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The Influence of Objective Function and Acceptability Threshold on Uncertainty Assessment of an Urban Drainage Hydraulic Model with Generalized Likelihood Uncertainty Estimation Methodology

Wei Zhang · Tian Li

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Abstract Urban drainage model is an important computer-aided tool in stormwater management and drainage planning and designing. A popular urban drainage hydraulic model, stormwater management model (SWMM), was applied in a pump lifting combined sewer system for a high-intensity urban catchment located in Shanghai, China. Uncertainty of SWMM water quantity parameters was assessed with generalized likelihood uncertainty estimation (GLUE) methodology. The sensitivity of parameters was discussed and compared based on the results of uncertainty analysis. To discuss the influence of the acceptability threshold on model parameter sensitivity and the margin of uncertainty band, the GLUE approach was applied several times varying acceptability threshold. The results indicated that a higher acceptability threshold value is contributed to achieve a stricter verification with a high confidence level, and the uncertainty analysis significant level can be featured by the value of acceptability threshold. The selection of acceptability threshold value can be regarded as a tradeoff process. Both reducing the low efficient simulation and reducing computation cost should be considered for the selection of acceptability threshold. Moreover, the GLUE approach was applied several times varying different objective functions with corresponding acceptability thresholds. The results indicated that some parameters may be sensitive to a specific objective function, and other parameters may be sensitive to another objective function. Some parameters cannot easily identified when a single objective function was used within the GLUE approach, and a multiple-objective function combined different objective functions requirements, may be a alternative approach to reduce the model prediction uncertainty.

Keyword Combined sewer system · Objective function · Acceptability threshold · Uncertainty analysis · Stormwater management model (SWMM) · Generalized likelihood uncertainty estimation (GLUE)

W. Zhang · T. Li (✉)
State Key Lab of Pollution Control and Resource Reuse, Tongji University, Shanghai 200092, China
e-mail: tianli@tongji.edu.cn

W. Zhang
e-mail: weizhang021@163.com

1 Introduction

With continuous urban development, increase of impervious surfaces was contributed to change of urban hydrology in global urban areas. Urban flooding and waterlog has been an important environmental issues all over the world (Butler and Davies 2010). As a computer-aided tool in stormwater management and drainage planning and designing, several models were developed in past few decades (Zoppou 2001; Elliott and Trowsdale 2007; Yang and Wang 2010). The stormwater management model (SWMM) released by the U.S. EPA is one of the most widespread urban drainage hydraulic models, for both research and practical projects (Rossman 2010). The public domain and open source hydraulic model, SWMM is adopted in this study.

Optimization, identification, sensitivity analysis and uncertainty analysis of model parameters are major field of urban drainage modeling researches. Model uncertainty is usually classified into three categories, input, model structure, and parameter uncertainties (Willems 2008). For a complex environmental model, model structure uncertainties analysis is not easily implemented, and it commonly is ignored when a specific model was used. Model input uncertainties can be carried out based on the analysis method using in parameter uncertainties (Notaro et al. 2013; Manz et al. 2013). Hence, the parameter uncertainty was the main focus of model uncertainty analysis.

In order to accurately simulate the behaviors of the physical process, a large number of parameter inputs were usually required for the distributed drainage models. The parameters of urban drainage model were normally divided into two types by the parameters can be measured or not. The parameters, which cannot be measured, should be calibrated. To identify the parameter values of SWMM, genetic algorithm and other optimization method have been used in previous researches (Liong et al. 1991; Balascio et al. 1998; Barco et al. 2008; Kang and Lee 2014). However, obtaining only a unique optimal parameter set was the common problem for optimization method used in some previous researches (Sun et al 2014).

Equifinality, which mean multiple parameter sets might lead to equally acceptable simulation results, is a generally accepted concept used in complex hydrological modeling researches (Beven and Binley 1992; Sorooshian and Gupta 1995; Perrin et al. 2001). The generalized likelihood uncertainty estimation (GLUE) methodology proposed by Beven and Binley, is one of the most commonly used method that adopted the equifinality concept, to evaluate model parameter uncertainty (Beven and Binley 1992).

Application of GLUE method has been reported in various rainfall-runoff model, such as TOPMODEL, HSPF, MOUSE, SWAT and MIKE SHE (Choi and Beven 2007; Jia and Culver 2008; Thorndahl et al. 2008; Vázquez et al 2009; Talebizadeh, et al 2010). However, uncertainty of SWMM parameters using the GLUE method has not been well studied. Based on the previous researches within the GLUE method, the acceptability threshold and the objective function have obvious influence on the results of uncertainty analysis within the GLUE framework. When the Nash-Sutcliffe (*NS*) efficiency index was adopted as the objective function, different acceptability thresholds may lead to influence on the results of uncertainty analysis.

