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Application of GLUE Methodology for Estimating the Parameters of the Rainfall-Runoff Model

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ABSTRACT

Parameter uncertainty of the distributed AFFDEF model was studied using GLUE (Generalized Likelihood Uncertainty Estimation) methodology which linked to the model in MATLAB software. Two historical floods with hourly time step for calibration periods were selected. Simulation runs were done to indicate convergence to a stationary posterior distribution. Finally posterior parameters were created with Latin Hyper Cubic Sampling. It was identified that some observations were not covered in the parameter uncertainty bounds, which suggest that more accurate predictions might be obtained if the model structure and the measured data are improved. The results for calibration period showed that observational discharge values especially peak values bracketed well within 95% confidence interval. Regarding rising and recessing limb as a result of initial conditions and uncertainties originate from base flow separation methods, they were predicted out of the confidence interval. For evaluating the uncertainty degree, P-95CI, ARIL and MNS criteria were used. Also for determining the best-fitting between the observed discharge and simulated discharge, SSE criterion was used.

KEYWORD

GLUE, AFFDEF, Uncertainty analysis, Distributed

INTRODUCTION

Inrecent years, there has been an increase in the application of physically-based, distributed, hydrological models. Such as MIKE-SHE introduced by Graham and Butts [1], TOPMODEL introduced by Bevenet al [2]. Many questions related to calibration of distributed models, however, are still quite unexplored.The model, AFFDEF, is spatially distributed (grid based) which can simulate river discharge by time step and at any location in the catchment, was introduced by Moretti and Montanari [3]. Due to complexity of physically-based distributed models, these models are more computationally demanding than lumped rainfall--runoff models. Moreover, a higher number of model runs are needed to calibrate and assess the uncertainty, due to a larger dimensionality of the parameter space. Applying more efficient calibration and uncertainty assessment procedures can, however, limit the computational burden [4]. In Iran for the first time, Mohammad nejad and Zahraie [5] used this model for considering climate change (increasing or decreasing runoff) in the next fifty years in Sistan Baloouchistan province.

It is an accepted fact that a hydrological model prediction, should not be deterministic, most-probable representation, but should also explicitly include an estimate of uncertainty. Uncertainty in model predictions arise from measurement errors associated with the system input (forcing) and output from model structure errors arising from the aggregation of spatially distributed real-world processes into a mathematical model and from problems with parameter estimation. Realistic assessment of this various sources of uncertainty is important for science-based decision making and will help direct resources towards model structural improvements and uncertainty reduction [4]. Methods to represent model parameter, state and prediction uncertainty include classical Bayesian[6], pseudo-Bayesian [2], set theoretic [7], sequential data

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assimilation [8], and multi-model averaging methods [9]. Among these models, Generalized Likelihood Uncertainty Estimation (GLUE) methodology of Beven and Binely [7] inspired by the Hornberger and Spear [20] method of sensitivity analysis was one of the first attempts to represent prediction uncertainty [9].

This study makes a comprehensive evaluation about the parameter uncertainty estimated by GLUE for spatially distributed grid based rainfall-runoff model (AFFDEF) in mountainous catchment from Iran. Special attention is paid: 1) model setup, parameterization and choice of calibration parameters 2) definition of performance criteria and likelihood function 3) implementation of GLUE using Latin Hyper Cubic sampler.

STUDY AREA

The data used in this study are from the catchment of-KalSalar river, which is located in the northern part of Torbat e Heidarieh township in Iran country. The KalSalarriver and its tributaries drain an area of 52.05 km^2. Its longitude is eastern from 59°,05',32" to 59°,13',45" and its latitude is northern from 35°,27',36" to 35°,30',47". The average elevation of the catchment is 1952.5 m above sea level.The annual average temperature is 11.9° C and the average of relative humidity is 53.9 percent. The geology of catchment is characterized by sedimentary volcanicy soils from third age with low permeability, so the runoff coefficient in the catchment is high. A database of hydro-meteorological measurements is available for the Kameh catchment and haspreviously been used in studies by Akbarpoorand Sharifi[10]. Thedatabase includes rainfall measurements from two stations (Bakavol station and Sanubar station),observeddischarge and temperature at hourly time step at the same time. In this catchment, first station is within the catchment and the second station is close to the catchment.

