cover data, soil data, hydrological and climatic data. They should be in a particular format compatible with AGWA GIS standards. Additional data are necessary for the flood regulation demand assessment. In the current study, spatial and non-spatial data have been collected for the case study and transformed into the appropriate formats. They have been used to build up a database for hydrologic modeling and spatial analyses.

A DEM with 25 m resolution had been extracted from topographic maps. The DEM was used to calculate subbasin parameters such as slope, slope length, and to define the stream network. The resulting stream network was used to define the layout and the number of subbasins. Characteristics of the stream network, such as channel slope, length, and width, were all derived from the DEM. Land cover and soil maps were adapted for the use in AGWA. The soil and land cover data set for the study area was provided by the national cartographic center of Iran. The precipitation and river discharge data collected from the Iran Meteorological Organization included those of 16 rain gauge stations in the study area and three river hydrometric stations on the Zayanderood River (Figure 2).

The GLUE framework

The GLUE method is a Bayesian analysis based on the Monte Carlo method for model calibration and uncertainty analysis. The framework used in this study is to make a

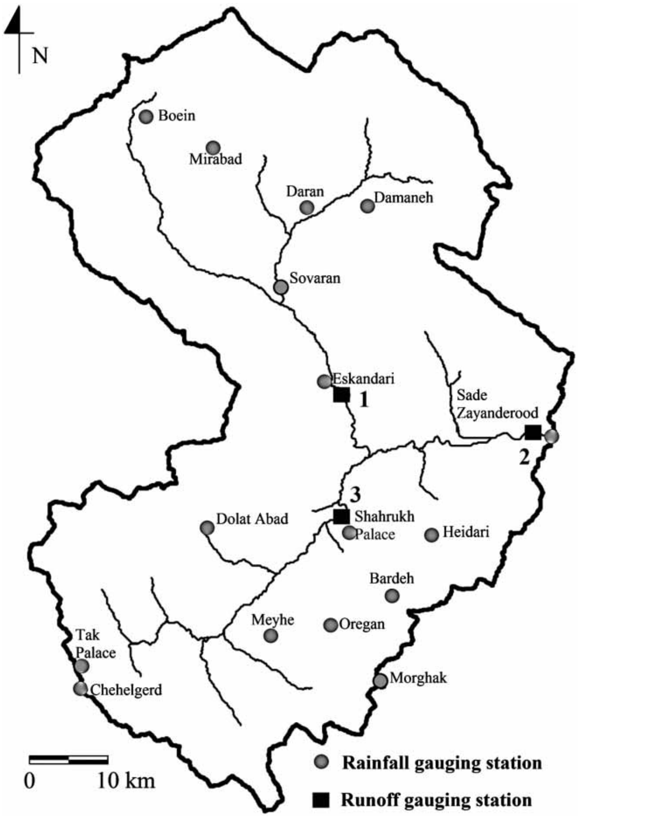

Figure 2 | Locations of the rainfall and runoff gauging stations in the study area.

quantitative analysis of uncertainty in the modeling process and to draw some indications on the effectiveness of the proposed method. Due to limitations in the model structure, data and calibration scheme, a common phenomenon in the rainfall-runoff modeling is that a great deal of very different sets of parameters can make equivalent accurate simulations (equifinality). GLUE waives the thought of the existence of one optimum set of parameters. Alternatively, it splits all the parameter sets into two categories of behavioral and unbehavioral sets according to the likelihood measure that defines the degree of belief of a set of parameters being a good simulator. All sets are used to conduct the simulation. The distribution of the likelihood value for sets of behavior is considered as a weighting function for probabilistic predictors (Beven & Binley 1992). Accordingly, a cumulative distribution of model predictions is formulated and uncertainty quantiles are calculated. In GLUE, subjective choices are explicit, which should be reasonable for the modeling work.

Implementation of GLUE in this study is as follows:

1. Generating random samples of the parameter space. A large number of parameter sets must be generated for Monte Carlo simulations based on distributions of previous settings. In this study, the uniform distribution with lower and upper bounds are assumed to present the *a priori* distributions of parameters.
2. Computation of the likelihood values for the parameter sets and selecting the behavioral ones. The probability measure quantifies the difference between the simulation and observations. It must be assigned to zero for all parameter sets that cannot reproduce the observations and should increase monotonically with increasing performance.

In the literature, the probability measure most commonly used for GLUE is the model efficiency Nash–Sutcliffe coefficient (NS) (Beven & Freer 2001), and is thus used in this study:

$$\mathrm{NS} = 1 - \frac{\sum_{t_i=1}^{n}\left(y_{t_i}^{M}(\theta) - y_{t_i}\right)^2}{\sum_{t_i=1}^{n}\left(y_{t_i} - \bar{y}\right)^2} \tag{1}$$

where n is the number of the observed data points, and y_{t_i} and $y_{t_i}^{M}(\theta)$ represent the observation and model simulation with parameters θ at time t_i, respectively, and $\bar{y}$ is the average value of the observations. Herein, the threshold value of GLUE application is chosen to be 0.70. The simulations with NS values of more than 0.70 are considered to be behavioral, otherwise they are considered non-behavioral.

