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An effective storage function model for an urban watershed in terms of hydrograph reproducibility and Akaike information criterion

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ABSTRACT

Rapid urbanization is considered to be an important factor that contributes to flood risk. Therefore, flood prediction in urban watersheds using appropriate runoff models is essential to avoid the harmful effects of floods. There are various storage function (SF) models such as Kimura, Prasad, Hoshi, and urban storage function (USF) models that have been widely used in different parts of the world as rainfall-runoff models in which the USF model was recently developed in Japan for the specific application in urban watersheds. However, the identification of an appropriate model remains challenging in the field of hydrology. Therefore, this study aims to identify an effective SF model for an urban watershed in terms of hydrograph reproducibility and from an Akaike information criterion (AIC) perspective. The SCE-UA global optimization method was used for the parameter optimization of each model with root mean square error (RMSE) as the objective function. The reproducibility of the hydrograph was evaluated using the performance evaluation criteria of RMSE, Nash-Sutcliffe efficiency (NSE), and other error functions of peak, volume, time to peak, lag time, and runoff coefficient. The results revealed that the higher values of NSE coupled with the lower values of RMSE and other error functions indicated that the hydrograph reproducibility of USF is the highest among the SF models. Furthermore, AIC and Akaike weight (AW) were used to identify the most effective model among all those based on the information criteria perspective. The USF model received the lowest AIC score and the highest AW during most of the events, which indicates that it is the most parsimonious model compared to the other SF models. Moreover, uncertainty characterization of the SF model parameters was also conducted to analyze the effect of each parameter on model performance.

1 Introduction

Flooding is a crucial issue in both rural and urban areas, but the severity level of floods is greater in urban areas because most of the population is concentrated near floodplains (Mason et al., 2007). Urban areas are characterized by high population, concentrated human activities, presence of sewer systems, and impervious surfaces (Zoppou, 2001) in which the latter two features will accelerate the rainfall-runoff transformation process, and flood flows are therefore higher and more rapid than is the case in rural catchments (Hollis, 1975). These flash floods cause damage to human life, properties, different crops, etc. and have a negative impact (Padiyedath et al., 2017b; Sahoo and Saritha, 2015) in urban watersheds. Therefore, it is very important to detect urban floods compared to those in rural areas because of the increased risks and costs associated with them (Mason et al., 2012). The modeling of the rainfall-runoff transformation process in an urban watershed is essential not only for flash flood estimation but also for flood control by the drainage optimization using the pumping systems. Flood mitigation is one of the water management strategies that can control the excessive damage caused by floods (Bubeck et al., 2012). Hence, the accurate prediction of the hydrograph in advance, which includes the estimation of flood peak, time to peak, volume, lag time, etc., is important in order to avoid losses due to floodplain inundation.

With the increasing population and urbanization, prediction of the urban flash flood is becoming an important problem to mitigate their impacts. For this purpose, the rainfall-runoff models are important tools and they play a central role, especially in urban watersheds. There is no universally accepted rainfall-runoff model classification as of now and there exist different ways of classifications depending on the criteria of interest (Dawdy, 1969; Singh, 1995; Sivakumar, 2017; Snyder and Stall,

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1965). According to Sivakumar (2017), based on simplicity and convenience, the models can be grouped into two categories, namely; physical models and abstract models. The physical models can represent the processes of a watershed in a physically realistic manner on a reduced size such as open channel hydrologic model of the river, the hydraulic model of dam spillway, etc. The abstract model is the representation of the system using mathematical equations which links the input to the output and it is also called as a mathematical model (Sivakumar, 2017). The abstract model can be further divided into empirical models, theoretical models, and conceptual models (Dooge, 1977). The empirical models extract information only from the existing data without considering the hydrological characteristics and highly depends on the boundary conditions. Unit hydrograph, rational method, least square method etc. are the examples of this method (Devi et al., 2015; Sivakumar, 2017). The theoretical model is based on physical laws governing the hydrological process and it includes MIKESHE, SWAT, etc. (Abbott et al., 1986). The conceptual model is an intermediary between the empirical and theoretical models. Generally, conceptual models consider physical laws but in highly simplified form. The examples of conceptual models include tank model (Sugawara, 1974) and the models based on the spatially lumped form of continuity equation and the storage-discharge relationship (Dooge, 1959; Nash, 1958; Sivakumar, 2017).

The rainfall-runoff models can also be divided as a function of their process description (lumped and distributed), time variability (event-based, continuous time, and large time-scale), and technique of solution (numerical, analog, and analytical) (Amaguchi et al., 2012; Singh, 1995; Singh and Woolhiser, 2002). The selection of appropriate models for the intended purpose is very important. Most of the conceptual rainfall-runoff models have been concerned with lumping up the dominant sub-watershed processes that contribute to the overall watershed response (Boyle et al., 2001). The lumped models are easy to use as they generally do not account for the spatial distribution of the input compared to the distributed models even though spatially-lumped models also exist (Carpenter and Georgakakos, 2006). Among the different conceptual lumped rainfall-runoff models, storage function (SF) models have been widely used in many parts of the world, especially in Japan, not only because of their ease of use in computation and handling but also the ease by which they express the nonlinear relationship of the rainfall-runoff process using simple equations (Kawamura et al., 2004).

Extensive studies have been conducted using SF models in order to analyze the rainfall-runoff transformation process. Kimura (1961) proposed the first SF model in Japan with two parameters and delay time. This nonlinear lumped model is still widely used in Japan for flood prediction. Later, Laurenson (1964) developed a procedure to reproduce the surface runoff hydrograph of a catchment from the effective rainfall using a different two-parameter SF model and tested the method in South Creek, Australia. Subsequently, Prasad (1967) presented a three-parameter SF model that had an additional term for the inclusion of the loop effect between storage and discharge as well as a parameter for the representation of wedge storage compared to that of Kimura's model. He considered the relationship between the effective rainfall and surface runoff in the model. Soon after, Kuribayashi and Sadamichi (1969) evaluated the characteristics of the kinematic wave and Kimura's SF model parameters. They compared the characteristics of both models and developed theoretical relationships under an assumption of constant rainfall. Later, Hoshihata (1972) examined the applicability of the SF model as a distributed model. He described a practical method for the estimation of the SF model parameters using the watershed slope but had insufficient data to conclude the results. Mein et al. (1974) extended the work of Laurenson (1965) by developing a nonlinear method for estimating surface runoff hydrographs by representing the basin as a series of conceptual reservoirs. Aoki et al. (1976) compared hydrograph estimates for a channel using the SF model and kinematic wave model and related their parameters. Subsequently, Hoshi and Yamaoka (1982) added another parameter and improved the robustness of SF model. Nagai et al. (1982) examined the physical significance of the SF model parameters obtained by applying a mathematical optimization technique. Thereafter, Sugiyama et al. (1997) theoretically analyzed the SF model parameters by comparing the SF and kinematic wave models and then evaluated SF model characteristics (Sugiyama et al., 1999).

However, all the aforementioned models require effective rainfall as their input for the prediction of direct runoff. Hence, they involve the separation of baseflow and effective rainfall components from total discharge and total rainfall, respectively. There was no adequate method of objectively quantifying effective rainfall after deducing losses until recently (Perumal and Sahoo, 2007). Also, numerous baseflow separation techniques are currently in use and thereby the baseflow separation will be a subjective process (Padiyedath et al., 2017a). This, subsequently, may further affect the value of parameters to be estimated and their relative stability. Later, in order to overcome these problems, Baba et al. (1999) introduced an SF model with the loss mechanism that uses the observed rainfall, and total runoff directly and applied to a mountainous river basin in Hokkaido, Japan. The incorporated loss mechanisms (infiltration and all other outflow components) avoided the need for effective rainfall estimation and baseflow separation. The use of the SF model of Baba for the prediction of runoff in urban areas may be difficult, because urban areas differ completely from mountainous areas in terms of their imperviousness, absence of vegetation, presence of sewer systems, etc. Therefore, Takasaki et al. (2009) developed a new urban SF (USF) model considering the urban runoff process. It uses the observed rainfall and runoff directly, without effective rainfall estimation and baseflow separation for flood prediction and compared with Baba's SF model. The model considers all possible inflow and outflow components, including groundwater inflow as an outflow from the basin. However, all the studies in the literature have mainly focused on the theoretical significance of the parameters involved and the modification of existing models.