INPUT DATA FOR AFFDEF MODEL

The input data for this model include the following:

- Rainfall depths (mm) at both stations simultaneously
- Air temperature (°C)
- Topography data as a grid based Digital Elevation Model(DEM)
- Curve Number(CN)associated to each DEM cell
- Different classes of roughness associated to each DEM cell

The input meteorological data consist of both observed precipitation (rainfall depths) and air temperature at the same time step. The input topography data, which are given in raster format by means of 50*50 square matrix, placed in an ASCII text file. To characterize the spatial pattern of the infiltration capacity, a second 50*50 matrix has to be provided in a separate ASCII file containing the Curve Number (CN) parameters. The soil type was found from maps and also estimated with prior knowledge of the catchment. Finally, a 50*50 matrix placed in an ASCII text file was used to represent the spatial variability of the soil roughness.

Classes of roughness determined from land use maps, and a Strickler coefficient was assigned to each cell. The Strickler coefficient may be estimated from the scientific literature to the land use type (e.g. Engman, [11]).

MODEL SETUP

The AFFDEF modelling system with quasi-3D computational grid of 50*50 m was used to setup a model of the Kalsalar river catchment. The model code, written in FORTRAN programming language. Model for each cell with coordinates *(i,j)*considers two reservoirs. The first reservoir is located on the ground level which is called the local reservoir (Interceptionreservoir). The second reservoir is located below the soil surface, which is called linear reservoir (infiltration reservoir). Interception reservoir collects local precipitation $P_l[t,(i,j)](mm)$ in itself. The capacity of the reservoir is equalto $C_{int}\,S(i,j)$, which $C_{int}$is a parameter, which is assumed to be constant in space and time, and *S(i,j)*is local storage capability that is calculated using soil type and CN method. When interception reservoir becomes full of water, excess precipitation will reach to the ground. The distinction between surface and subsurface flow is determined based on CN method which is assumed that an infiltration reservoir, which collects permeated water, correspond to each DEM cell, is placed on the soil surface. Intensity of surface runoff $P_n[t,(i,j)](mm)$is calculated from the (Eq.1).

$$\frac{P_n[t,(i,j)]}{P[t,(i,j)]} = \frac{F[t,(i,j)]}{HS(i,j)} \tag{1}$$

In the above equation, $P[t,(i,j)](mm)$ is the rainfall intensity reached to the ground at time t and $F[t,(i,j)](mm)$ is water content of infiltration reservoir at time t. $HS(i,j)(mm)$ is the capacity of infiltration reservoir itself, given by parameter H (dimensionless) multiplied by the soilstorativity defined in (Eq.2).

$$S(i,j) = 254\left(\frac{100}{CN(i,j)}\right) \tag{2}$$

$CN(i,j)$ (dimensionless) is the Curve Number at the given cell location. The infiltrated water at time t is computed as: $P[t,(i,j)] - P_n[t,(i,j)] = I[t,(i,j)]$. Each Infiltration reservoir releases an outflow $W[t,(i,j)](mm\,s^{-1})$to the sub-surface river network through a linear bottom discharge, according to the (Eq.3).

$$W[t,(i,j)] = \frac{F[t,(i,j)]}{HS} \tag{3}$$

Where H_S (dimensionless) is calibration parameter.

Hourly intensity of potential evapotranspiration is also-$E_P[t,(i,j)]$, which is calculated using Radiation method [12]. When some water is stored in the interception reservoir, the effective evapotranspiration $E[t,(i,j)]$ is considered equal to $E_P[t,(i,j)](mm\,s^{-1})$and is subtracted from the water content of the interception reservoir itself. When the latter is empty, or is emptied while subtracting the

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evapotranspiration, the remaining part of $E_P[t,(i,j)]$ is subtracted from the water content of the infiltration reservoir. In this case it is assumed that $E[t,(i,j)](mm\ s^{-1})$is varying linearly from 0 when $F[t,(i,j)]$ =0, to $E_P[t,(i,j)]$ when $F[t,(i,j)] = HS(i,j)$. Finally, by combining the following continuity equation the governing the infiltration reservoir, following equation will be written as (Eq.4).

$$I[t,(i,j)] - W[t,(i,j)] = \frac{dF[t,(i,j)]}{dt} \quad (4)$$

By combining(Eqs 1 and 3 and4)and considering the effective evapotranspiration, the massbalance equation for infiltration reservoir can be written as (Eq.5).

$$\frac{dF[t,(i,j)]}{dt} = -\frac{F[t,(i,j)]}{H_S} - E[t,(i,j)] + P[t,(i,j)]\left\{1 - \frac{F[t,(i,j)]}{HS(i,j)}\right\} \quad (5)$$