1. Calculating the posterior likelihood distribution for behavioral parameter sets.
2. Determination of uncertainty quantiles.

RESULTS AND DISCUSSION

Application of KINEROS2 in combination with the automated functionality of AGWA respectively reduces the required time to run the watershed model. Due to the robust and interactive interface, the user selects an outlet from which AGWA delineates and discretizes the watershed using the DEM. The watershed elements are then intersected with the ground land use/cover and precipitation (uniform or distributed) data layers to calculate the input parameters of the model. The model is then executed and the results are imported back into AGWA for visual display.

Initial inputs of KINEROS2, maps, and other input data were prepared for the Zayanderood Basin. The catchment was split into 78 planes with 31 associated channel reaches (Figure 3). The planes were based on topography, land cover and soil type. Channels represent the locations of identifiable channels. The slopes and geometries of planes and channels were estimated from the DEM, and the channel cross-section data.

Evaluation procedure

A complete model testing requires calibration of the model using some of the available hydrologic records and evaluating the performance of the calibrated model using some other records. KINEROS2 was approximately calibrated using the hydrograph of storms and then validated against other storms. The complete rainfall hyetographs were not used in running the model in some cases to ease the computational strain. In such cases, only the most intense portion of the storm was modeled. Runoff data are used in evaluating the model.

Parameter sensitivity

The first step in the evaluation of the model is to determine which parameters are the most sensitive and which ones have the most influence on the output. Tests of significance were carried out upon the parameters that had been estimated. In this study, the parameter sensitivity analysis was performed using stepwise regression analysis, which was carried out on ranks of input–output data pairs that were generated based on a Monte Carlo technique sampling. Following the same approach, parameters that showed significant sensitivity to model output during model calibration were the relative saturated hydraulic conductivity

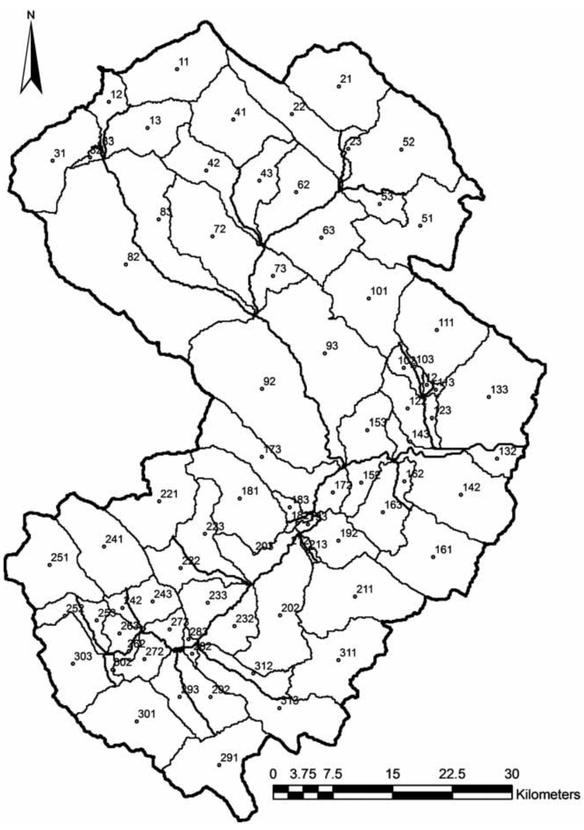

Figure 3 | Position of planes and channels in Zayanderood basin.

Table 1 | Selected parameters for uncertainty analysis and their prior distributions

Parameter	Symbol	Units	Range of initial KINEROS2 parameters	Prior distribution of aggregate parameters
Manning's coefficient of PLANES	np	–	0.0–1.0	Uniform
Manning's coefficient of Channels	nc	–	0.0–1.0	Uniform
Saturated hydraulic conductivity of PLANES	Ksp	mm/h	0.0–20.0	Uniform
Saturated hydraulic conductivity of Channels	Ksc	mm/h	0.0–200	Uniform
Mean capillary drive of PLANES	Gp	mm	0.0–300	Uniform
Mean capillary drive of Channels	Gc	mm	0.0–300	Uniform

(K_s) and Manning's n. Sensitivity analysis result of the parameter values gave a strong initial impression that K_s, n and mean capillary drive (G) in planes and channels were consistently the most important parameters affecting the simulated hydrograph for every event. It also implies that other parameters and initial conditions had practically zero influence.

The parameters listed in Table 1 represent single global values to the distributed default values of the corresponding KINEROS2 parameters.