There was a need for the comparative studies of rainfall-runoff models due to the existence of a variety of models which was identified quite early by the WMO (1975) in order to evaluate the ability of models to predict discharge and to provide information and guidelines for end-users on the use of such models with regard to specific conditions and accuracy requirements. Also, the comparative assessments of models serve to highlight strengths and weaknesses of modeling approaches of various complexity (Perrin et al., 2001). The inferences of comparative assessments may be different from study to study based on the calibration methodology, model structure, study area, and the model performance evaluation criteria. There are several studies which compared the performance of different rainfall-runoff models. For instance, Michaud and Sorooshian (1994) compared the discharge simulation accuracy of three models such as a complex distributed model, a simple distributed model, and a simple lumped model using root mean square error (RMSE) and average bias as the evaluation criteria. Subsequently, Refsgaard and Knudsen (1996) inter-compared the lumped conceptual, distributed physically based, and intermediate models using evaluation criteria of Nash-Sutcliffe efficiency (NSE) and other index based on flow duration curve. Later, Perrin et al. (2001) examined the role of complexity in hydrological models by relating the number of optimized parameters with their model performance using four different criteria in 19 models whose number of parameters ranges from three to nine. He concluded that very simple models can achieve a level of performance almost as high as models with more parameters, and the complexity alone cannot guarantee good and reliable performances. This is because, the over-parameterization will add complexity and sometimes face the problem of equifinality (Beven, 1993) during calibration. Therefore, it is essential to address this issue through assessing the performance of different rainfall-runoff models with different complexity to identify an effective one for urban watersheds that have a promising future scope.

Despite the progress in the aforementioned direction, none of the studies have evaluated the various SF models not only in terms of the prediction accuracy but also the information criteria point of view, as far as the authors know. Specifically, there are no studies that describe the performance evaluation of different SF models for an urban area including the USF model. Hence, this study aims to identify an effective SF model, among those selected, for an urban watershed in terms of hydrograph reproducibility and from an Akaike information criterion (AIC) perspective. For this purpose, we have selected the relatively new USF model and four conventional SF models of Hoshi, Prasad, Kimura, and the linear model in order to conduct the performance evaluation. The Kanda River basin, a typical small- to medium-sized urban watershed in Tokyo was selected as the target basin and the five SF models were applied to five selected flood events. In order to assess the performance in terms of the reproducibility of the hydrograph, we first formulated the SF models with optimal parameters identified using the Shuffled Complex Evolution – University of Arizona (SCE-UA) global optimization method (Duan et al., 1992, 1993). The RMSE was chosen as the objective function for optimization. These SF models with optimal parameters were further assessed for reproducibility of the hydrograph with minimum RMSE and maximum NSE and other error functions of peak, volume, time to peak, lag time, and runoff coefficient. Also, for the first time in SF model research, the authors have utilized AIC and Akaike weight (AW) to identify the most effective SF model for an urban watershed based on the information criteria perspective (Akaike, 1998).

In light of the aforementioned discussions, the main objectives of this study were conducted in four steps as follows:

1) The selection of different existing SF models and modification of the framework in order to consider the total rainfall and discharge directly and thereby reduce the associated errors of separation.
2) The estimation of parameters for the selected models in each selected event using the SCE-UA global optimization method.
3) The evaluation of the performance of the different SF models in terms of hydrograph reproducibility and from an AIC perspective.
4) The characterization of the uncertainty of parameter values for each model due to their variability in values during each event.

2 Methodology

2.1 Conventional SF models

SF models are flood-event-based lumped models used as short-term models for simulating a few or individual flood events. They are characterized by the relationship between storage and discharge. They have different degrees of simplification that affect the input-output transformation (Takasao and Takara, 1988). The four conventional SF models are linear, Kimura, Prasad, and Hoshi models, and are shown in Table 1 with their associated continuity equations where s is the storage (mm), Q is the observed river discharge (mm/min), t is the time (min), and k_1, k_2, p_1, p_2 are model parameters.

Among the models, Hoshi's model has been found to be superior in terms of an additional parameter p_2, which was quantified by numerical experiments and can well define the flow characteristics based on kinematic wave theory (Hoshi and Yamaoka, 1982). Some simplifications of Hoshi's storage model can lead to Prasad's storage model. If $p_2 = 1$ in Hoshi's model, we obtain Prasad's storage model. In a similar fashion, if we set $k_2 = 0$ in Prasad's model, the model can be transformed into Kimura's model. Furthermore, the most simplified linear model can be obtained by maintaining $p_1 = 1$ in Kimura's model. In this study, the authors used Kimura's SF model with one storage tank, which is widely used as a special case of Kimura's original model with the delay time (third parameter) equal to zero (Takasao and Takara, 1988). Because delay time is a function of effective rainfall and basin characteristics, its estimation becomes a difficult process especially for small watersheds where small stream channels are not printed on a map (Sugiyama et al., 1997). Also, the linear model considered herein is used to check how efficiently a model can reproduce the hydrograph with a limited number of parameters.

2.2 USF model

In order to develop an SF model for an urban watershed without the separation of effective rainfall and baseflow components from total rainfall and discharge respectively, it is essential to consider all inflow and outflow components of the watershed. Fig. 1 shows the schematic diagram of all the possible inflow and outflow components of an urban watershed with the combined sewer system. We are considering the combined sewer system because many older cities in different parts of the world continue to operate combined sewers with a high installed rate instead of the separate system due to the high cost involved (Metcalf and Eddy, 1972; US EPA, 1999). The model is a lumped one based on the relationship between the rainfall over the basin and the runoff at the outlet point. The runoff at the outlet point is the river discharge although both pluvial and fluvial floods occur within the basin which have a delayed effect in the river discharge at the outlet point. During light rain, only the pluvial flood occurs but finally discharging to the river and contributing to the river discharge. During heavy rain, both pluvial and fluvial floods occur and the fluvial flood causes more damage than the pluvial flood by overflowing the river. Therefore, the USF model measures the combined effect of both the floods at the outlet point. The basin storage is mainly composed of river storage, surface and sub-surface storage, and the sewer system storage. The storage has been considered as just one independent cell for the entire basin. There is no other inflows from other basins but an outflow from the basin to the treatment plant through the combined sewer system rather than discharging into the river as lateral inflow. The inflow components in Fig. 1 are represented by rainfall R(mm/min) and urban-specific and groundwater inflows from other basins I(mm/min). Urban-specific inflows include leakage from water distribution pipes, irrigational flow, etc. The outflow components are constituted by the river discharge Q(mm/min); evapotranspiration E(mm/min); storm drainage from the basin through the combined sewer system q_R(mm/min); water intake from the basin for intended purposes such as water supply, agricultural needs, etc. O(mm/min), and groundwater-related

Table 1
Storage function models with their associated continuity equations. (PAR represents parameter).