Above equationis solvedwith thefourth order Runge-Kuttamethod[3]. For surface flow, kinematics velocity is calculated by considering a rectangular cross-section with a constant ratio of height to width. Kinematic velocity and channel roughness will be changed along the river network. Surface flow and subsurface flowrouting runoff toward catchment outlet is done by applying Muskingum-Cunge method with variable parameters [13].This means that each cell receives the highest slopes of the neighboring cells, and discharged it in direction of greatest slope of downstream cells. For cells where several flow paths join together, upstream hydrograph is obtained from total of outflow hydrographs from neighboring cells.A complete description of the AFFDEF model structure can be found in Moretti and Montanai [3].

CALIBRATION PARAMETERS

The calibration parameters have been shown in Table 1. A first trial value of parameters obtained from the scientific literature about the AFFDEF model written by (Moretti and Montanari[3] and PourrezaBilondi [19] and by knowing previous knowledge of catchment, finally calibration parameters were listed as below.

Tab1: Rainfall-runoff model input parameters and their values

Parameter	Default value	Lower limit	Upper limit
A0(km^2)	0.5	0.3	1.5
Wv(dimensionless)	600	300	100000
Ksv(I) I=1,..,3 ($m^{1/3}\ s^{-1}$)	1 0.5 5	0.05 0.05 0.5	10 10 20
K_{sat}($m\ s^{-1}$)	0.01	0.001	0.1
Hs(s)	80000	20000	800000
H(dimensionless)	0.4	0.05	0.9
Cint(dimensionless)	0.2	0.05	0.7

IMPLIMENTATION OF GLUE

In the Generalized Likelihood Estimation Uncertainty (GLUE) methodology, a large number of model runs are made with very different randomly chosen parameter values selected from a prior probability distribution. The acceptability of each run is evaluated against observed values and, if the acceptability is below a certain subjective threshold, the run is considered to be "non- behavioral" and that parameter combination is removed from further analysis. In this method the likelihood values serve as relative weights of each parameter set or simulated value. It is noted that the likelihood function and the threshold are subjectively determined and this was discussed by Freer et al. [14].In this study, the Nash-Sutcliffe (NS) value was chosen as likelihood function:

$$L(\theta_i|Y) = 1 - \frac{\sum_{t=1}^{T}\left(R_{obs,t} - R_{sim,t}\right)^2}{\sum_{t=1}^{T}\left(R_{obs,t} - \bar{R}_{obs}\right)^2} = 1 - \frac{\sigma_i^2}{\sigma_{obs}^2}\sigma_i^2 < \sigma_{obs}^2 \quad (6)$$

Where $L(\theta_i|Y)$ is the likelihood measure, $R_{obs,t}$ is the observed discharge, which is depending on the model - parameter θ_i, $\bar{R}_{obs}$ is the average value of$R_{obs,t}$, δ_i^2 is the variance of errors for the given parameter set θ_i and the observed discharge data set Y, and δ_{obs}^2 is the variance of observed data set.

95% CONFIDENCE INTERVAL OF DISCHARGE

10000 discharge values for 24 hours were obtained by running the AFFDEF model with 10000 parameter sets, which are from the Hyper Cubic Sampling. The 95% confidence intervals for discharge due to parameter uncertainty were estimated by these discharge samples. The 5percentile of discharge are derived by sorting ascending of 10000 discharge values at 24 hours. The intervals in GLUE method consider weighted values. After sorting ascending of all discharge, the quantiles of discharge is calculated according to following equation:

$$P_G(y < y_i) = {NS_i}\Big/{\sum_{i=1}^{n} NS_i} \quad (7)$$

In which i is the position order of y_i after sorting ascending, n is the number of sample simulations, $P_G(y < y_i)$ is the quantile of discharge y_i in GLUE method, NS_i is the weighted Nash- Sutcliffe values of y_i, which is equal to $L(\theta_i|Y)$.