The NS efficiency index was normally used in the GLUE approach. Not only the *NS* efficiency index, but also the percent bias (*BIAS*), correlation coefficient (*R*) and root mean square error (*RMSE*) can be used to assess the goodness of fit between observed data and model outputs. Each of them has its characteristic and underestimates or overestimates another character of the model outputs.

In this study, different acceptability thresholds were used within a normal GLUE approach to discuss the impact on uncertainty analysis results. Moreover, four common likelihood functions were used as objective functions within the GLUE approach to assess the uncertainty of SWMM parameters. The discussion of objective function and acceptability thresholds used in GLUE method would be contributed to get reasonable parameter sets to reduce the model output uncertainty.

2 Materials and Methods

2.1 Experimental Catchment and Hydraulic Model

The experimental catchment is located in the downtown of Shanghai, a metropolitan city in eastern China. The average annual precipitation is approximately 1184 mm and the average annual number of rainy days is 122.

The monitored Anshan system is a pump lifting combined sewer system in a high urbanized catchment (Fig. 1). The catchment area is 130 ha, and the resident population is around 48,100. The pump station has four stormwater lifting pumps and four interception pumps. The nameplate flow of two stormwater lifting pumps is 2.8 m^3/s, and the other two are 2.3 m^3/s. The nameplate flow of two interception pumps is 0.41 m^3/s, and the other two are 0.28 m^3/s.

The rainfall, dry/wet weather flow, and water level data were obtained from the SCADA (supervisory control and data acquisition) system of the pump station.

The hydraulic model of Anshan drainage system based on SWMM was established. Total of 83 sub-catchments, 37 junction nodes and 42 conduits were included in Anshan drainage system model.

2.2 The GLUE Methodology

The Generalized Likelihood Uncertainty Estimation (GLUE) methodology was adopted in uncertainty analysis in this study. For the application of the GLUE methodology, the SWMM

Fig. 1 Anshan experimental catchment (Shanghai, China)

has been simulated by randomly sampled parameter sets through Monte Carlo sampling. According to an objective function, parameter sets are classified with a user-defined acceptability threshold (*Tr*).

The objective function indicated the goodness of fit between model outputs and observed data. The acceptability threshold is a user-defined value which reveals the minimum value of the objective function. The Nash-Sutcliffe efficiency index was a commonly used objective function in GLUE methodology (Eq. (1)). The behavior simulations are defined in the ranged from *Tr* to 1.

$$E_{NS} = 1 - \frac{\sum_{t=1}^{n} \left(L_{obs}^{t} - L_{sim}^{t}\right)^2}{\sum_{t=1}^{n} \left(L_{obs}^{t} - \overline{L_{obs}}\right)^2}, \tag{1}$$

where L_{sim}^{t} is the simulated value, L_{obs}^{t} is the observed value at time t, n is the total number of time steps, and $\overline{L_{obs}}$ is the mean of the observed value.

A method of deriving predictive uncertainty bands using the likelihood weights from the behavioral simulations has been proposed by Beven and Binley (1992). The uncertainty bands are calculated using the 5 and 95 % percentiles of model outputs likelihood weighted distributions. The wider uncertainty band, the higher uncertainty in the estimation of model output exists. Conversely, the small uncertainty band indicates that the model results are reliable.

The GLUE methodology was implemented as following steps.

a. The priori distribution and ranges of model parameters was determined.
b. Parameter sets were obtained by Monte Carlo sampling.
c. The model (in this study, SWMM was used) was simulated with each parameter set.
d. The objective function (such as *NS* efficiency index, etc.) of each simulation was calculated. If it is higher than the user-defined acceptability threshold (*Tr*), the model simulation is regarded as “behavioral”, and used for following analysis. Otherwise, it is regarded as “non-behavioral” and is rejected.
e. The cumulate likelihood distribution was calculated for each parameter and each model output.
f. For each model output, 5 and 95 % cumulate likelihood distribution reveal the uncertainty band; For each model parameter, 5 and 95 % represent the range in the parameter space, which is most likely the reasonable parameter values (with a confidence level equal to 0.1).
g. Check the consistency of the model hypotheses by comparing the observed data with uncertainty band (with a confidence level equal to 0.1).

Nevertheless, some subjectivity exists within the GLUE approach. One of subjectivities is the selection of parameter variation range. Small range will lead to a low uncertainty in model outputs. However, the result will be rejected because the observed data fall outside the uncertainty band. On the other hand, wide parameter range will widen the uncertainty band, and reduce the confidence level. Considering the issues mentioned above, the parameter and variation ranges were listed in Table 1.