No.	Models	Storage equation	Continuity equation
1	Linear (3-PAR)	$s = k_1Q$	$\frac{ds}{dt} = R + I - E - O - Q - q_l$
2	Kimura (4-PAR)	$s = k_1(Q)^{p_1}$	$\frac{ds}{dt} = R + I - E - O - Q - q_l$
3	Prasad (5-PAR)	$s = k_1(Q)^{p_1} + k_2\frac{dQ}{dt}$	$\frac{ds}{dt} = R + I - E - O - Q - q_l$
4	Hoshi (6-PAR)	$s = k_1(Q)^{p_1} + k_2\frac{d}{dt}(Q)^{p_2}$	$\frac{ds}{dt} = R + I - E - O - Q - q_l$
5	USF (7-PAR)	$s = k_1(Q + q_R)^{p_1} + k_2\frac{d}{dt}(Q + q_R)^{p_2}$	$\frac{ds}{dt} = R + I - E - O - (Q + q_R) - q_l$

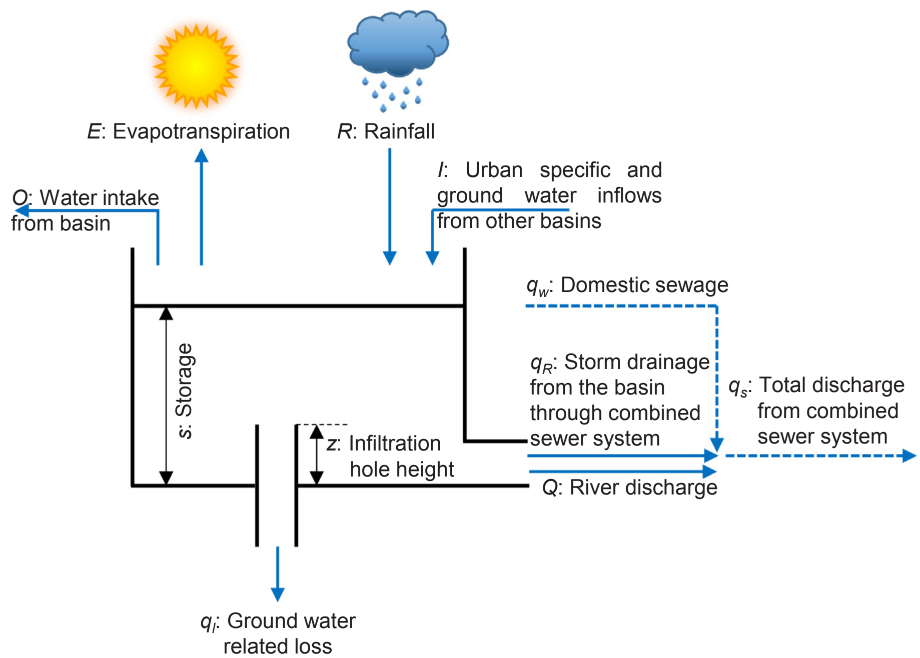

Fig. 1. Schematic diagram of all inflow and outflow components of an urban watershed with combined sewer system.

loss q_l (mm/min). In addition, domestic sewage q_w has also been depicted in Fig. 1 even though it does not contribute to the watershed storage s (mm).

The USF model is the empirical representation of Hoshi's SF model shown in Table 1 in which the river discharge Q is replaced by the discharge including the storm drainage $Q + q_R$. Combining the expression of storage for USF model with the associated continuity equation given in Table 1 yields the nonlinear expression of the USF model (Takasaki et al., 2009).

Groundwater-related loss (q_l) was defined by considering the infiltration hole height (z) and is given by the following equation (Takasaki et al., 2009):

$$q_l = \begin{Bmatrix} k_3(s-z)(s \geqslant z) \\ 0 \qquad (s < z) \end{Bmatrix} \tag{1}$$

where k_3 and z are the parameters. The expression for storm drainage q_R from the combined sewer system discharged out of the basin is developed by assuming a linear relationship between total discharge $Q + q_R$ and the storm drainage q_R immediately after the rainfall. The q_R is defined (Takasaki et al., 2009) as follows:

$$q_R = \begin{Bmatrix} \alpha(Q + q_R - Q_0)\, \alpha(Q + q_R - Q_0) < q_{R\,max} \\ q_{R\,max} \qquad \alpha(Q + q_R - Q_0) \geqslant q_{R\,max} \end{Bmatrix} \tag{2}$$

where α is the slope of the linear relationship between total discharge $Q + q_R$ and the drainage q_R; and Q_0 is the initial river discharge just before the rain starts (Takasaki et al., 2009). The maximum volume of q_R cannot exceed the sewer maximum carrying capacity q_{Rmax}. Substituting the storage equation into the continuity equation will lead to a second-order ordinary differential equation (ODE) as follows:

$$k_2 \frac{d^2}{dt^2}(Q + q_R)^{p_2} = -k_1 \frac{d}{dt}(Q + q_R)^{p_1} + R + I - E - O - (Q + q_R) - q_l \tag{3}$$

In order to solve the second-order ODE, the change of variables is performed as follows:

$$x_1 = (Q + q_R)^{p_2} \tag{4}$$

$$x_2 = \frac{dx_1}{dt} = \frac{d}{dt}\{(Q + q_R)^{p_2}\} \tag{5}$$

Substituting Eq. (1) into Eq. (3) and performing the change of variables will lead to the emergence of two first-order ODEs concerning two conditions as shown in Eq. (1). When $s \geqslant z$, the first-order ODE is as follows:

$$\frac{dx_2}{dt} = -\left(\frac{k_1}{k_2}\right)\left(\frac{p_1}{p_2}\right)x_1^{(p_1/p_2-1)}x_2 - \left(\frac{1}{k_2}\right)x_1^{(1/p_2)} - \left(\frac{k_1 k_3}{k_2}\right)x_1^{(p_1/p_2)} - k_3 x_2 + \left(\frac{1}{k_2}\right)(R + I - E - O + k_3 z) \tag{6a}$$

In the case of $s < z$, the first-order ODE concerning the same processes are given by the following:

$$\frac{dx_2}{dt} = -\left(\frac{k_1}{k_2}\right)\left(\frac{p_1}{p_2}\right)x_1^{(p_1/p_2-1)}x_2 - \left(\frac{1}{k_2}\right)x_1^{(1/p_2)} + \left(\frac{1}{k_2}\right)(R + I - E - O) \tag{6b}$$

By solving the two, simultaneous, non-linear ODEs of $\frac{dx_1}{dt}$ (Eq. (5)) and $\frac{dx_2}{dt}$ (Eqs. (6a,6b)) numerically, we obtain the total discharge $Q + q_R$. In order to solve the two first-order simultaneous ODEs, we used the Runge-Kuta-Gill method. The river discharge Q is obtained as the solution after subtracting the q_R, which is calculated using Eq. (2), from the total discharge.

The USF model is a seven-parameter model with parameters k_1, k_2, k_3, p_1, p_2, z, α used in the rainfall-runoff modeling. Generally, the conventional Hoshi SF is a four-parameter model with parameters k_1, k_2, p_1, p_2 used for the transformation of effective rainfall into direct runoff. However, the separation techniques involved result in uncertainties and erroneous estimation of runoff. Hence, in order to incorporate the loss related to groundwater q_l and to consider the observed discharge as a whole in urban watersheds, we added the term q_l (Eq. (1)) with the addition of two more parameters k_3 and z and modified the framework. Therefore, now Hoshi's SF model can be designated as a 6-parameter model. In a similar way, the Prasad, Kimura and linear models were transformed into 5, 4, and 3-parameter models, respectively. For this present study, the USF, Hoshi, Prasad, Kimura, and the linear models will be the 7, 6, 5, 4, and 3 parameter models, respectively.

2.3 Parameter estimation

The SCE-UA method proposed by Duan et al. (1992) was used to estimate the optimum parameter values of all the aforementioned models. It is a well-known, global optimization strategy developed for effective and efficient optimization for calibrating the watershed models. The SCE-UA method has been found to be a useful technique for complex parameter identification problems in hydrologic modeling (Canfield and Lopes, 2004; Canfield et al., 2002; Eckhardt and Arnold, 2001; Kawamura et al., 2004). This method is based on the synthesis of four concepts: competitive evolution, controlled random search, simplex method, and complex shuffling. The algorithmic parameters of SCE-UA were selected as per the recommendations of Duan et al. (1993). The population is partitioned into several complexes, each of which is permitted to evolve independently. The number of complexes, C, was set equal to 20 and the number of populations in each complex, $r = 2K + 1$, where K is the number of parameters to be estimated. The objective function to be minimized using the SCE-UA method was selected as the RMSE between the observed and computed using the estimated parameters. The search range of parameters for SCE-UA was set as, k_1(10–500), k_2(100–5000), k_3(0.001–0.05), p_1(0.1–1), p_2(0.1–1), z (1–50), and α(0.1–1) (Takasaki et al., 2009).

2.4 Performance evaluation

The river discharge computed for each event using the different SF models was compared in order to assess the reproducibility of the observed hydrographs using seven performance evaluation criteria.