CALIBRATION CRITERIA

In this study, four indices were used to compare the derived 95% confidence interval (95CI) of 24 hour discharge, which are the percent of observations bracketed by the 95CI (P-95CI) used by Li et al.[15], Average Relative Interval Length (ARIL) defined by Jin et al[16] and the Maximum Nash- Sutcliffe value (MNS)[17]. Also the function used to represent the fit of the model simulations to the observations is Sum Square Error (SSE). These indices are expressed as follows:

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$$P - 95CI = \frac{NQ_{in}}{n} \times 100\% \qquad (8)$$

Where NQ_{in} is the number of observations which are contained95CI.

$$ARIL = \frac{1}{n}\sum \frac{limit_{upper,t} - limit_{lower,t}}{R_{obs,t}} \qquad (10)$$

Where $limit_{upper,t}$ and$limit_{lower,t}$ are the upper and lower boundary values of 95CI, n is the number of time steps and $R_{obs,t}$ is the observed discharge.

$$MNS = max_{i=1}^{N}\{NS_i\} \qquad (11)$$

In which *i*is the acceptable index, t is the time index, $R_{obs,t}$ is the observed discharge, and $\bar{R}_{obs}$ is the average value of $R_{obs,t}$

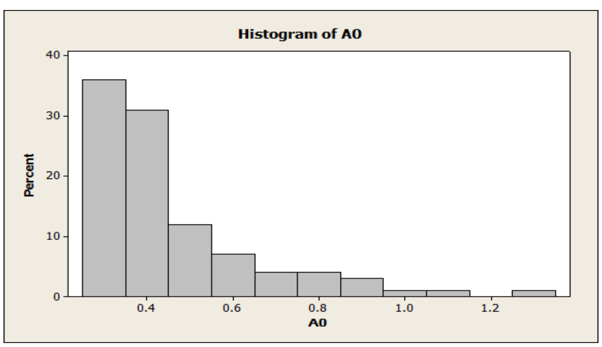
$$SSE = \sum_{i=1}^{n}(Qobs - Qsim)^2 \qquad (12)$$

Where: *Qobs* is observed discharge values, *Qsim* is simulated discharge values.
The goodness of the simulation was judged on the basis of - the closeness of SSE to 0, the $P - 95CI$ to 100% and $ARIL$ to 1.MNS should be as close to 1 as possible.

RESULTS

POSTERIOR PARAMETER DISTRIBUTION

The posterior distributions of nine parameters considered for two floods in calibration period are shown in Figures 1 to 9.



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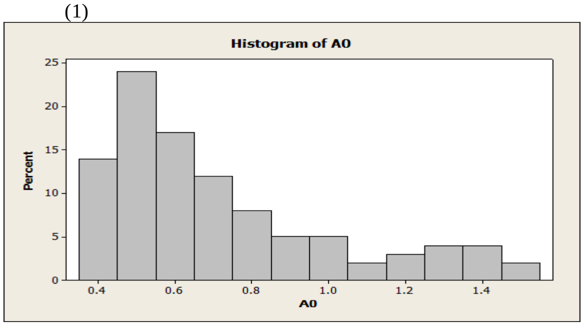

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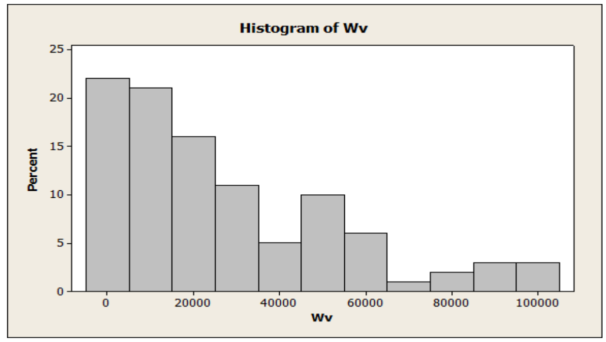
Fig.1.Histograms of the posterior probability distribution of parameter A_0 (Constant critical source area) for the two floods of calibration, (1) 30 April 1998, (2) 1 June 1998



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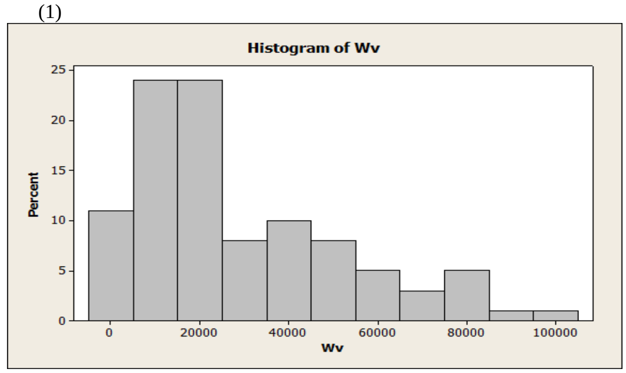