Another part of subjectivity is from the selection of acceptability threshold. As the existence of a large uncertainty, 0.0–0.3 of *NS* efficiency index are commonly acceptable for water quality for urban drainage system (Freni et al. 2010; Manz et al. 2013). Meanwhile, for hydraulic modeling for urban drainage system, 0.7 of *NS* efficiency index is normally

Table 1 Parameters in SWMM hydraulic and hydrology module

	Parameter	Symbol	Unit	Minimum value	Maximum value
1	Subcatchment impervious Manning's coefficient	*N-imp*	–	0.010	0.025
2	Subcatchment pervious Manning's coefficient	*N-per*	–	0.025	0.300
3	Impervious depression storage	*S-imp*	mm	0.5	3.0
4	Pervious depression storage	*S-per*	mm	3.0	10.0
5	Max infiltration	*I-max*	mm/h	38	150
6	Min infiltration	*I-min*	mm/h	0	30
7	Conduit Manning coefficient	*N-con*	–	0.010	0.025
8	Percent of impervious area	*P-imp*	%	40	85
9	Width of overland path	*Width*	m	30	260
10	Average surface slope	*Slope*	%	0.5	3

acceptable (Sun et al. 2014). In this study, the GLUE analysis has been applied several times, varying the acceptability threshold from 0.65 to 0.85.

The third source of subjectivity is from the selection of likelihood measure function (objective function). In most of applications with GLUE approach, the *NS* efficiency index was used (Freni et al. 2010; Manz et al. 2013). In order to discuss the influence of objective function, other three likelihood measure function, including *BIAS*, *R* and *RMSE*, were used in this study (Eq. (2)–(4)).

$$BIAS\% = \frac{\sum_{t=1}^{n}\left(L_{obs}^{t} - L_{sim}^{t}\right)}{\sum_{t=1}^{n} L_{obs}^{t}} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(L_{sim}^{t} - L_{obs}^{t}\right)^{2}} \tag{3}$$

$$R = \frac{\sum_{t=1}^{n}\left(L_{obs}^{t} - \overline{L_{obs}^{t}}\right)\left(L_{sim}^{t} - \overline{L_{sim}^{t}}\right)}{\left(\sqrt{\sum_{t=1}^{n}\left(L_{obs}^{t} - \overline{L_{obs}^{t}}\right)^{2}}\right)\left(\sqrt{\sum_{t=1}^{n}\left(L_{sim}^{t} - \overline{L_{sim}^{t}}\right)^{2}}\right)} \tag{4}$$

where $\overline{L_{sim}}$ is the mean of the simulated value.

Once the objective function was set, the corresponding *Tr* should be determined to compare the influence of objective function. Based on the previous researches on rainfall-runoff modeling, the *Tr* values of each objective function was determined. A threshold level of 0.7 is determined for *NS* efficiency index. The best 30 % rule is used for *RMSE*, the relative error less than 10 % is used for *BIAS*, and 0.95 is used for *R*.

3 Results and Discussion

3.1 Predicted Uncertainty of the Calibration Event

A rainfall event on 21 Sep. 2013, which last 255 min with a maximum intensity of 0.48 mm/min and a total amount of 15.6 mm, was selected as a calibrated event. The uncertainty analysis was carried out according to the GLUE methodology mentioned above. Uniform distribution is used as the prior distribution for each SWMM parameters according to parameter variation ranges in Table 1. Total of 1000 parameter sets were sampled for each parameter. According to the *Tr* of objective functions, corresponding behavioral simulations were collected.

Scatter plot of model parameters was made to identify the sensitivity and consistency of parameters. Scatter plot of *P-imp*, *N-con*, *Width* and *Slope* was shown in Fig. 2. Each dot represents one run of the model with different randomly sampled parameter values within the range listed in Table 1.

As shown in Fig. 2b, a rising tendency of *NS* efficiency index was observed with increasing the values of *P-imp*. A similar trend was observed for parameter *N-imp*. A slight decline trend of *NS* efficiency index was shown with the increasing the values of *N-con*. A much steeper