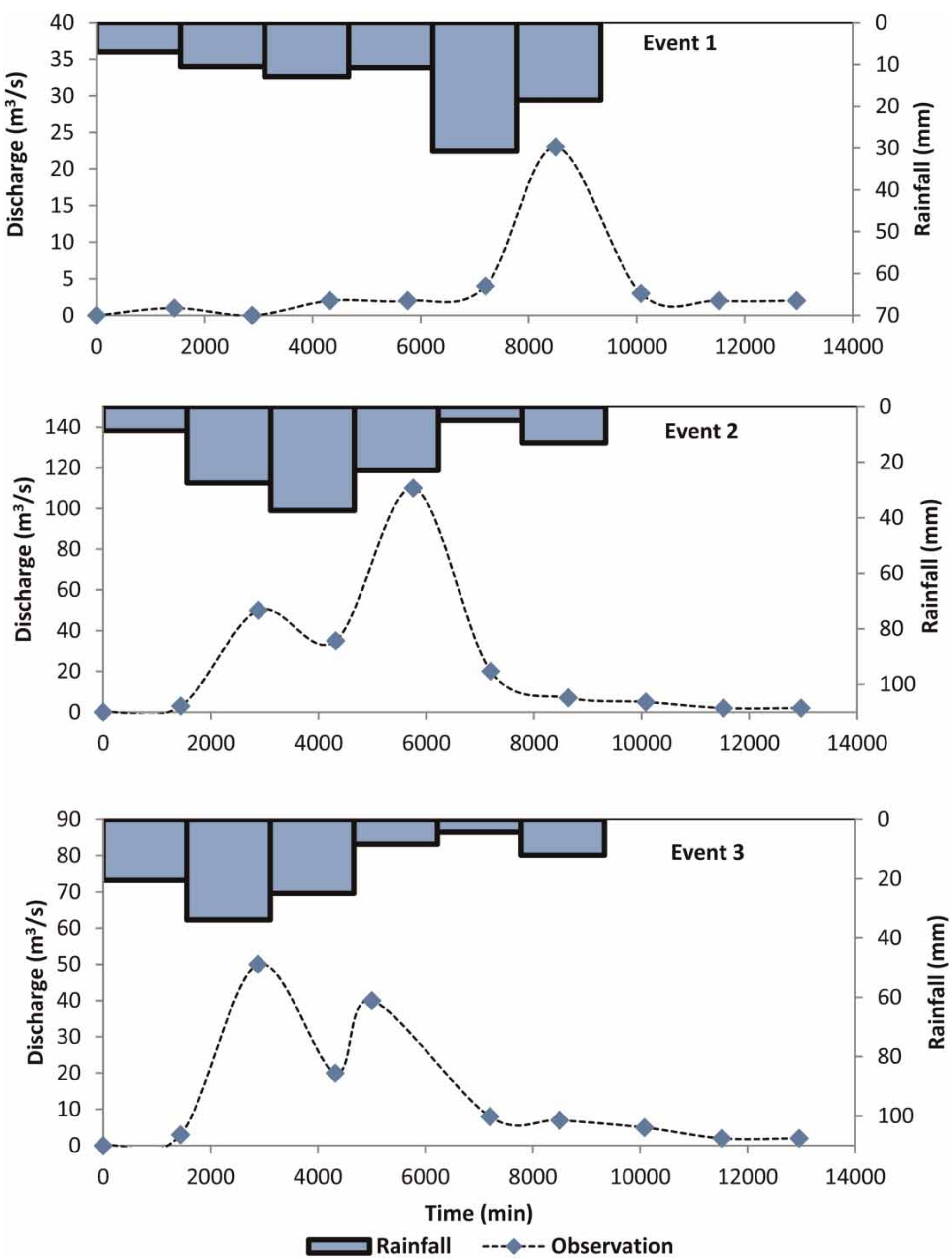

Figure 4 | Rainfall and discharge time-series for the three events selected for calibration.

Storm event selection for calibration and validation

Five runoff events from 2001 to 2005 based on the availability of the daily rainfall and discharge data were selected. These events are plotted in Figures 3 and 4 (in this plot, rainfall has been averaged without weighting over the gauges). Three events were selected for calibration and two events for validation. Measuring the time lags between peak rainfall and peak discharge is complicated because some events contain more than one rainfall and discharge peak, and in other cases more than one rain peak can be associated with the single discharge peak. In order to make a precise calibration, events were selected from three different runoff gauging stations. Event 1, event 2 and event 3 were recorded at stations 1, 2 and 3, respectively.

GLUE analysis

Six parameters were explored in a Monte Carlo test (Table 1). Up to 1,000 parameter sets, randomly sampled over a uniform distribution of the defined parameter space, were generated and put into operation using two laptops with two 32-bit processors (Intel® Core™ 2 Duo), whereas the rest of the parameters were set at fixed values. Total Central Processing Unit (CPU) time for simulation of the one event was about 53 hours.