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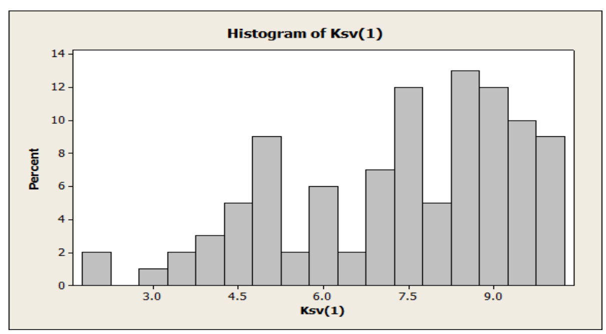
Fig.2.Histograms of the posterior probability distribution of parameter Wv(Channelwidth/height ratio for the hillslope) for the two floods of calibration, (1) 30 April 1998, (2) 1 June 1998



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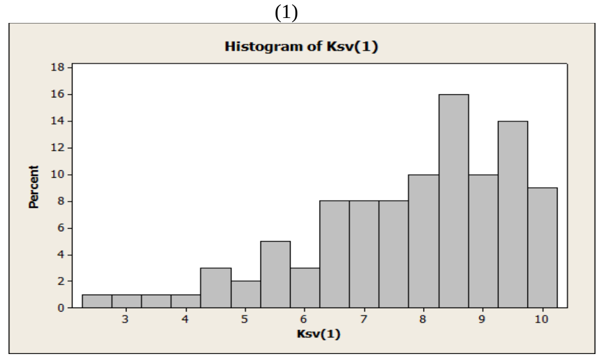

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Fig .3.Histograms of the posterior probability distribution of parameter $K_{SV(1)}$ (Strickler coefficients of roughness on the hillslope) first Class roughness for the two floods of calibration,(1) 30 April 1998, (2) 1 June 1998

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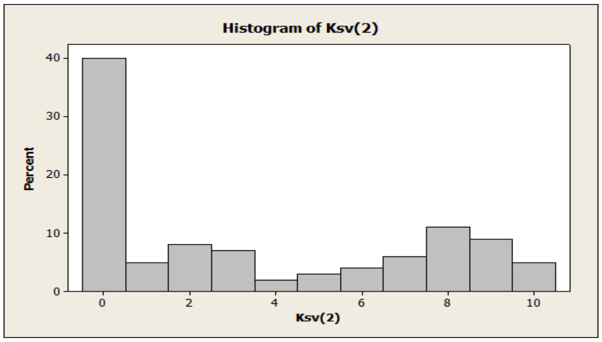

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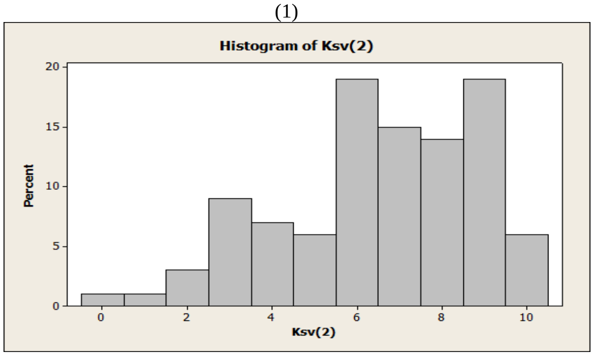

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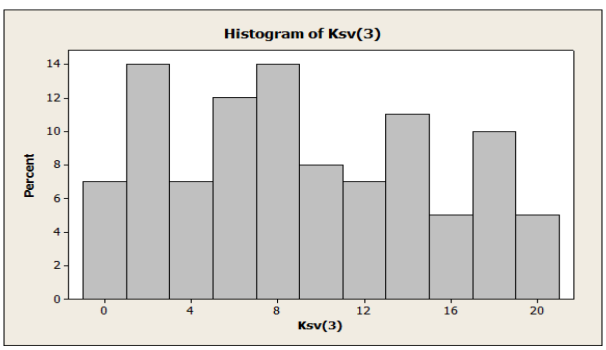
Fig. 4.Histograms of the posterior probability distribution of parameter $K_{SV(2)}$ Strickler coefficients of roughness on the hillslope)for the two floods of calibration, (1) 30 April 1998,(2) 1 June 1998