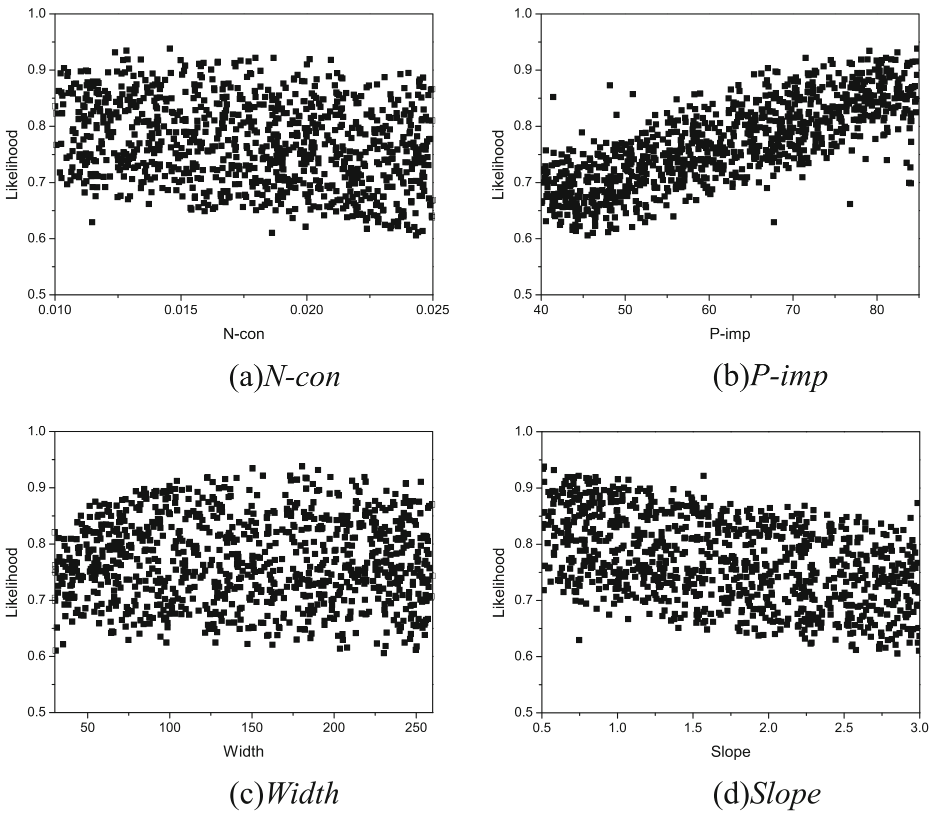


Fig. 2 Scatter plot of parameter *N-con*, *P-imp*, *Width*, and *Slope*

decreasing trend was observed for both parameter *S-imp* and *Slope*. *N-imp* and *P-imp* were the two most sensitive parameters based on scatter plot of likelihood and parameter values.

The parameter *P-imp*, *N-imp*, *S-imp*, *Slope*, and *N-con* have a great influence on model efficiency demonstrate that these are very important parameters that should be assessed empirically to get a better goodness of fit between model outputs and observed data. There was no obvious trend for parameter *N-per*, *S-per*, *I-max*, *I-min*, and *Width*. It indicated that these five parameters were less sensitive to the model outputs.

The uncertainty band for model outputs in term of water level of suction well for the event on 21 Sep. 2013 was shown in Fig. 3. Through comparing the available observed data with the uncertainty band, the consistency of the modeling hypotheses was confirmed.

As most of the rainfall volume occurred before the lifting pumps switched on, a relative wider uncertainty band appeared initial phase of water level graph before the peak water level. The water level rapidly declined after the lifting pumps switched on. The posterior phase of water level graph was less affected by the hydraulic and hydrographic parameters. Hence the uncertainty band of the posterior phase was relatively narrower than the initial phase.

It should be noted that the *NS* efficiency index of all the simulations within the GLUE approach were relatively higher than the values reported in previous researches (Sun et al. 2014; Fontanazza et al. 2012). It may be a consequence of in-line storage volume in system, which is one of the main characteristics of a pump lifting system. For a pump lifting system, water level at suction well (in pump station at the outlet of the sewer system) is commonly adopted as model outputs to calibrate the model parameter, rather than the flow rate at the outlet for a gravity system. For a certain rainfall volume, the influence degree on the water level for a pump lifting system is less than the flow rate for a gravity system, because of the existence of in-line storage volume.

Moreover, for a pump lifting combined sewer system like Anshan system in this study, a difference exists between the water level of system operation during the dry weather and water level of the lifting pumps switch on during wet weather. Hence, a certain storage volume caused by the difference in water levels will be utilized for light rainfall and the initial phase of heavy rainfall. Figure 4 shows the relationship between total volume in system and water level in suction well calculated using the hydraulic model.

According to the operation water level on both dry and wet weather, around 4000 m^3 in-line storage volume exists at the Anshan experimental site. Due to the existence of in-line storage volume, the influence of hydraulic and hydrographic parameters was weakened. The

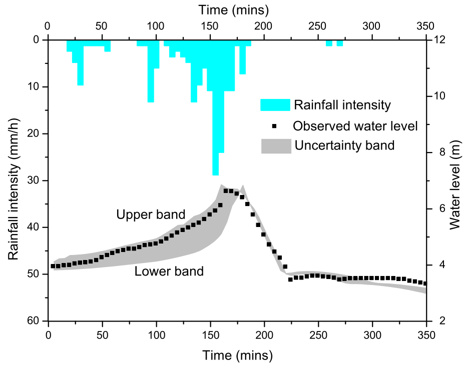


Fig. 3 Uncertainty band for model outputs in term of water level of suction well (21 Sep. 2013)

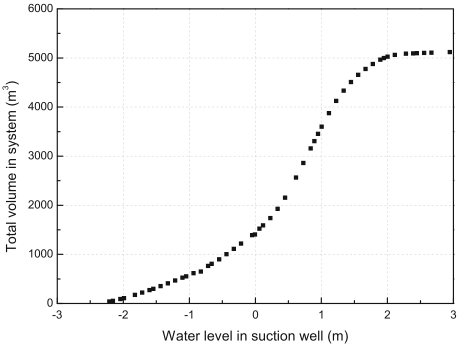


Fig. 4 Relationship between total volume in system and water level in suction well

uncertainty band of model outputs for water level would be narrower than model outputs for flow rate.