1. RMSE
2. NSE (Nash and Sutcliffe, 1970; ASCE, 1993)
3. Percentage error in peak discharge (PEP): PEP = [1 − (computed peak discharge/observed peak discharge)] × 100
4. Percentage error in volume (PEV): PEV = [1 − (computed volume of discharge/observed volume of discharge)] × 100
5. Percentage error in time to peak discharge (PETP): PETP = [1 − (computed time to peak/observed time to peak)] × 100
6. Percentage error in lag time (PELT): PELT = [1 − (computed lag time/observed lag time)] × 100; and
7. Percentage error in runoff coefficient (PERC): PERC = [1 − (computed runoff coefficient/observed runoff coefficient)] × 100

Further, AIC was also used in order to identify the most effective model by comparing the different models for each event. The most effective model is then the model with the lowest AIC score and is given by the following expression (Akaike, 1981, 1998),

$$AIC = 2K - 2\log(\mathscr{L}(\hat{\theta}|y)) \tag{7}$$

where K is the number of parameters to be estimated and $\log(\mathscr{L}(\hat{\theta}|y)$ is the log likelihood at its maximum likelihood estimator $\hat{\theta}$ based on y observations. Later, this concept was refined to correct for small data samples (Hurvich and Tsai, 1989) as follows:

$$AIC_C = AIC + \frac{2K(K+1)}{n-K-1} \tag{8}$$

where n is the sample size. A better way of interpreting the AIC_C score is to normalize the relative likelihood values as AW. The weight of all models summed together equals one and the model with the highest AW is considered to be the most effective. The AW is considered as the weight of evidence that the model i is the best-approximating model for the given data and candidate models. The AW for the ith model (AW_i) is as follows:

$$AW_i = \frac{\exp(-0.5\Delta AIC_{c,i})}{\sum_{m=1}^{M}\exp(-0.5\Delta AIC_{c,m})} \tag{9}$$

where the $\Delta AIC_{C,i}$ is calculated as follows:

$$\Delta AIC_{C,i} = AIC_{C,i} + AIC_{C,min} \tag{10}$$

where $AIC_{C,i}$ is the individual AIC_C score for the ith model, $AIC_{C,min}$ is the minimum $AIC_{C,i}$ score among M models, and M is the number of models.

2.5 Uncertainty characterization

For the target watershed, optimal parameter sets were obtained for each event using all the models. However, the obtained parameter values were different for each event corresponding to each model. The variability in the model parameters induced due to the spatial averaging of rainfall received at different gauging points is termed as the parameter uncertainty (Chaubey et al., 1999) and is quantitatively assessed using Relative Error (RE), and Coefficient of Variation (CV). The different errors for the ith model and pth parameter are as follows:

$$RE_{i,p} = \frac{\frac{1}{N}\sum_{j=1}^{N}|P_{i,j} - \bar{P}_i|}{|\bar{P}_i|} \tag{11}$$

$$CV_{i,p} = \frac{\sigma_{i,p}}{\bar{P}_i} \times 100 \tag{12}$$

where N is the number of target events, $P_{i,j}$ is the estimated parameter value for the ith model and jth event, $\bar{P}_i$ is the average parameter value from all the events, and $\sigma_{i,p}$ is the standard deviation for the ith model and the pth parameter value.

3 Study area and data used

The selected urban watershed for the particular study was the upper Kanda River basin and is shown in Fig. 2. The different SF models were applied in the target basin, having an area of 7.7 km^2 at Koyo Bridge, in order to determine the effective model. The Kanda River basin lies between latitudes 35.70° N and 35.64° N and longitudes 139.56° E and 139.64° E in Tokyo, Japan, with an urbanization rate of more than 95%. The source of the river is the Inokashira pond and it joins the Zenpukuji River and flows east (Ando and Takahasi, 1997). The drainage pattern follows the combined sewer system and the sewer installed population rate is 100%. The main flow path length of the river, sewer density of pipes having a diameter greater than 25 cm, and the average slope of the watershed are 6.017 km, 22.76 km^{-1}, and 0.025 radians respectively. The computed time of concentration of surface runoff from the upstream reaches to the watershed outlet was about 30 min. The impervious area percentage was precisely estimated as 68% using the urban landscape GIS delineation (Koga et al., 2016) that further reduced the water retention capacity of the basin significantly. There is a wide variety of land cover features with different impermeable properties within all land use classifications (Koga et al., 2016).

The smaller time of concentration indicated that the river discharge will occur immediately after the rainfall within a short period and it is desirable to use hydrological data at very short time intervals for the rainfall-runoff analysis. Therefore, the rainfall and water level data were collected at one-minute intervals from the Bureau of Construction, Tokyo Metropolitan Government (TMG), from 2003 to 2006 for the present study. The average rainfall of the basin was determined using the Thiessen polygon method from the eight rain gauges scattered over the basin as shown in Fig. 2. Five target events were selected from the data, whose 60-minute maximum rainfall (R_{60}) is greater than 30 mm and is capable of producing flash floods. Table 2 shows the characteristics of the five selected rainfall events. The inflow component I in the continuity equation was fixed at 0.0012 mm/min based on the annual report of the Bureau of Construction, TMG. The water intake O from the

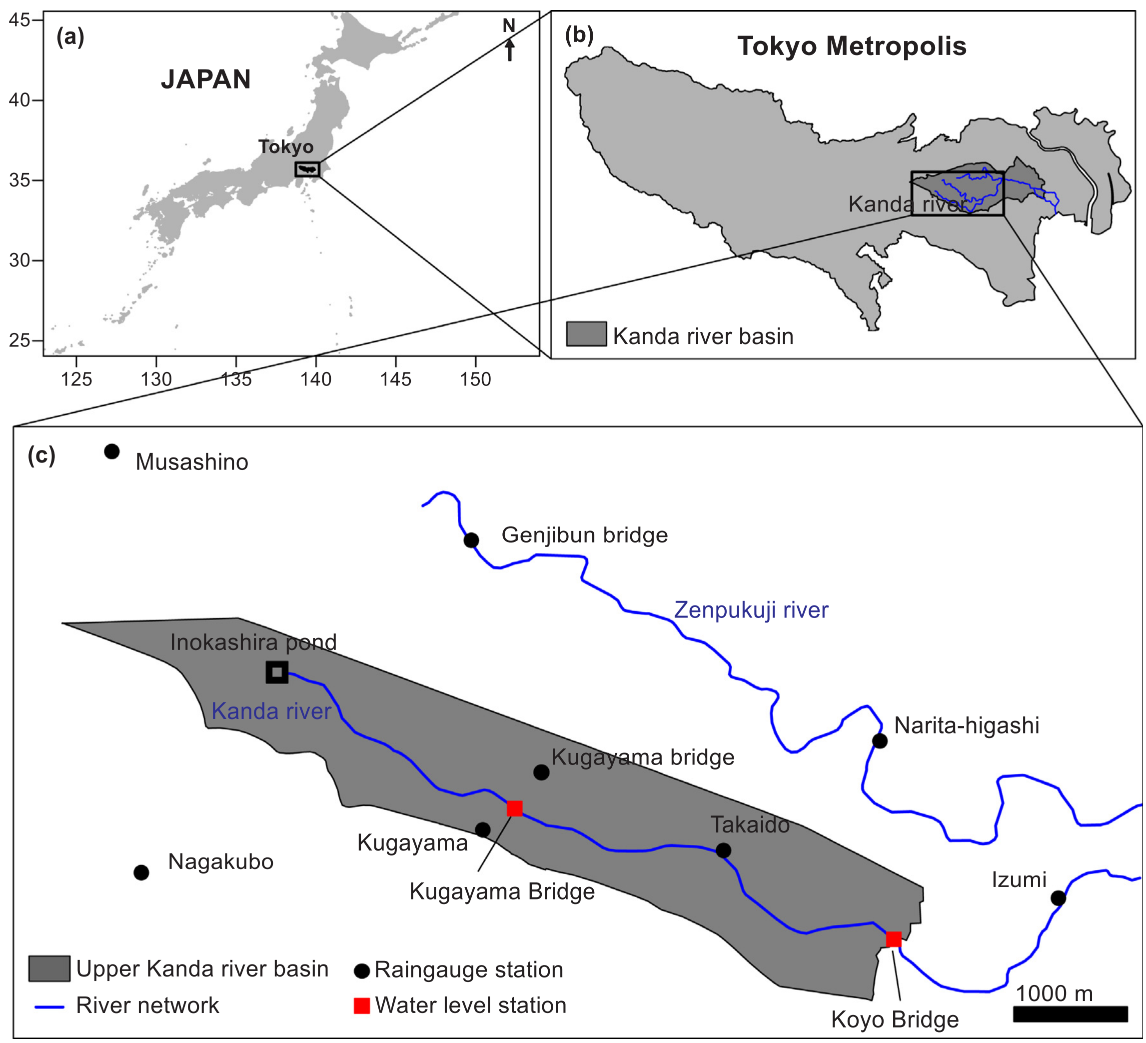

Fig. 2. Index map of (a) Japan, (b) Kanda river basin in Tokyo and (c) target area – upper Kanda basin at Koyo Bridge.