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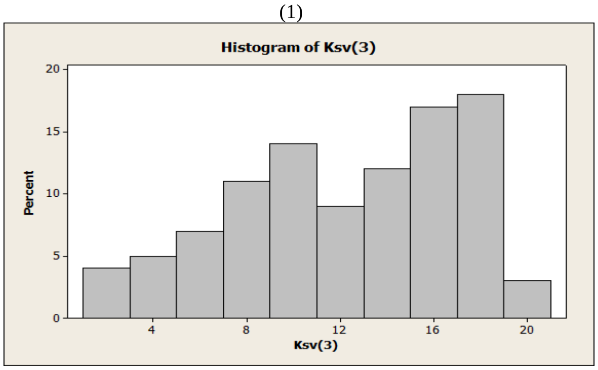

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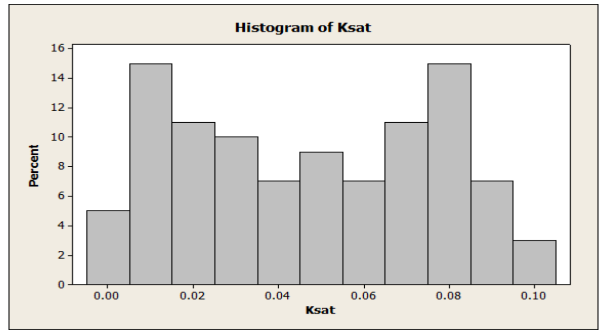
Fig.5.Histograms of the posterior probability distribution of parameter $K_{SV(3)}$ for the two floods of calibration, (1) 30 April 1998, (2) 1 June 1998



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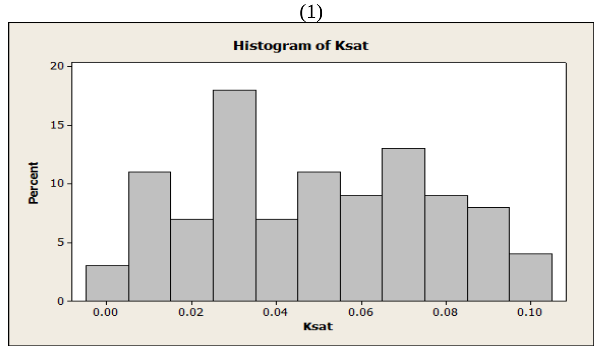

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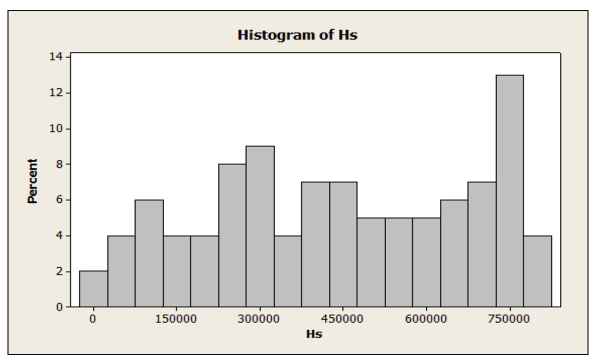
Fig. 6.Histograms of the posterior probability distribution of Ksat- (Saturated hydraulic conductivity) parameter for the two floods of calibration, (1) 30 April 1998, (2) 1 June 1998



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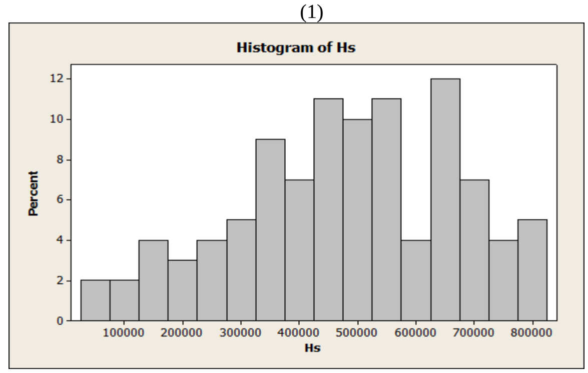

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Figure 7.Histograms of the posterior probability distribution of parameter H_S **(**Bottom discharge parameter for the infiltration reservoir capacity) for the two floods of calibration, (1) 30 April 1998, (2) 1 June 1998

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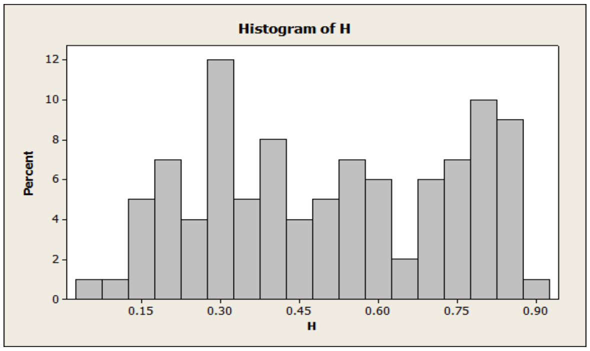