On the other hand, even for a same pump lifting system, the water level in the system during the dry weather is different. A high water level in the system while the rainfall occurred would be conductive to increase the sensitivity of hydraulic and hydrographic parameters to water level, and widen the uncertainty band of model outputs.

3.2 Comparison of Different Acceptability Thresholds

In order to discuss the influence of the *Tr* on model parameter sensitivity and the margin of uncertainty band, the GLUE approach was applied several times varying acceptability threshold from 0.65 to 0.85 with a 0.05 steps.

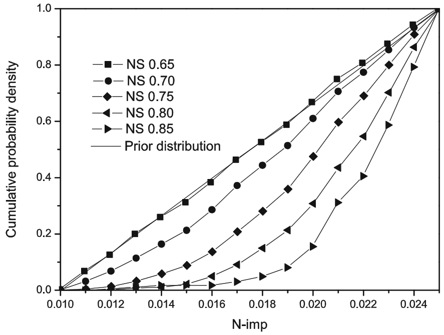
According to the GLUE approach, 5 and 95 % of cumulative likelihood distributions are calculated and used to determine the uncertainty band of model outputs. The cumulative likelihood distributions of *N-imp*, *S-imp*, *P-imp*, and *Slope*, which demonstrated higher likelihood variability, were shown in Fig. 5a–d. A relative small variability of the cumulative likelihood distributions of *N-con* was shown in Fig. 5e. There was no obvious variability of cumulative likelihood distributions for *N-per*, *I-max*, *I-min*, and *Width*, which is like the cumulative likelihood distributions of *S-per* shown in Fig. 5f. These four parameters were not demonstrated in Fig. 5.

As illustrated in Fig. 5, when a relatively low *Tr* value was adopted, the cumulative probability density was close to a uniform distribution. It indicated that no high-efficient interval in the parameter range within the GLUE approach.

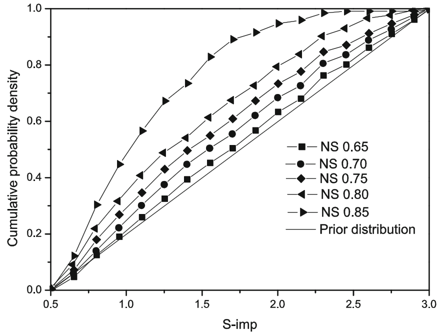
This phenomenon may be a consequence of model over-parameterization for a complex model, which is a common issue that has been discussed in previous researches (Coles et al. 1997). The parameters with no obvious high-efficient interval cannot be easily identified by this approach to realize model calibration. In this case, the *Tr* value should considered not only the experience, but also the particularity and complexity of the certain modeling application.

Moreover, the cumulative likelihood distributions are much more deviated from the prior distribution (uniform distribution) with increasing the *Tr* values, and the sensitivity of parameter seems to be obvious. In other words, the sensitivity of the parameter can be easily observed. The interval with a steep slope is the high-efficient interval.

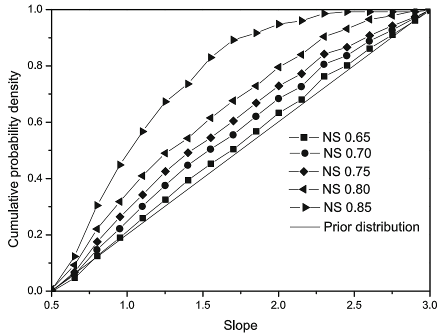
It should be noted that adopting a low *Tr* value will be conductive to insensitivity of parameter. It is a consequence of influence of large low efficient simulations. In addition, positive and negative effect between different parameters is another factor to make the



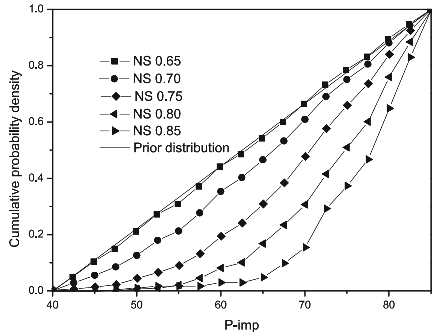
(a) *N-imp*



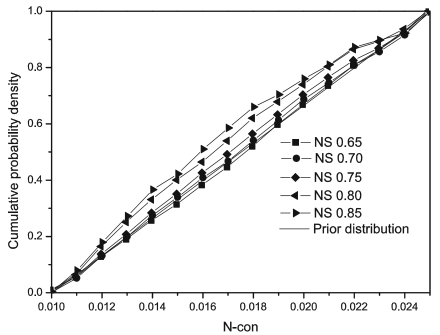
(b) *S-imp*



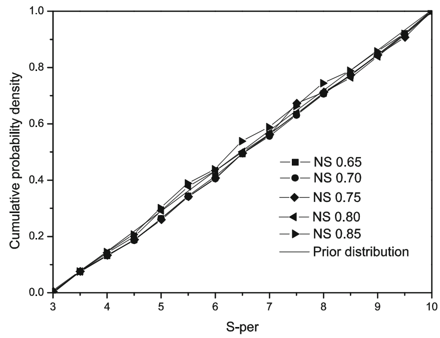
(c) *Slope*



(d) *P-imp*



(e) *N-con*



(f) *S-per*

Fig. 5 Cumulative probability density of parameters according to different acceptability thresholds