During the calibration exercise, only 9.7% of explored parameter sets gave more than 70% efficiency. Thus, 9.7% of parameter set were behavioral according to NS coefficient criterion and were retained for a first trial (preliminary behavioral sets, Figure 5). The highest obtained value of calibration efficiency was 0.85 and models with high values of efficiency

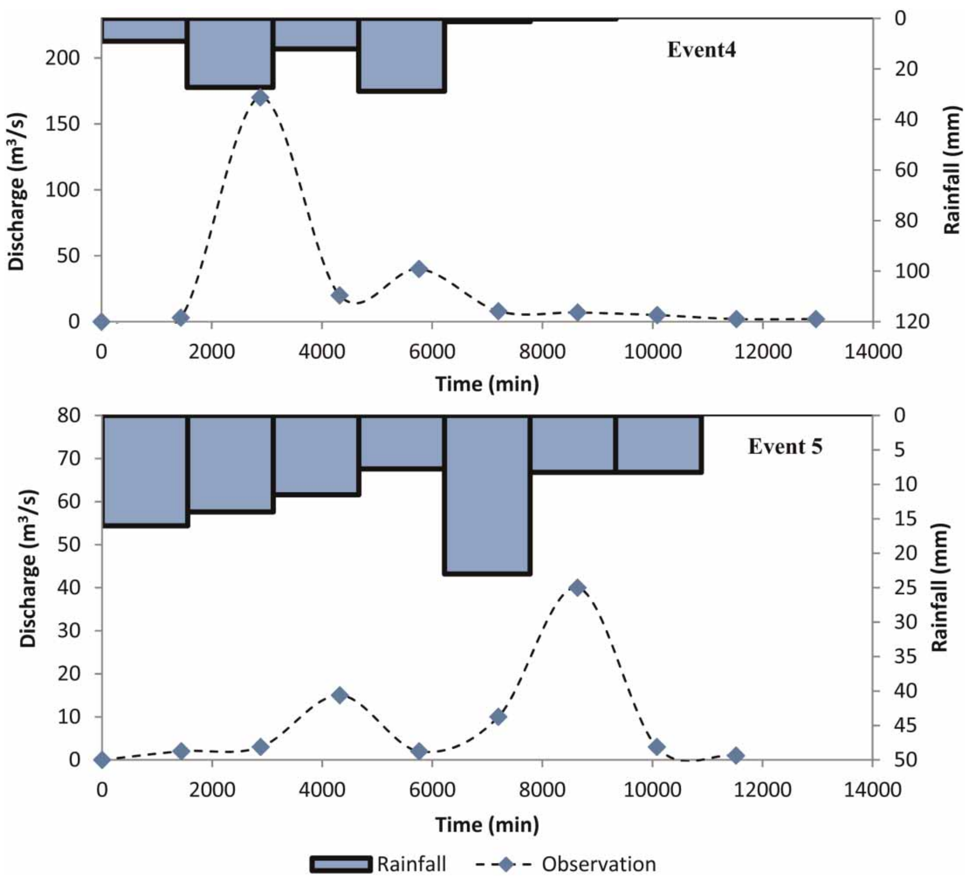

Figure 5 | Rainfall and discharge time-series for the two events selected for validation.

were obtained from different combinations of calibrated parameter values, confirming the equifinality effect. Moreover, it should be noted that the parameters are treated as sets, and the efficiency coefficient is calculated as a function of how well these parameter sets provide a goodness of fit of the simulated output to the observed data for the entire calibration (Figure 6). According to the earlier discussed GLUE threshold value and regulations, only the parameter sets that gave NS values greater than 0.70 efficiencies were considered behavioral and retained. Following this, these retained parameter sets were used to simulate the three events that were chosen for calibration.

As mentioned before and considering that the prior distribution of selected parameters was selected on uniform but with separated behavioral parameter sets, the posterior distribution is expected. Monte Carlo sampling was run to