Table 2
Characteristics of target events.

Event No.	Event date	R_{60} (mm)	Total R (mm)	Climatic factors	Number of peaks
1	13-10-2003	53.9	57.5	Intensive localized storm	Single-peak
2	25-06-2003	42.6	46.2	Frontal rainfall	Single-peak
3	8–10/10/2004	42.0	261.1	Typhoon	Multi-peak
4	11-09-2006	32.7	37.9	Frontal rainfall	Single-peak
5	15-07-2006	31.5	31.5	Frontal rainfall	Single-peak

basin and evapotranspiration E were set at 0 as there is no intake from the target basin and the evapotranspiration during heavy rainfall is insignificant. The maximum storm drainage, q_{Rmax} was estimated as 0.033 mm/min using Manning's equation.

4 Results and discussion

4.1 Parameter estimation

The SCE-UA method was applied for parameter estimation of the five SF models for the five selected flood events in the target watershed with RMSE as the objective function. The model parameters are estimated by calibration using the average watershed rainfall and the observed river discharge. The convergence of parameters was also checked and it was found that the parameters converged before the 50th generation in each SCE-UA application run. The total population generated was different from model-to-model based on the number of parameters in each model. The best parameter set among the total population at the 50th generation with the minimum RMSE was used for further hydrograph reproduction. Table 3 shows the elapsed time for calibration of models using SCE-UA and the computational time of each model for each event using the estimated parameters. All the model simulations carried out in this study were run on Windows 10 with Intel Core i7-6700 CPU as the processor and 16 GB RAM. The parameter calibration and evaluation were conducted on MATLAB. It is clear from the table that the USF has taken the longest time for computation because it has the most number of parameters. On the other hand, the 3-parameter model has received the least time for simulations.

Fig. 3 shows the estimated model parameters for each selected event and SF model. Fig. 3(a)–(c) show the k_1, k_3, z parameters, respectively, and these are associated with all of the five models. The k_1 values are quite close for all the models except for the 3-parameter model during events 4 and 5. Parameter k_3 was found to be similar for the USF (7-parameter) and 6-parameter models during all the events even though it varies among events. The k_3 value for the other models was also found to be similar and they were close to zero. The z parameter for the USF,

Table 3
Elapsed time taken for the calibration and evaluation of storage function models in each event.

Model	USF (sec)		Hoshi (sec)		Prasad (sec)		Kimura (sec)		Linear (sec)	
Event	Calibration	Evaluation	Calibration	Evaluation	Calibration	Evaluation	Calibration	Evaluation	Calibration	Evaluation
1	665.12	0.57	592.46	0.40	452.54	0.36	103.51	0.28	29.75	0.26
2	653.99	0.56	547.38	0.39	412.80	0.33	95.93	0.26	27.86	0.23
3	2923.85	1.44	2570.06	1.24	1916.46	1.08	422.18	0.88	124.65	0.66
4	869.76	0.73	703.16	0.46	627.52	0.42	121.47	0.31	36.92	0.26
5	540.99	0.42	422.18	0.32	343.36	0.29	74.21	0.25	23.60	0.21

6, and 5-parameter models varies among events, while the 4 and 3-parameter models have quite similar values close to zero during all the events. Fig. 3(d) exhibits parameter p_1 which is common for all the models except the 3-parameter model. The p_1 values are sufficiently close for the 6, 5, and 4-parameter models during all the events. However, the USF model has the highest p_1 value among all the models even though the value is closer to the other models during events 1 and 3. Fig. 3(e) demonstrates parameter k_2 which is present in the USF, 6, and 5-parameter models, while Fig. 3(f) shows the parameter p_2 which forms a part of the USF and 6-parameter models only. We observed a high level of agreement between the USF and 6-parameter models in the k_2 value from Fig. 3(e). On the other hand, the 5-parameter model

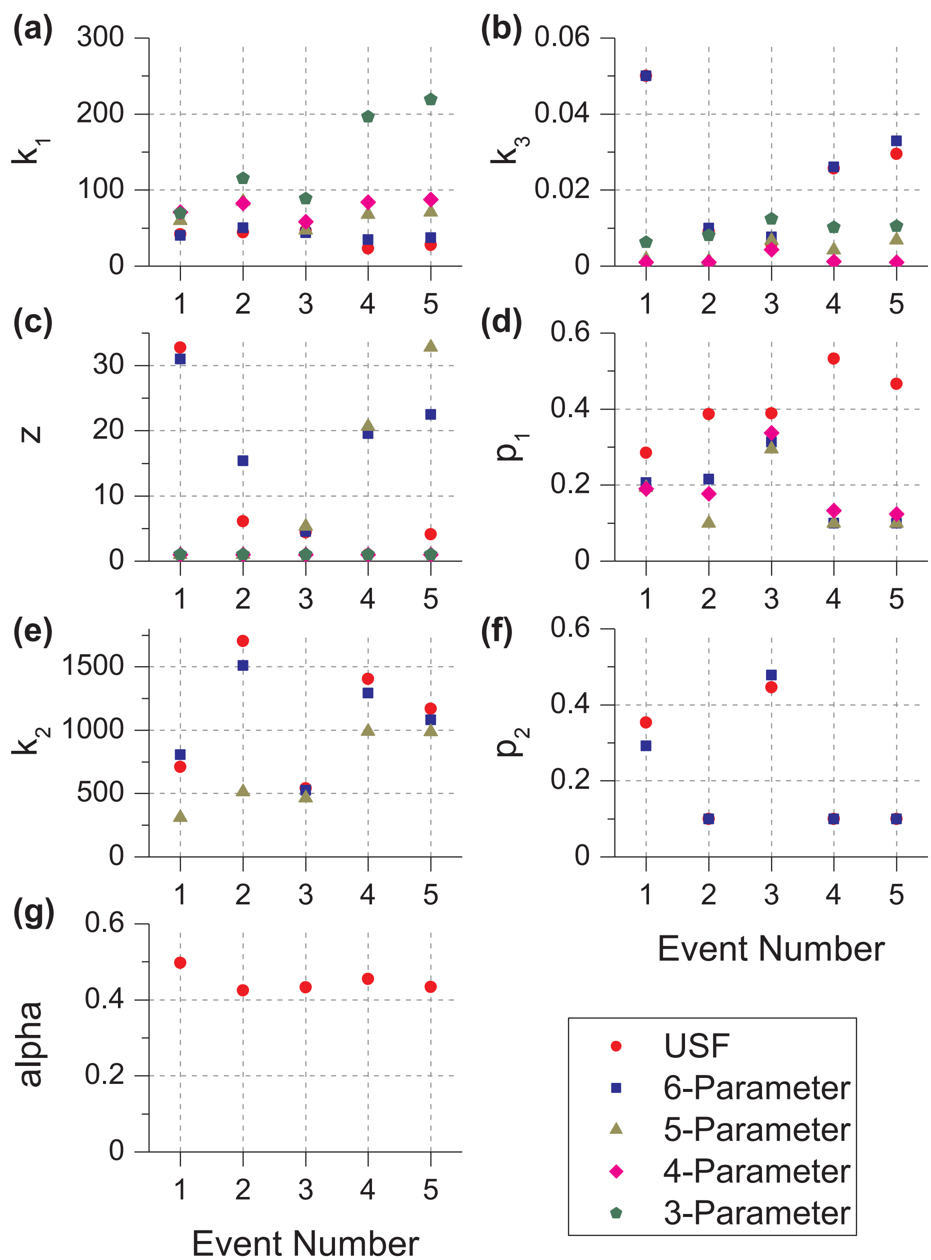

Fig. 3. The estimated model parameter values for various storage function models in each event.

shows small disparities in the values as compared to those of the USF and 6-parameter models. However, the parameter fluctuates substantially during all the events for all the models. The parameter values of p_2 in Fig. 3(f) for the USF and 6-parameter models are identical during all the events although it varies among the events. Fig. 3(g) depicts parameter α which is associated with the USF model only. The α values were found to be consistent during all the events for the USF model.