indeterminate results of uncertainty analysis. The higher *Tr* value, the more obvious result of parameter uncertainty can be obtained, and the possibility of high efficient model calibration is larger. Further, it will be contributed to achieving a better verification with a high confidence level. The uncertainty analysis significant level can be featured by the value of *Tr*.

On the other hand, for getting a certain number of behavioral simulations, the number of Monte Carlo simulations would be obviously increased when a higher *Tr* value was adopted

(Freni et al 2008). Hence, not only the reducing the low efficient simulation, but also the increased computation cost also should be considered when selection of *Tr* value within the GLUE approach.

3.3 Comparison of Different Objective Functions

As mentioned above, some parameters, such as *N-per*, *S-per*, *I-max*, *I-min* and *Width*, cannot be easily identified when the objective function *NS* efficiency index was adopted. The objective function may affect the results of uncertainty analysis, and the selection of different objective functions may improve the result of uncertainty analysis.

The GLUE approach was applied several times varying different objective functions with corresponding acceptability threshold, including *NS*, *RMSE*, *BIAS*, and *R*. The posterior probability distributions for *N-imp*, *S-imp*, *P-imp*, *Width*, *Slope* and *S-per* were illustrated in Fig. 6.

The posterior distributions of *N-per*, *S-per*, *I-max*, *I-min*, and *N-con* were uniform distribution, just like the *S-per* shown in Fig. 6f. It indicated that these five parameters were less sensitive, and parameters cannot easily identified by the approach with different single objective functions

As illustrated in Fig. 6a–e, the posterior distributions of *N-imp*, *S-imp*, *P-imp*, *Width*, and *Slope* were non-uniform distribution. It indicated that these five parameters were sensitive to the model outputs. Moreover, difference between probability distribution obtained from different objective functions was observed for *N-imp*, *S-imp*, *P-imp*, *Width*, and *Slope*, especially for *N-imp* and *P-imp*, the difference is significant ($P<0.01$). Comparing to the *N-imp*, *S-imp*, *P-imp*, and *Slope*, *Width* is relatively less sensitive.

Through calculating cumulative probability distribution of parameters, the relative sensitivity of parameter obtained from different objective functions was observed, such as the sensitivity of *N-imp* (*RMSE* 30 % best) > sensitivity (*BIAS*<10 %) > sensitivity (*NS*>0.7) > sensitivity (*R*>0.95). Similar trends were shown for the parameter *S-imp*, *P-imp* and *Slope*. The sensitivity of *Width* obtained from different objective function was almost the same. There was no significant difference between probability distributions obtained from different objective functions as their 95 % confidence intervals for the parameter *Width*.

In addition, the posterior probability distributions of *N-imp* and *P-imp* obtained from the function *R*>0.95 were close to the uniform distribution (the prior distribution). It meant that the *N-imp* and *P-imp* obtained from the function *R*>0.95 can be regarded as insensitive. However, the *N-imp* and *P-imp* obtained from other functions, *RMSE* 30 % best, *BIAS*<10 % or *NS*>0.7, especially for the function *RMSE* 30 % best, were sensitive. Hence, some parameters may be sensitive to a specific objective function, and other parameters may be sensitive to a different objective functions.

It is a consequence that characters of different objective functions. *NS* efficiency index emphasizes the mean of observed data. *RMSE* controls prediction error of the peak of the time series, but it may underestimate the low value period of the time series. The *NS* efficiency index and *RMSE* measure the goodness of fit through comparing both the total amount and shape of time series (Arabi et al. 2007). *BIAS* is the relative percentage difference between the average of the simulated and observed time series over n time steps, it may underestimate the total amount (Tolson and Shoemaker 2007). *R* is to determine if the simulated and observed time series is the same pattern (Sourisseau et al. 2008). But the total amount is not considered in *R*. There may be some problems exist for model parameter optimization when a single objective function was used.

The relationship between different objective functions were shown in Fig. 7.