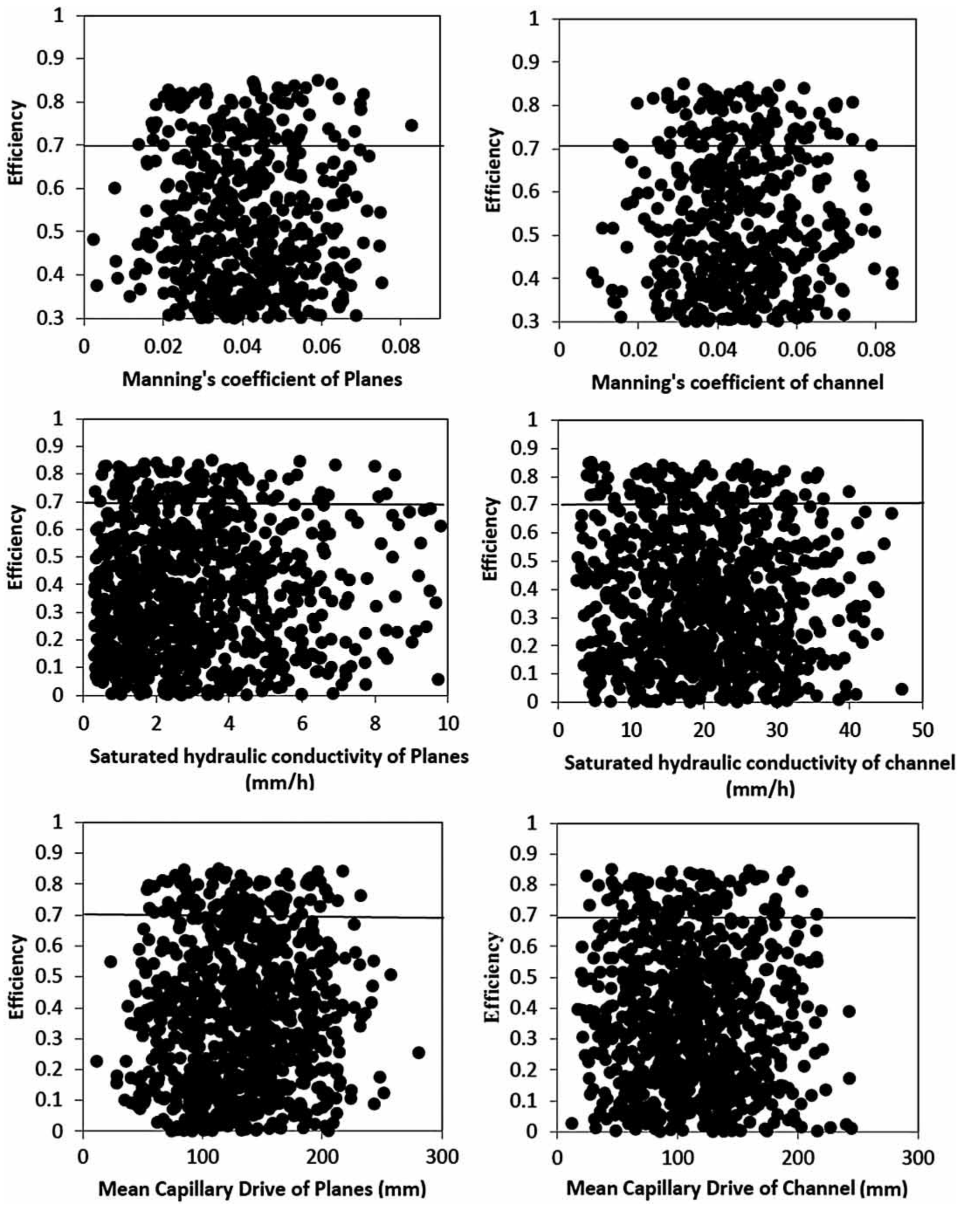

Figure 6 | Dotty plot of NS coefficient against KINEROS2 parameters conditioning with GLUE based on 1,000 samples with threshold 0.70 (solid line), above which the parameter sets are behavioral. (Only positive efficiencies are shown.)

