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Effect of Lag Time in Kimura's Storage Function Model on Hydrograph Reproducibility for an Urban Watershed Compared with Prasad's Model

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The storage function (SF) models have been extensively used for the rainfall-runoff modeling in which the Kimura's model with lag time is widely used as a fundamental flow model, especially in Japan, due to its simple model structure. In this study, therefore, we aim to analyze the effect of lag time in the conventional Kimura's SF model on hydrograph reproducibility and compared with Prasad's SF model for an urban watershed in terms of error functions, storage hysteresis loop, and Akaike information criterion (AIC) perspective. The analysis of the effect of lag time on hydrograph reproducibility revealed that the use of optimum lag time in Kimura's model can greatly improve the performance. Further, the Kimura's SF model with optimum lag time exhibited higher hydrograph reproducibility associated with lowest error evaluation criteria and lowest AIC values in the single-peak events which makes it the superior model for single-peak events. Concurrently, Prasad's model depicted better performance in terms of reproducibility and AIC aspect during the multi-peak events, which indicates that it is the parsimonious model for multi-peak events.

Key Words: *Kimura's model, Prasad's model, lag time, storage hysteresis loop, Akaike information criterion*

1. INTRODUCTION

The estimation of urban discharge is a thriving challenge in the field of hydrology due to the associated flood risk and cost. Therefore, the accurate prediction of urban discharge hydrograph, which includes the estimation of flood peak, time to peak, volume, etc., is important in order to avoid the losses due to flood risk. The storage function (SF) model was invented by Kimura[1)] with two parameters and lag time which has been widely used in many parts of the world, especially in Japan, due to its relatively simple model structure and numerical procedure[2)]. The model was originally developed for the calculation of flood flow resulted from the effective rainfall by dividing the basin into pervious and impervious areas[1)]. The storage equation of Kimura is a monovalent function of discharge. However, the bivalency was achieved by the introduction of lag time in the continuity equation and attained the storage-discharge hysteresis loop. Additionally, the incorporated lag time skilfully addresses the hydrograph lagging by delaying the runoff as a function of effective rainfall. Subsequently, Prasad proposed a three parameter SF model by assuming the storage as a bivalent function of discharge by the introduction of an additional parameter in the storage equation itself, rather than in the continuity equation, which handled the loop shape of the storage-discharge relationship[3]. The model also presented an additional term for the representation of unsteady flow effects which is observed in natural channels.

Later, several improved SF models have been proposed in terms of how to express its nonlinearity, model structure, and the storage hysteresis loop[2), 4]. However, all these developed models requiring rainfall loss estimation to link the effective rainfall input with direct runoff. Hence it further involves the use of different subjective methods for the separation of baseflow and effective rainfall component from total discharge and total rainfall respectively, which may further add uncertainties to the model parameters and simulation. In order to eliminate the deficiencies included in the separation processes, Baba et al. introduced an SF model with loss mechanism by directly relating the observed rainfall to the observed discharge and implemented in the mountainous river basin of Hokkaido, Japan[5]. Soon after, Takasaki et al. developed a new urban SF (USF) model considering the urban runoff process which also uses the observed rainfall and runoff for the flood prediction[6]. The authors have already evaluated different SF models which include Kimura's model without lag time[7].

The SF models with the same number of parameters have not been evaluated not only in terms of the hydrograph reproducibility but also the storage hysteresis loop point of view for an urban watershed as far as the authors know. Specifically, there are no studies which compare the effectiveness of SF models in terms of the number of optimized parameters and the information criteria aspect. Hence, this study aims to compare the performance of two 3-parameter SF models of Kimura and Prasad in terms of hydrograph reproducibility, storage hysteresis loop, and Akaike information criterion (AIC) [8] perspective and analyze the effect of lag time in the performance of Kimura's model by directly coupling the observed rainfall to observed discharge for an urban watershed. The Kimura's model with and without lag time was considered to analyze the effect of lag time, and compared with Prasad's SF model for the selected flood events of the upper Kanda river basin, a typical small to medium-sized urban watershed in Tokyo. The Shuffled Complex Evolution-University of Arizona (SCE-UA) global optimization method[9] was used to estimate the model parameters of each event with root mean squared error (RMSE) as the objective function. First, the effect of lag time in Kimura's model on different performance evaluation criteria of RMSE, Nash Sutcliffe Efficiency (NSE) and other error functions was analyzed. Further, the optimized SF models were assessed for reproducibility of hydrograph using the same performance evaluation criteria and error functions. Also, the storage hysteresis loop effect was examined by fitting the storage loop estimated by the models. Additionally, the authors have utilized AIC to identify the effective SF model by considering the lag time for an urban watershed based on the information theory perspective[8].