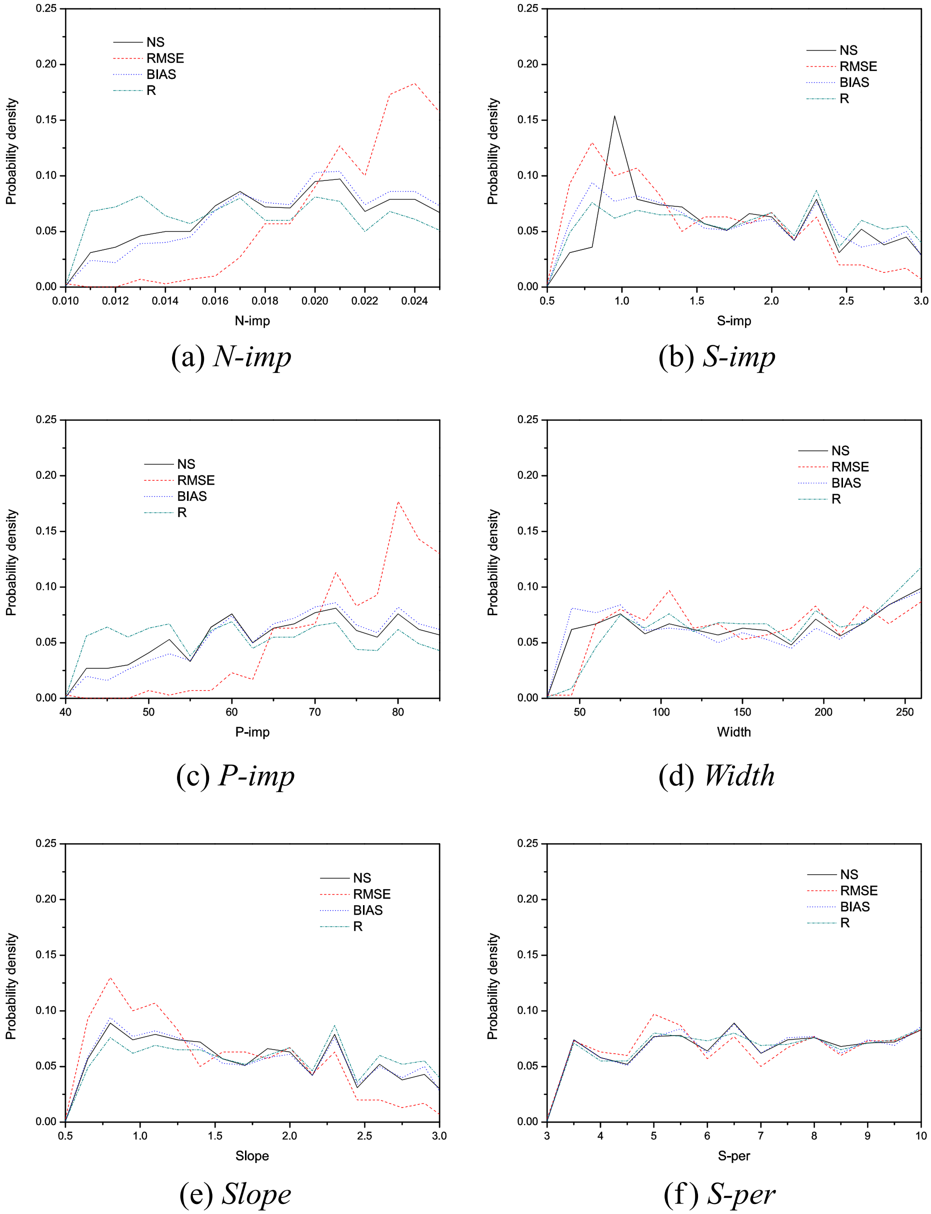
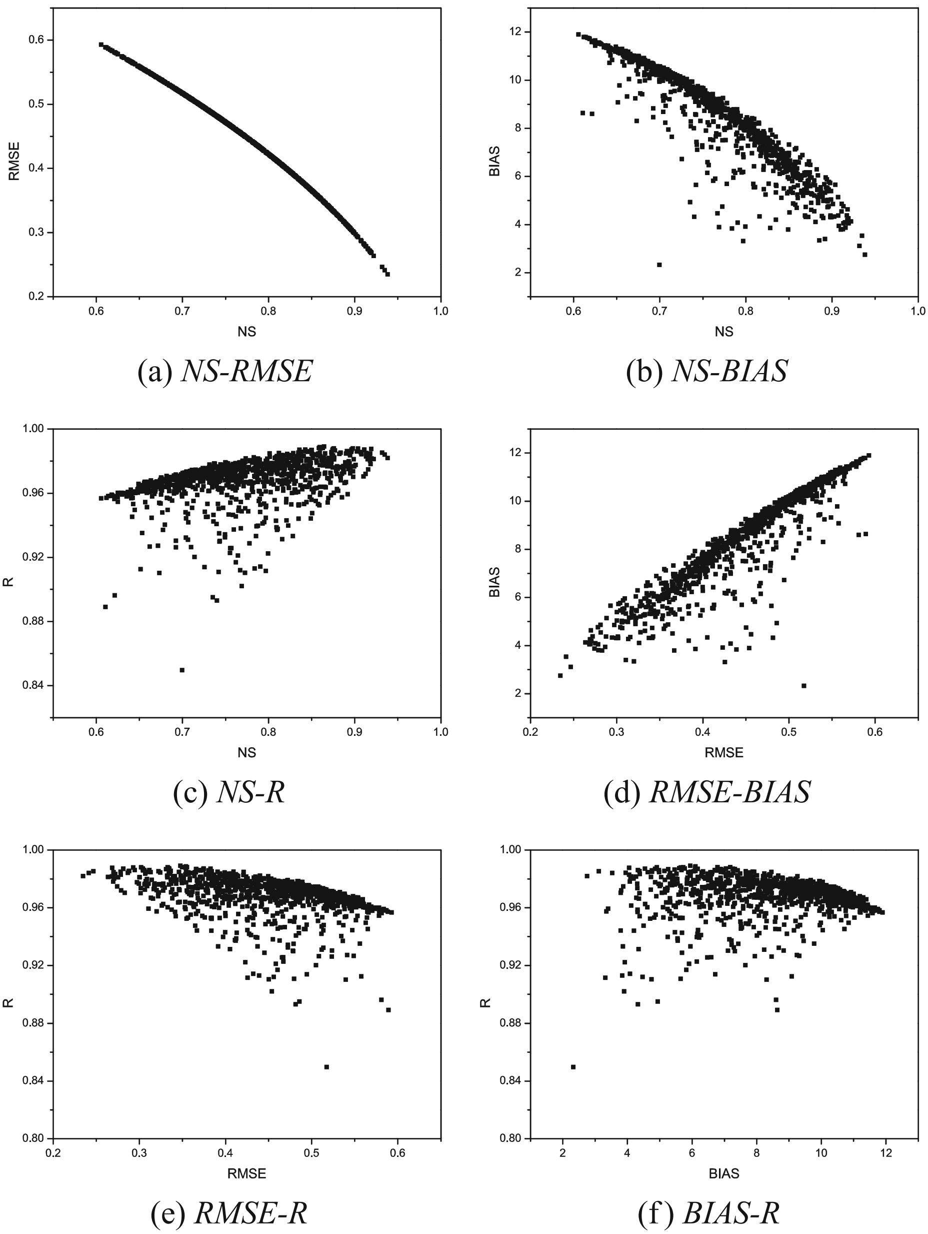