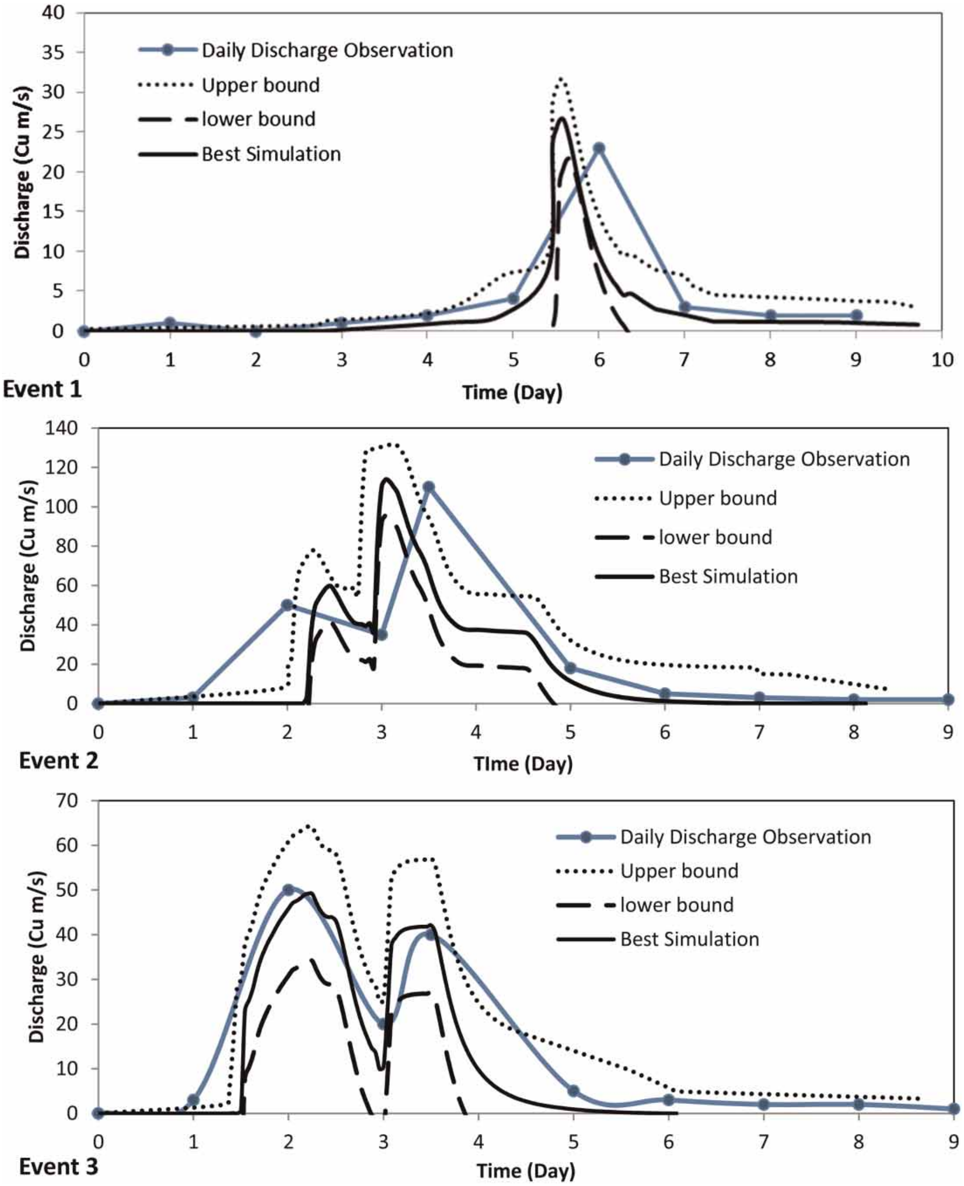

Figure 7 | The 95% confidence intervals bound derived by GLUE during the calibration for events 1, 2 and 3. The dots correspond to the observed discharge at the basin outlet, while the solid line represents the best simulation obtained by GLUE.

generate new parameter sets. Next, KINEROS2 was applied to runoff simulation by new parameter sets and the results are shown in Figure 7 and show the predicted 90% confidence intervals for events using new parameter sets.

For validation of the model, KINEROS2 was run using events 4 and 5, utilizing the best parameter set obtained from the previous section. The obtained NS coefficient was 0.79 and 0.70 for events 4 and 5, respectively (Figure 8).

CONCLUSIONS

Hydrological models should be calibrated before they are used as a decision making aid in the water resources planning and management. Although manual procedures for calibration are still frequently used, they are extremely time-consuming, tedious, frustrating and require experienced personnel. In order to avoid these limitations, in this study, to perform the

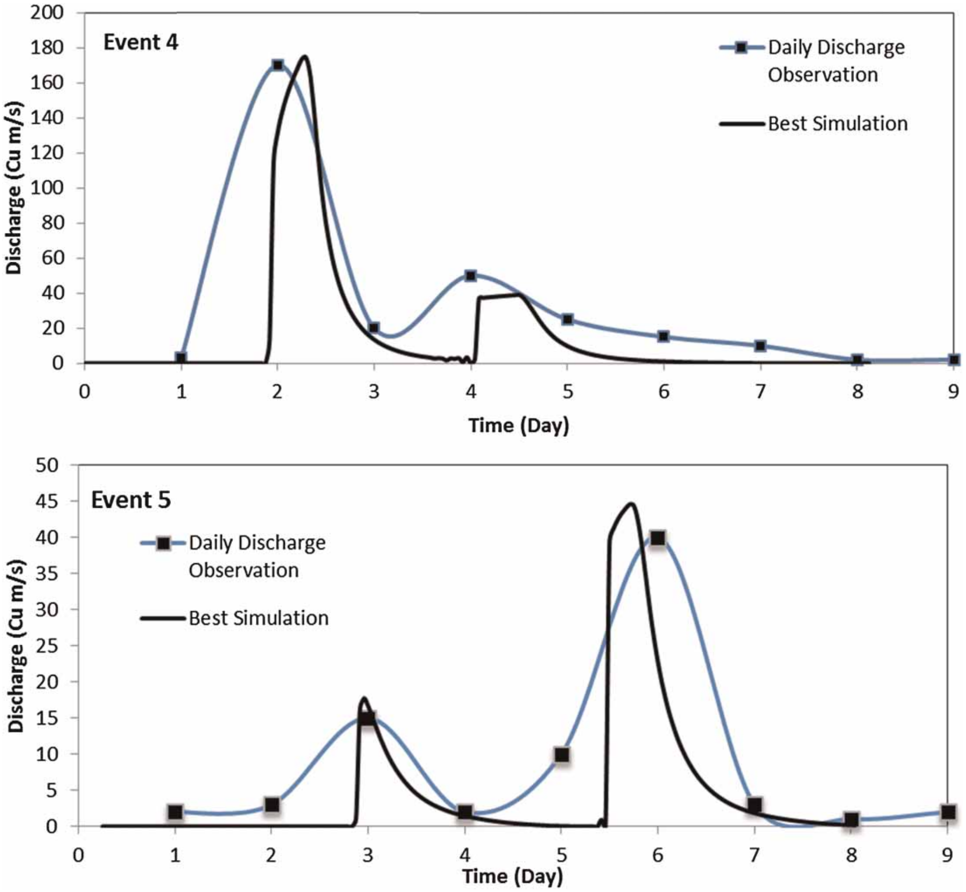

Figure 8 | Validation results for events 4 and 5. Dots are observed discharge data and lines are simulated discharge.

calibration and verification steps, GLUE is integrated and developed into an event oriented and physically-based model, the kinematic runoff and erosion model (KINEROS2), for analyzing watershed uncertainty in the flow estimates. To demonstrate the parameter estimation, model calibaration, and uncertainty analysis techniques are applied to a watershed located in the center of Iran. Application of the uncertainty estimation model indicates that the KINEROS2 model streamflow forecasts that involve a great deal of uncertainty; however, the lack of sufficient data at the study area was another influential factor for increasing the uncertainty band. Furthermore, the capabilities of GLUE and uncertainty analysis method could be more effectively merged and used for uncertainty analysis in a watershed that had sufficient data readily available in the study area.