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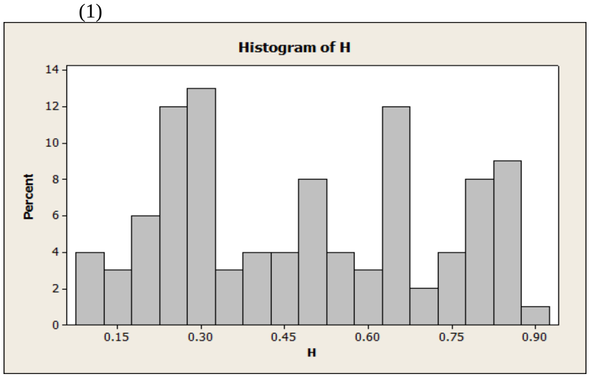

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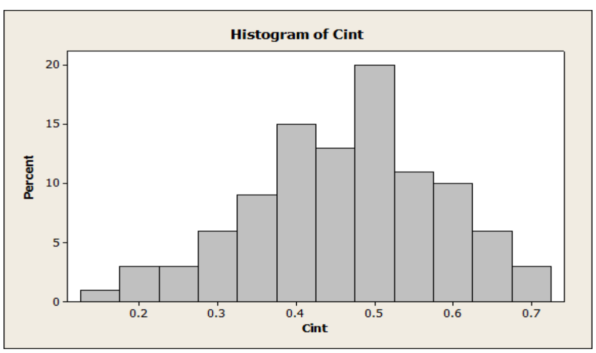
Fig. 8.Histograms of the posterior probability distribution of parameter H(Multiplying parameter for the infiltration reservoir) for the two floods of calibration, (1) 30 April 1998, (2) 1 June 1998



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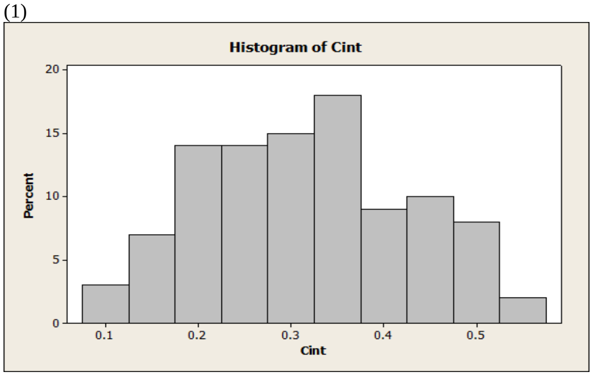

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Fig. 9.Histograms of the posterior probability distribution of parameter C_{int}(Multiplying parameter for the interception reservoir capacity) for the two floods of calibration, (1) 30 April 1998, (2) 1 June 1998

Almost the distribution of whole of the parameters at all floods have been demonstrated sensitive manners and can not specify insensitive and ineffective parameter (uniform distribution with primary range of parameter). Though, some parameters such as: parameter H, K_{SV2} in both floods have been known parameters with lower sensitivity, because they have high dispersion around their values meaning high variance. Most of the parameters have normal (bell-shape) distribution and exponential distribution. For example: distribution of parameter A_0 which has smaller range than primary range of parameter (0.3 km^2 to 1.5 km^2) is exponential distribution in both floods and C_{int} has normal distribution in both floods.

Confidence limits of the simulated hydrographs in the calibration process

The GLUE estimation of the hydrographs at the catchment outlet, are shown in Figure 10.