Fig. 6 Posterior probability distributions for parameters according to different objective functions with corresponding acceptability thresholds

As shown in Fig. 7, the values of *RMSE*, *R* decrease with increasing the *NS* values. The values of *R* generally increase with increasing the *NS* values. The values of *RMSE* generally increase with increasing the *NS* values. The relationships between *R* and *RMSE* and *BIAS* were not clear. When the value of *RMSE* is relatively high, other three objective functions may be outside the acceptability threshold. The uncertainty obtained from 30 % of *RMSE* used in this



(a) *NS-RMSE* (b) *NS-BIAS*

(c) *NS-R* (d) *RMSE-BIAS*

(e) *RMSE-R* (f) *BIAS-R*

Fig. 7 Relationships between different objective functions of 1000 samples

study was lower than other three objective functions with corresponding acceptability thresholds.

As discussed above, one single objective function may focus a part of the characteristics of the actual observed data, while some other part of characteristics. Some parameters cannot be identified with the GLUE method with a one single objective function, and a multiple-objective function combined different objective functions requirements would effectively reduce the model prediction uncertainty.

4 Conclusions

The uncertainty of hydraulic and hydrographic parameters of SWMM was analyzed with a well known GLUE approach. Based on the analysis in this study, several findings and considerations were summarized as follows.

Through implementation of the GLUE approach, uncertainty of main hydraulic and hydrographic parameters was effectively determined. The reasons for the pump lifting system with a narrowed uncertainty band and a relatively high *NS* efficiency index were discussed. It may be a consequence of in-line storage volume.

The uncertainty analysis significant level can be featured by the value of *Tr*. The higher *Tr* value, the more obvious result of parameter uncertainty can be obtained, and the possibility of high efficient model calibration will be larger. Further, it will be contributed to achieving a better verification with a high confidence level. The selection of *Tr* value can be regarded as a tradeoff process. Not only the reducing the low efficient simulation, but also the increased computation cost also should be considered.

Different parameters may be sensitive to different objective functions. There may be a certain risk exists for model parameter optimization when a single objective function was used within the GLUE approach.

It should be noted that the results are based on a specific case study. Due to the randomness of the rainfall event and complexity of the drainage system, further research and applications of different rainfall events and different experimental catchments are required for verification and generalization. Moreover, a multiple-objective function combined different objective functions requirements, considered characteristics of observed data, may be a alternative approach for uncertainty analysis within the GLUE method to reduce the model prediction uncertainty.

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