In this study, the KINEROS2 model was calibrated and validated for the upstream of the Zayanderood River basin by using the GLUE method. The model performance was satisfactory for the calibration and the verification periods. Values of NS are 0.85 and 0.79 for calibration and validation periods, respectively. The results prove that the model is appropriate for estimating flood hazards.

REFERENCES

Ajami, N., Duan, Q. & Sorooshian, S. 2007 An integrated hydrologic bayesian multi-model combination framework: confronting input, parameter and model structural uncertainty. *Water Resour. Res.* **43**, W01403.

Aronica, G., Hankin, B. & Beven, K. 1998 Uncertainty and equifinality in calibrating distributed roughness coefficients in a flood propagation model with limited data. *Adv. Water Resour.* **22** (4), 349–365.

Beven, K. & Binley, A. 1992 The future of distributed models: model calibration and uncertainty prediction. *Hydrol. Process*. **6**, 279–298.

Beven, K. & Freer, J. 2001 Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *J. Hydrol*. **249** (1–4), 11–29.

Blasone, R.-S., Vrugt, J., Madsen, H., Rosbjerg, D., Robinson, B. & Zyvoloski, G. 2008 Generalized likelihood uncertainty estimation (GLUE) using adaptive Markov Chain Monte Carlo sampling. *Adv. Water Resour*. **31**, 630–648.

Boyle, D., Gupta, H. & Sorooshian, S. 2000 Toward improved calibration of hydrological models: combining the strengths of manual and automatic methods. *Water Resour. Res*. **36**, 3663–3674.

Cameron, D., Beven, K., Tawn, J., Blazkova, S. & Naden, P. 1999 Flood frequency estimation by continuous simulation for a gauged upland catchment (with uncertainty). *J. Hydrol*. **219** (3–4), 169–187.

Chau, K. W., Wu, C. & Li, Y. 2005 Comparison of several flood forecasting models in Yangtze River. *J. Hydrol. Eng. ASCE* **10** (6), 485–491.

Chen, W. & Chau, K. W. 2006 Intelligent manipulation and calibration of parameters for hydrological models. *Int. J. Environ. Pollut*. **28** (3–4), 432–447.

Cheng, C. T., Chau, K. W. & Li, X.-Y. 2007 Hydrologic Uncertainty for Bayesian Probabilistic Forecasting Model Based on BP ANN. *Third International Conference on Natural Computation*. IEEE Computer Society, Haikou, China, pp. 197–201.

Feyen, L., Beven, K., De Smedt, F. & Freer, J. 2001 Stochastic capture zone delineation within the generalized likelihood uncertainty estimation methodology: conditioning on head observations. *Water Resour. Res*. **37** (3), 625–638.

Feyen, L., Ribeiro Jr., P., De Smedt, F. & Diggle, P. 2002 Bayesian methodology to stochastic capture zone delineation: conditioning on transmissivity measurements. *Water Resour. Res*. **38** (9), 1164.

Feyen, L., Ribeiro Jr., P., Gomez-Hernandez, J., Beven, K. & De Smedt, F. 2003a Bayesian methodology for stochastic capture zone delineation incorporating transmissivity measurements and hydraulic head observations. *J. Hydrol*. **271**, 156–170.

Feyen, L., Gomez-Hernandez, J., Ribeiro Jr., P., Beven, K. & De Smedt, F. 2003b Bayesian approach to stochastic capture zone delineation incorporating tracer travel times, conductivity measurements, and hydraulic head observations. *Water Resour. Res*. **39** (5), 1126.

Franks, S. & Beven, K. 1997 Bayesian estimation of uncertainty in land surface–atmosphere flux predictions. *J. Geophys. Res*. **102** (D20), 23991–23999.

Georgekakos, K., Seo, D., Gupta, H., Schaake, J. & Butts, M. 2004 Characterizing streamflow simulation uncertainty through multimodel ensembles. *J. Hydrol*. **298** (1–4), 222–241.

Gupta, H., Sorooshian, S. & Yapo, P. 1998 Toward improved calibration of hydrologic models: multiple and noncommensurable measures of information. *Water Resour. Res*. **34**, 751–763.

Hassan, A., Bekhit, H. & Chapman, J. 2008 Uncertainty assessment of a stochastic groundwater flow model using GLUE analysis. *J. Hydrol*. **362**, 89–109.

Hunter, N., Bates, P., Horritt, M., De Roo, A. & Werner, M. 2005 Utility of different data types for calibrating flood inundation models within a GLUE framework. *Hydrol. Earth Syst. Sci*. **9** (4), 412–430.

Keesman, K. 1990 Set theoretic parameter estimation using random scanning and principal component analysis. *Math. Comput. Simul*. **32**, 535–543.