It is evident from the above discussion that the USF and 6-parameter model parameters values are identical in all the events except for the parameters z and p_1 in events 2, 4, and 5. During these events, the $z$and p_1 parameters of both the models lie farther from each other, and the 6-parameter model lies close to the values of 5-parameter model. Generally, during the parameter estimation, each model attempts to either reduce or increase each parameter in association with the other parameters based on their model structure in order to get the best combination which will lead to the better performance. Therefore, this could be a reason for the differences in values of parameters z and p_1 in association with other parameters in USF and other models during events 2, 4, and 5, whose climatic factor is frontal rainfall as shown in Table 2. The effect of parameter uncertainty and variability based on the model structure are discussed in more detail in Section 4.4.

4.2 Hydrograph reproducibility

The SF models with these identified parameters were used to estimate river discharge in order to evaluate hydrograph reproducibility from the observed rainfall as input. Fig. 4 shows the reproduced hydrograph using the different SF models with the parameters shown in Fig. 3. In Fig. 4, the x-axis and y-axis increments are different from event to event. It can be seen from Fig. 4 that the 7-parameter USF model nearly overlaps with the observed river discharge and precisely reproduces the shape of the observed hydrograph. It is also capable of accurate reproduction of the peak during all the events even though it shows slight deviations during events 4 and 5. During events 4 and 5, it was most close to the observed peak compared with the peaks estimated by other SF models. Therefore, the USF model can most exactly reproduce the shape of the observed hydrograph as well as the peak discharge compared to that of the other SF models irrespective of the number of peaks. Even though the 6-parameter model shows a slight deviation in the reproduced hydrograph on the rising and recession limbs during all the events, the model accurately reproduces the peak discharge which is slightly less than that estimated by the USF model. The model does not preserve the shape of the hydrograph particularly well in the multi-peak event 3 although it estimates the peak accurately. The 5-parameter model underestimated the peak discharge during all the events except for event 1. The model failed to reproduce not only the shape of the hydrograph but also the peak, particularly in the multi-peak event. Both the 4 and 3-parameter models, especially the 3-parameter model, were unable to reproduce the observed hydrograph. They underestimated and early estimated the peak discharge during all the events. The models failed to conserve the shape as well as the peak discharge regardless of the number of peaks.

Fig. 5 shows the values of various error functions, i.e. RMSE, NSE, PEP, PEV, PETP, PELT, and PERC, as described in Section 2.4, for the five events using the five models. From Fig. 5(a) and (b), we can see that the USF model generates the lowest RMSE, close to zero, and highest NSE, close to 100%, among the five SF models, followed by the 6, 5, 4, and 3-parameter models during all the events. It is evident that the model with a large number of parameters will have the lowest RMSE and highest NSE which further reveals that the SCE-UA method has successfully identified the optimal parameters for each model during each event. The low RMSE and high NSE can be interpreted as high hydrograph reproducibility. However, the 4 and 3-parameter models have high RMSE and low NSE values as compared to those of the other models. This is because of the absence of parameters that

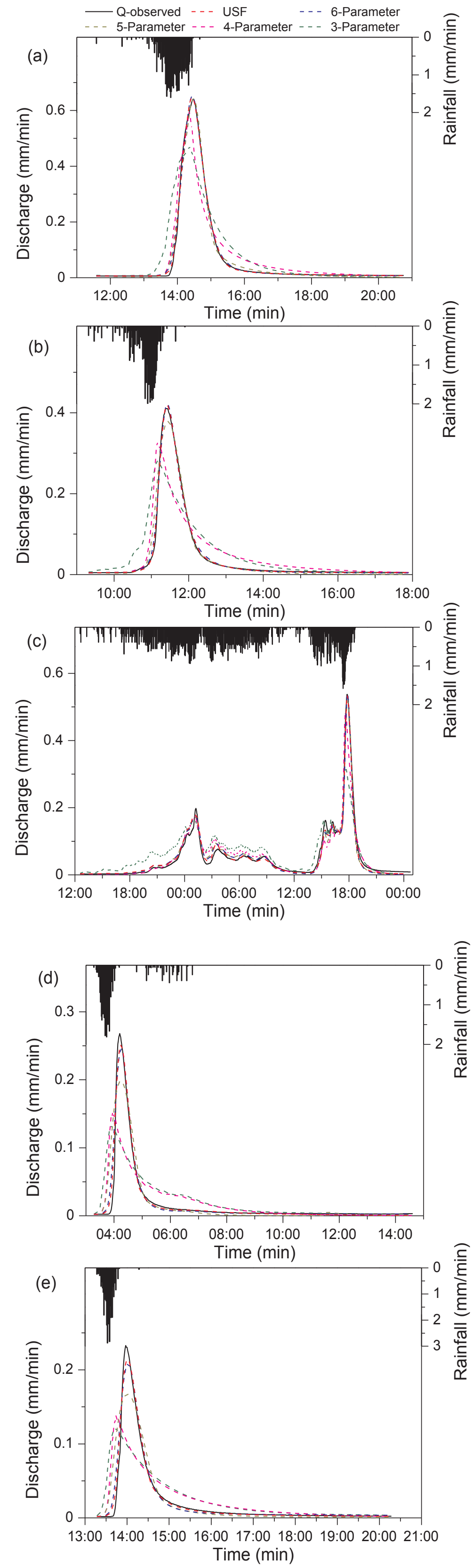

Fig. 4. Reproduced hydrograph by each model for (a) Event 1; (b) Event 2; (c) Event 3; (d) Event 4; and (e) Event 5.