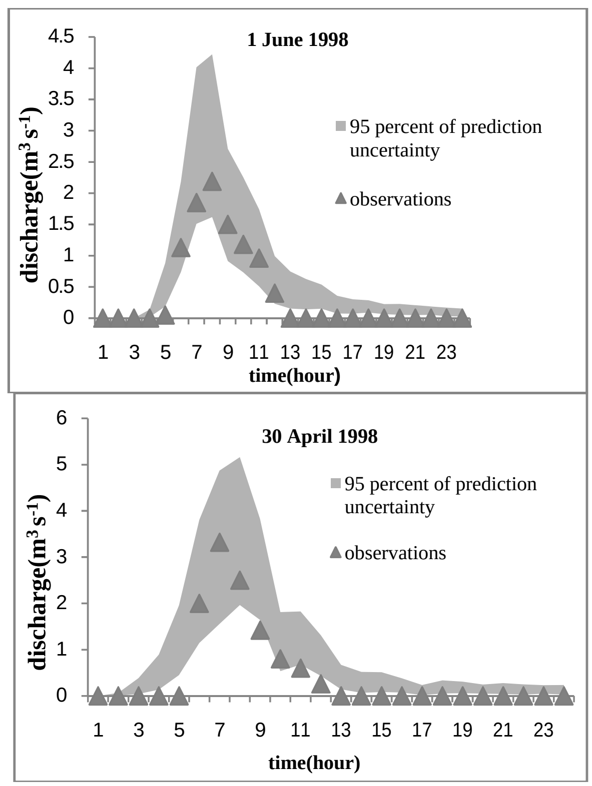

Fig.10. Parameter uncertainty estimations for flood events in calibration period

Many observations in the rising and recessing limb are located outside the uncertainty parameters or confidence interval. According toLaloy and Bielders,[18] it can be interpreted about recessing limb of hydrograph that due to the high sensitivity of base flow determination method and parameters related to subsurface flow (H_s, K_{sat}), recessing limb of hydrographs is severity affected with this procedure

too. Thus, flood simulation with data for longer term so that simulations were done several days before simulating, not only for the event day, it will have great influence at improvement of simulation and decrease of output simulation uncertainty for the beginning and ending points of thehydrograph. Also, using the usual methods of determining base flow due to the many errors, makes more uncertainty at both ends of hydrographs.

CALCULATION OF PREDICTED UNCERTAINTY

The results of model calibration for two single- event floods have been illustrated in Table 2.

Tab.2. Statistical coefficients of calibration periods for Kameh catchment

Date of flood	P-95CI(%)	ARIL	MNS	SSE
30 April 1998	40	0.52	0.85	0.71
1 June 1998	41	0.51	0.9	0.34

According to the above table, ARIL and P-95CI values of both floodswith a slight approximation are equal together. Because both floods have equal moisture conditions,In this study both floods are in normal antecedent moisture conditions (AMC2), also the monthswhich rainfall occurred, are close (June and July) together, meaning, whether conditions are almost identical. The small value of ARIL in both floods indicates quite good calibration of the catchment. The amount of P-95CI is approximately small and indicates that the uncertainty of predictions is high. One reason for increasing the uncertainty estimation refers to the structure ofthe AFFDEF model. AFFDEF does not consider the influence of snowmelt on runoff. Since theKameh catchment is mountainous and most of the days of years has been covered with snow, so the values of runoff resulted from snowmelt is not considered, especially in spring and summer seasons when the snow begin melting.According tothe table 2, Nash-Sutcliffe Coefficient has high value in both floods. . According to these values,calibration of AFFDEF model has very good accuracy at the catchment outlet which represents the Kameh catchment flow rate is well simulated. The values of SSE are quite small for both floods which represents the appropriate prediction of parameter values during calibration step by the model.

CONCLUTION

Uncertainty Evaluation and quantification of rainfall-runoff model parameters with determining the range of flood hydrograph prediction arising from this uncertainty, is currently one of the research fields. GLUE procedure with Latin Hyper cubic sampling was applied in parameter estimation of a physically-based, distributed and hydrological model with nine parameters and also posterior output distributions. Two events with hourly rainfall in the catchment with their hydrographs were selected for calibration. 10000 parameter sets generated by GLUE were run in rainfall- runoff model for events in calibrationperiods. The results related to posterior distribution histograms illustrated sensitive manner of almost all parameters. The results of two single-eventfloods in calibration periods were very close together. Because both floods hadequalmoisture-conditions, In this study both floods were in normal antecedent moisture conditions (AMC2). Although the flood seasons are different, but the months which two floods occurred were very close (June and July). The P-95CI values indicated that almost half of the observations are outside the 95% confidence interval especially in arising and recessing limb of both hydrographs. This problem refers to model structure. Because due to the simplification of the model, there is not distinction between near surface and deep groundwater fluxes. This approximations might result in significant imprecision in the modelling of the recessing limb of the hydrograph. In totally, the parameter uncertainty alone cannot explain at all the sites, the total uncertainty in simulating spatially- distributed variables. This is particularly true when biases are present in the model estimates, such as those arising from systematic measurement errors. However, the modeler should be aware that the GLUE procedure implemented in this study is just a tool to assess the errors

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