Klepper, O., Scholten, H. & van de Kamer, J. 1991 Prediction uncertainty in an ecological model of the Oosterschelde Estuary. *J. Forecast*. **10**, 191–209.

Kuczera, G. & Parent, E. 1998 Monte Carlo assessment of parameter uncertainty in conceptual catchment models: the Metropolis algorithm. *J. Hydrol*. **211**, 69–85.

Lamb, R., Beven, K. & Myrabo, S. 1998 Use of spatially distributed water table observations to constrain uncertainty in a rainfall–runoff model. *Adv. Water Resour*. **22** (4), 305–317.

Madsen, H. 2000 Automatic calibration of a conceptual rainfall-runoff model using multiple objectives. *J Hydrol*. **235** (3–4), 276–288.

Madsen, H. 2003 Parameter estimation in distributed hydrological catchment modelling using automatic calibration with multiple objectives. *Adv. Water Resour*. **26**, 205–216.

Madsen, H., Rosbjerg, D., Damgard, J. & Hansen, F. 2003 Data assimilation in the MIKE 11 flood forecasting system using Kalman filtering, water resources systems – hydrological risk, management and development. *Proceedings of Symposium HS02b, IUGG2003*. IAHS, Sapporo, pp. 75–81.

Miller, S., Semmens, D., Miller, R., Hernandez, M., Goodrich, D., Miller, W., Kepner, W. & Ebert, D. 2002 GIS-based hydrologic modeling: the automated geospatial watershed assessment tool. *Proceedings of the Second Federal Interagency Hydrologic Modeling Conference*. Las Vegas, Nevada.

Montanari, A. 2005 Large sample behaviors of the generalized likelihood uncertainty estimation (GLUE) in assessing the uncertainty of rainfall–runoff simulations. *Water Resour. Res*. **41**, W08406

Moradkhani, H., Hsu, K.-L., Gupta, H. & Sorooshian, S. 2005 Uncertainty assessment of hydrologic model states and parameters: sequential data assimilation using the particle filter. *Water Resour. Res*. **41** (5), 1–17.

Muttil, N. & Chau, K. W. 2006 Neural network and genetic programming for modelling. *Int. J. Environ. Pollut*. **28** (3–4), 223–238.

Nedkov, S. & Burkhard, B. 2011 Flood regulating ecosystem services – mapping supply and demand, in the Etropole municipality, Bulgaria. *Ecol. Indic*. **21**, 67–79.

Schuol, J. & Abbaspour, K. 2006 Calibration and uncertainty issues of a hydrological model (SWAT) applied to West Africa. *Adv. Geosci*. **9**, 137–143.

Semmens, D., Goodrich, D., Uncrich, C., Smith, R., Woolliser, D. & Miller, S. 2005 KINEROS2 and the AGWA modeling framework. In: International G-WADI Modeling Workshop. Retrieved from http://gwadi.org/shortcourses/chapters/SemmensL6.pdf.

Sohn, M., Small, M. & Pantazidou, M. 2000 Reducing uncertainty in site characterization using Bayes Monte Carlo methods. *ASCE J. Environ. Eng*. **126** (10), 893–902.

Thiemann, M., Trosset, M., Gupta, H. & Sorooshian, S. 2001 Bayesian recursive parameter estimation for hydrological models. *Water Resour. Res*. **37** (10), 2521–2535.

van Straten, G. & Keesman, K. 1991 Uncertainty propagation and speculation in projective forecasts of environmental change: a lake eutrophication example. *J. Forecast*. **10**, 163–190.

Vrugt, J. & Robinson, B. 2007 Treatment of uncertainty using ensemble methods: comparison of sequential data assimilation and Bayesian model averaging. *Water Resour. Res*. **43**, W01411.

Vrugt, J., Diks, C., Gupta, H., Bouten, W. & Verstraten, J. 2005 Improved treatment of uncertainty in hydrologic modeling: combining the strengths of global optimization and data assimilation. *Water Resour. Res*. **41** (1), 1–17.

Vrugt, J., Gupta, H., Bastidas, L., Bouten, W. & Sorooshian, S. 2003a Effective and efficient algorithm for multi-objective optimization of hydrologic models. *Water Resour. Res*. **39** (8), 1214.

Vrugt, J., Gupta, H., Bouten, W. & Sorooshian, S. 2003b A Shuffled Complex Evolution Metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters. *Water Resour. Res*. **39** (8), 1201.

Vrugt, J., Weerts, A. & Bouten, W. 2001 Information content of data for identifying soil hydraulic parameters from outflow experiments. *Soil Sci. Soc. Am. J*. **65**, 19–27.

Xu, Y. P., Booij, J. M. & Tong, B. Y. 2010 Uncertainty analysis in statistical modeling of extreme hydrological events. *Stoch. Environ. Res. Risk. Assess*. **24**, 567–578.

Yapo, P., Gupta, H. & Sorooshian, S. 1998 Multi-objective optimization for hydrologic models. *J. Hydrol*. **204**, 83–97.

First received 22 February 2013; accepted in revised form 17 May 2013