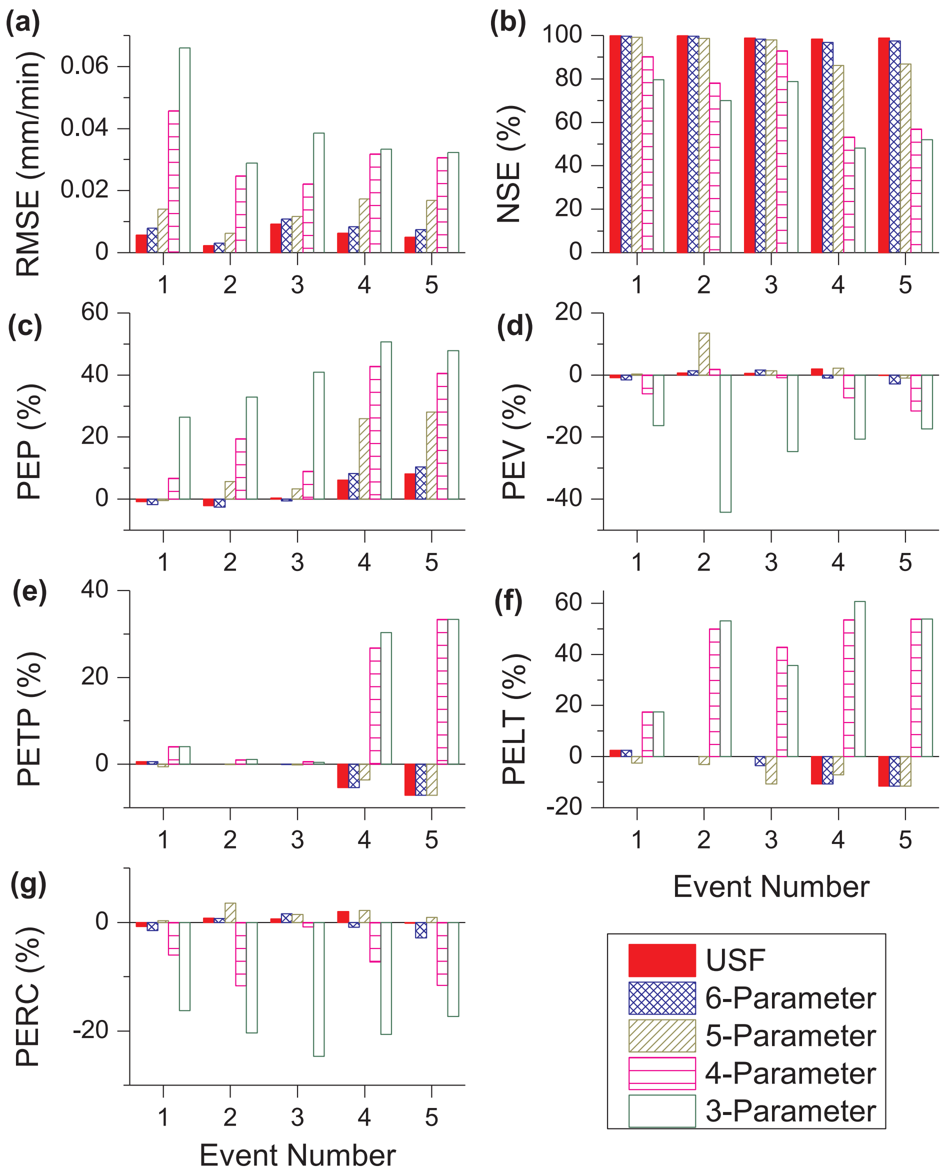

Fig. 5. Comparison of different error evaluation functions of (a) RMSE, (b) NSE, (c) PEP, (d) PEV, (e) PETP, (f) PELT, and (g) PERC by the different storage function models.

describe the loop effect between storage and discharge during the rising and recession limbs. Fig. 5(c) depicts that the PEP estimated using the USF and 6-parameter models are very low and not greater than 10% during any of the events, even though the 6-parameter model shows PEP > 10% during event 5. Both the models estimated a PEP close to zero during the first three events, while they slightly underestimated (positive PEP) the peak during events 4 and 5. In contrast, the 5, 4 and 3-parameter models largely vary in their PEP values and always underestimate the peak discharge. Like the PEP, the USF and 6-parameter models show the best performance in PEV and PETP values as shown in Fig. 5(d) and (e) respectively, which is close to zero as compared to that of the other models. Simultaneously, the 5, 4 and 3-parameter models generate higher values of PEV and PETP. They overestimated the volume (negative PEV) and early estimated the peak discharge.

Fig. 5(f) demonstrates the PELT generated by different models for the selected events. The USF model has values of either zero or close to zero which was immediately followed by the 6 and 5-parameter models respectively. The 4 and 3-parameter models have similar PELT values among themselves and are far from those of the other SF model values. Fig. 5(g) additionally shows the PERC and we can see that the PERC value of the USF, 6, and 5-parameter models are very close to zero except for the 5-parameter model during event 2 and 6-parameter model during event 5. The high PERC value of the 5-parameter model during event 2 indicates a low volume of runoff estimated by the model as well as high PEV as shown in Fig. 5(d). In the same way, the negative PERC values generated by the 6-parameter model during event 5 can be interpreted as a high volume of runoff estimated by the model. The 4 and 3-parameter models exhibit greater discrepancies compared to those of the other models during all events.

The higher values of NSE coupled with the lower values of RMSE, PEP, PEV, PETP, PELP, and PERC for the USF model indicate that the hydrograph reproducibility of the USF model is the highest among the SF models. The 6-parameter model was also found to be good for urban discharge estimation just after the USF model. The 5-parameter model can be used as a substitute for the USF and 6-parameter models in urban rainfall-runoff transformation process with little deviation to some extent. However, the 4, and 3-parameter models were found to be inappropriate for hydrograph reproducibility.

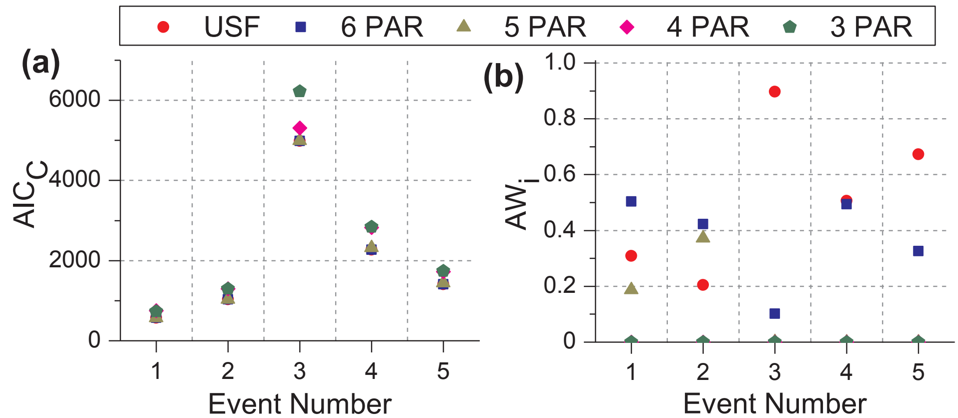

Fig. 6. The summary of Akaike information criterion (AIC) results, (a) corrected AIC (AIC_C) and (b) Akaike weight (AW) values for the five events. (PAR represents parameter).

4.3 AIC aspect

In addition to hydrograph reproducibility, AIC aspect was also used in order to determine the effectiveness of the models for each selected event. Fig. 6(a) shows the AIC_C values (Eq. (8)) for each model during each event. It can be seen from the figure that the 6-parameter model has the lowest AIC_C during event 1 and event 2. However, the USF had the lowest AIC_C during events 3, 4 and 5. Even though the USF model did not receive the lowest AIC_C during the first two events, it was very close to the lowest value of the 6-parameter model. There is nearly no support for 4 and 3-parameter models from Fig. 6(a) because they generate a far higher AIC_C score, which indicates the necessity of more parameters in order to describe the storage characteristics of the urban watershed more accurately. The exclusion of the delay time parameter in Kimura's 4-parameter model could also be a reason for this high AIC_C score. From Fig. 6(a), it is not easy to clearly distinguish the difference between the AIC_C values of the USF, 6, and 5-parameter models. Hence, we analyzed the AIC_C values using an associated statistic known as AW (Eq. (9)) to depict the differences distinctly. As a general rule of thumb, the AW of the candidate models during each event should be higher than 10% of the highest AW of that event (Royall, 1997) so that we can easily exclude models with a weight lower than 10% of the highest AW model. Based on this rule, we can exclude the 4 and 3-parameter models.

Fig. 6(b) shows the AW for each event using the different SF models. The weight exhibits an opposite trend to that of the AIC_C values and the model with the highest weight is the best (Hurvich and Tsai, 1989). Like the AIC_C score, the 6-parameter model received the highest weights during events 1 and 2. During the remaining events, the USF model has the highest weight followed by the 6-parameter model. Even though the 6-parameter is followed by the USF model, the difference between the AW values of these models is quite large, significantly greater for events 3 and 5. Therefore, the USF model is much more effective than the 6-parameter model during such multi-peak event 3 and single-peak event 5 based on the AW values. During event 1, the 6-parameter model was followed by the USF model and during event 2, it was followed by the 5-parameter model. The difference in AW values between the 6-parameter and USF models are not as great as compared to that during events 3 and 5. Consequently, the USF model can be more suitable for multi-peak events as compared to the other models as per the AIC aspect.