2. MATERIALS AND METHODS

Urban watersheds are characterized by the presence of sewer systems and a high percentage of impervious surfaces, which will accelerate the rainfall-runoff transformation process[10]. Consequently, the runoff response at the outlet will occur immediately after the rainfall within a short lag time and will lead to the generation of flash floods. Therefore, it is important to use the rainfall-runoff models that incorporate lag time for the accurate prediction of urban floods. The Kimura's SF model uses lag time parameter and Sugiyama represented this parameter as a function of basin area, mainstream length, mean slope length, etc[2]. Therefore, the use of Kimura's model with lag time can closely predict the observed hydrograph. Since the lag time estimation is a tedious process, we analyzed the effect of lag time on Kimura's model and made an attempt to understand whether the Kimura's model without lag time can exhibit a comparable performance with Kimura's model with lag time. Also, in order to check how effective the Kimura's model with lag time, we selected another 3-parameter SF model of Prasad.

(1) Kimura's SF model with lag time

In this paper, the authors used the Kimura's SF model with one storage tank for the pervious area which is widely used as a special case of Kimura's original model and is given as[1]:

$$s(t) = k_1 Q^{p_1}(t) \tag{1}$$

where $s(t)$: storage at time t (mm), $Q(t)$: direct runoff at time t (mm/min), and k_1, p_1: model parameters. Kimura introduced the bivalence of storage by the inclusion of lag time in the continuity equation and is as follows:

$$\frac{ds(t)}{dt} = R_e(t - T_l) - Q(t) \tag{2}$$

where T_l: lag time, R_e: effective rainfall at time t-T_l. The above continuity equation requires the estimation of effective rainfall and baseflow separation for the evaluation of direct runoff, which

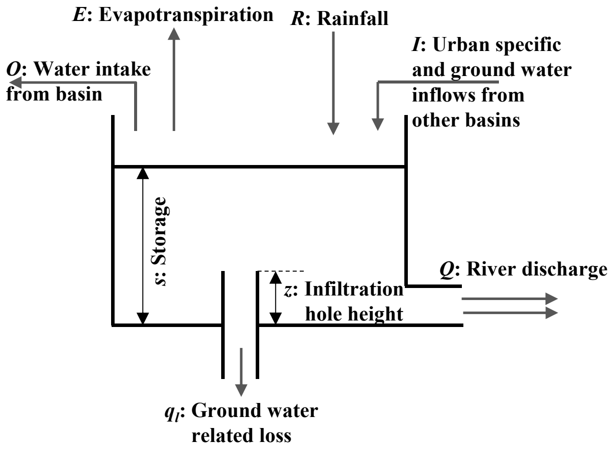

Fig.1 Schematic diagram of all possible inflow and outflow components of an urban watershed.

is a subjective process. Therefore, in order to avoid the separation process, we used a different continuity equation which can include all the possible inflows and outflows with lag time instead of Eq. (2). **Fig.1** shows the schematic diagram of all the possible inflow and outflow components of an urban watershed. The continuity equation associated with the components of **Fig.1** is given as[6]:

$$\frac{ds(t)}{dt} = R(t - T_l) - E(t - T_l) + I(t) - O(t) - q_l(t) - Q(t) \quad (3)$$