4.4 Parameter uncertainty

Fig. 7 shows the parameter variability of five SF models represented by two statistical indices (Eqs. (11) and (12)). The seven symbols in the figure represent the different parameters of each SF model. Fig. 7(a) demonstrates the RE values of each parameter and are entirely different for each model. The RE of parameter k_1, which is used to represent the physical watershed characteristics such as watershed area, land use, etc., is small compared to that of the other parameters for all the SF models, except for the 3-parameter model in which it is the parameter with the highest RE. The parameters k_3 and z are used to depict the groundwater-related loss. From Fig. 7(a), we can see that the RE of parameter k_3 is quite high in all models and the parameter z received the highest RE for the USF and 5-parameter models. The high RE of these two parameters plays an important role in hydrograph reproducibility of the SF models. The RE of z in the 4, and 3-parameter models is very low and the models are least affected by this parameter. The p_1 parameter is controlled by the flow regime (Sugiyama et al., 1997). It has higher RE values in the 6, 5, and 4-parameter models. It was found to be one among other parameters with a low RE in the USF model. The parameter k_2 is a complicated function of several variables that can affect the wedge storage as well as the storage-discharge relationship (Prasad, 1967). This parameter was included only in the USF, 6, and 5-parameter models and had a medium level of RE values. The parameter p_2 is incorporated in the USF and 6-parameter models and had quite high RE values in both models. The parameter α is associated only with the USF model to represent the effect of storm drainage and is that with the least variability in the USF model.

Fig. 7(b) shows the CV values for the estimated parameters. CV is the numerical representation of variability in data. The parameter pattern in CV values is quite similar to that in RE values, even though it shows slight deviations. The observed deviations are (i) the parameter order changed for some models and (ii) the CV values of parameters were more closely located or sometimes overlapped. The parameter z had higher variability in its values for the USF and 5-parameter models. On the other hand, p_2 was more uncertain in nature for the 6-parameter model. k_3 and k_1 are the parameters with the highest CV value for the 4 and 3-parameter models, respectively.

In general, a higher variability in rainfall resulted a higher variability in the parameters. A larger variation in rainfall values within a single event will result in a higher variation in all estimated parameters. The parameter estimates for each event may be quite inconsistent and this uncertainty in the model parameters can be attributed to the spatial variability in rainfall, change in watershed characteristics, etc.

It cannot be argued that the better performance of USF model over the other four models is essentially due to the additional parameter α. It is not because of just one additional parameter, but a combination of all the parameters. If the number of parameters was the criteria for model performance, the 3-parameter model should have comparable performance at least with the 4-parameter model. However, the 4-parameter model exhibits substantial improvement in performance compared with the 3-parameter model as shown in Fig. 5. The addition of parameter p_1

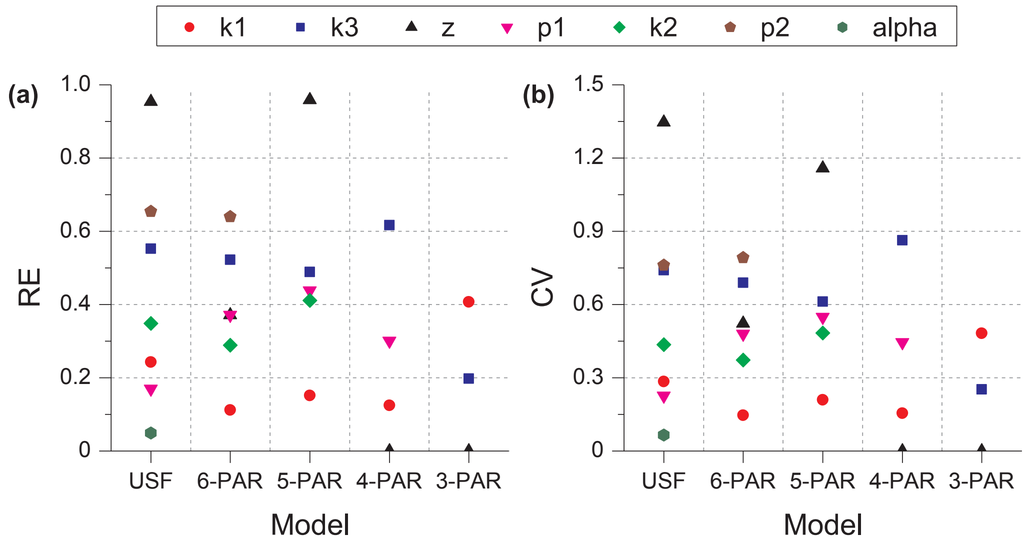

Fig. 7. Model parameter uncertainty represented using two statistical indices, (a) relative error (RE) and (b) coefficient of variation (CV). (PAR represents parameter).

transformed the linear storage model into a non-linear SF model and improved its structure. However, the 4 and 3-parameter models depicted a non-linear and linear monovalent storage-discharge relationship respectively. On the other hand, the USF, 6, and 5-parameter models considered the looped storage-discharge relationship and hence asserted that the inclusion of loop effect can considerably enhance the performance. The 6-parameter model revealed an improved performance than the 5-parameter model even though both the model take care of the loop effect. This can be attributed to the representation of non-linear unsteady flow in 6-parameter model while the 5-parameter model constituted only the linear unsteady flow effects. Therefore, it can be deduced that the introduction of non-linear wedge storage can additionally increase the model performance. The difference in performance between the USF and 6-parameter models can be ascribed to the effect of storm drainage diverting to the treatment plant through the combined sewer system instead of going to the river in the USF model. According to the above discussion, it was noted that the models with a different number of optimized parameters produced quite different results, especially for 4 and 3-parameter models with a difference of one parameter each. This strengthens the argument raised by Gan et al. (1997), in which the structure of the model is of critical importance for the model performance rather than the number of optimized parameters. Also, the effectiveness of a model cannot be defined in terms of the individual additional parameters alone but should be considered as a combination of parameters which describe different watershed and flow attributes.

Steefel and Van Cappellen (1998) commented that an effective model is determined based on its simplicity relative to its performance for a given number of observations. But the simple 4 and 3-parameter models were not capable of reproducing the observed hydrographs and could not demonstrate an equivalent performance of that produced by the other SF models. Therefore, simplicity alone cannot be used as a valid criterion for how effective a model is. Perrin et al. (2001) suggested that the number of free parameters might be restricted between three and five in lumped rainfall-runoff models. However, even the 5-parameter model failed to exactly reproduce the hydrograph and peak. Therefore, the number of free parameters from three to five is not sufficient to clearly represent urban discharge at least in this particular study.

5 Conclusions

The five SF models with optimal parameters identified using the SCE-UA method were applied to five flood events in an urban watershed in Tokyo to evaluate performance with minimum RMSE. First, the models were assessed for their hydrograph reproducibility using the seven error functions of RMSE, NSE, PEP, PEV, PETP, PELT, and PERC. The results revealed that the USF model had the lowest RMSE (high NSE) among all the models for all the events, which implies that the SCE-UA method successfully identified the optimal parameters. The lower values of PEP, PEV, PETP, PELT, and PERC of the USF model further indicate that the hydrograph reproducibility of USF model is the highest among the studied SF models. In addition, the summary of AIC results shows that the USF received the highest AW during most of the events compared to that of the other SF models, which makes it the most effective model. The other SF models have lower AW scores, indicating the necessity of the addition of more parameters that describe the storage characteristics of an urban watershed. In conclusion, the USF model can be considered as the best model not only for hydrograph reproducibility but also the most parsimonious based on the AIC perspective during most of the flood events in an urban watershed, when compared to the conventional models, if the optimal parameters are successfully identified for the events.

The uncertainty characteristics reveal that it is necessary to investigate the aspect of uncertainty of the parameters in more detail to identify the key parameters of runoff response in an urban basin. The validation process of the models is very crucial with an ultimate goal of producing an accurate and credible model and it involves parameter uncertainty. However, in this study, we are mainly concerned with the calibration of the selected SF models and their associated performance. Therefore, our future work will mainly cover the detailed uncertainty analysis of parameters and their relative stability.

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