where R: observed rainfall at time $(t - T_l)$ (mm/min), E: evapotranspiration at time $(t - T_l)$ (mm/min), I: urban specific and groundwater inflows from other basins at time t (mm/min), O: water intake from the basin at time t (mm/min), q_l: groundwater related loss at time t (mm/min), Q: observed river discharge at time t (mm/min). The loss to groundwater (q_l) was defined by considering the infiltration hole height (z) and is given by[6]:

$$q_l(t) = \begin{Bmatrix} k_3(s(t) - z) & (s(t) \geq z) \\ 0 & (s(t) < z) \end{Bmatrix} \quad (4)$$

where k_3 and z are the parameters. Substituting Eq. (1) into Eq. (3) will lead to a first-order ordinary differential equation (ODE) as follows:

$$k_1 \frac{dQ^{p_1}(t)}{dt} = R(t - T_l) - E(t - T_l) + I(t) - O(t) - q_l(t) - Q(t) \quad (5)$$

In order to solve this first-order ODE, the change of variable is performed as follows:

$$x_1 = Q^{p_1}(t) \quad (6)$$

Substituting Eq. (4) into Eq. (5) and performing the change of variables will lead to the emergence of two first-order ODEs concerning two conditions as shown in Eq. (4). When $s \geq z$, the first-order ODE is as follows:

$$\frac{dx_1}{dt} = -k_3 x_1 - \left(\frac{1}{k_1}\right) x_1^{\frac{1}{p_1}} + \left(\frac{1}{k_1}\right)(R(t - T_l) - E(t - T_l) + I(t) - O(t) + k_3 z) \quad (7a)$$

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

$$\frac{dx_1}{dt} = -\left(\frac{1}{k_1}\right) x_1^{\frac{1}{p_1}} + \left(\frac{1}{k_1}\right)(R(t - T_l) - E(t - T_l) + I(t) - O(t)) \quad (7b)$$

By solving the non-linear ODE of (7a) and (7b) numerically, we obtain the total discharge Q. In order to solve the first-order ODE, we used the Runge-Kuta-Gill (RKG) method which is one of the numerical solution methods.

(2) Prasad's SF model

The SF model equation proposed by Prasad in order to describe the looped storage-discharge relationship is given as[3]:

$$s = k_1(Q)^{p_1} + k_2 \frac{dQ}{dt} \quad (8)$$

where k_2 is the model parameter. The authors have utilized the same continuity Eq. (3) without lag time in order to avoid the separation process. Solving Eqs. (8), and (3) without lag time in the same way as described in the aforementioned section using the RKG method will lead to the total river discharge estimated by the Prasad's SF model.

The conventional Kimura's and Prasad's SF models are three parameter models with parameters k_1, p_1, T_l and k_1, p_1, k_2 respectively. However, in order to consider the observed discharge as a whole and to reduce the efforts taken for the separation, we considered all possible inflows and outflows in Eq. (3) which further added two more parameters k_3 and z to each model and transformed the 3-parameter models into 5-parameter models. In order to analyze the effect of lag time, the same Kimura's model was considered with the lag time equal to zero which is referred to as Kimura's model without lag time hereafter in the study. The Kimura's model with optimized lag time was mentioned as Kimura's model throughout the study.

The performance of a model highly depends on how well the model is calibrated. There are chances for the existence of multiple optima (more than one solution) due to the non-linear structural characteristics of SF models. In order to overcome this problem, the SCE-UA method proposed by Duan[9], which will identify the global optimum parameters associated with a given calibration dataset, was used to identify the optimal parameters of all the three models. The SCE-UA method has been successfully utilized for the parameter estimation of different rainfall-runoff models including the SF models[11]. The search range of parameters for SCE-

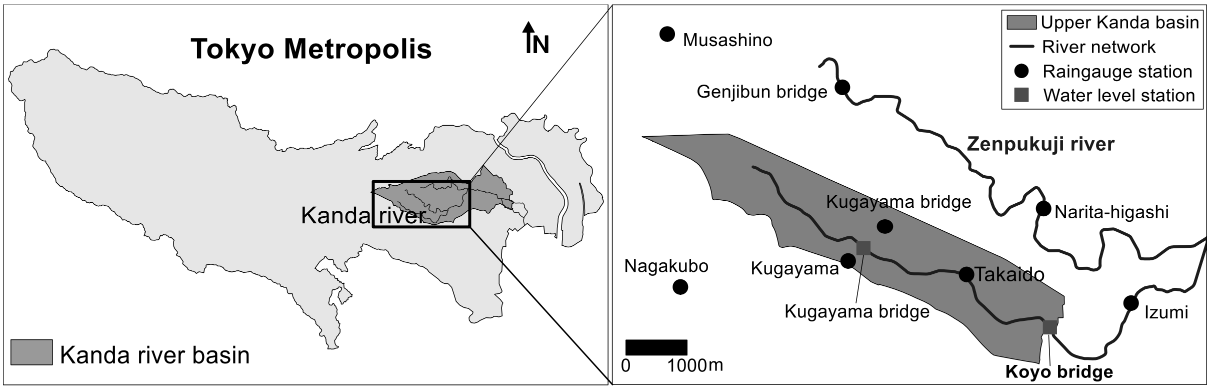

Fig.2 Index map of the study area.

UA was set as, k_1(10-500), k_2(100-5000), k_3(0.001-0.05), p_1(0.1-1), z (1-50), and T_l (0-25).

(3) Hydrograph Reproducibility

The hydrograph reproducibility of models with the observed one was assessed using the RMSE, NSE, and other error functions of percentage error in peak (PEP), percentage error in volume (PEV) [12] and error in time to peak (ETP). The ETP is defined as,

$$ETP = t_{po} - t_{pc} \tag{9}$$

where t_{po}: observed time to peak discharge (min), t_{pc}: computed time to peak discharge (min).

The lag time in Kimura's model is the lag between the peak rainfall and discharge and have a significant influence on the hydrograph reproducibility by delaying the runoff. Hence, it is important to assess the effect of lag time on the hydrograph reproducibility by Kimura's model. To this purpose, lag times ranging from 0 to 25 min was considered and analyzed the associated changes in different hydrograph reproducibility characteristics such as RMSE, NSE, PEP, PEV, and ETP for each event. Then, the hydrograph reproducibility by the Kimura's model was compared with the Prasad's model for further performance evaluation. Additionally, AIC was also used in order to identify the best model for each event[8]. The best model is the one with the lowest AIC score and is given by,

$$AIC = 2K - 2\log(\mathcal{L}) \tag{10}$$

where K: number of parameters to be estimated and $\log(\mathcal{L})$: the maximized log-likelihood function of the model estimated. Later, this concept was refined to correct for small data samples as[13]:

$$AIC_C = AIC + \frac{2K(K+1)}{n-K-1} \tag{11}$$

where n: sample size.

(4) Study area and data used

The target basin is the upper Kanda river basin with an area of about 7.7 km^2 at Koyo Bridge as shown in **Fig.2**. The rainfall and water level data at one-minute interval was collected from the Tokyo Metropolitan Government (TMG) during 2003-2006 for the study. Five target events were selected from the data, whose 60-minute maximum rainfall (R_{60}) is greater than 30 mm, for the application of SF models and are shown in **Table 1**. The rainfall data from the eight rain gauges were used to compute the catchment average rainfall by using the Thiessen polygon method. The inflow component I was fixed at 0.0012 mm/min based on the business annual report of the TMG. The other outflow components O and E were set at zero[6].

Table 1. Characteristics of target events.

Event No.	Event date	R_{60} (mm)	Total R (mm)	Climatic factors
1	13/10/2003	50.4	56.2	Intensive localized storm
2	25/6/2003	42.3	42.7	Frontal event
3	8~10/10/2004	34.2	247.4	Typhoon
4	11/09/2006	32.6	37.8	Frontal event
5	15/07/2006	31.5	31.5	Frontal event

3. RESULTS AND DISCUSSIONS

(1) Parameter estimation

The event-based optimal parameters of all the models were estimated using the SCE-UA optimization method and are shown in **Fig.3**. 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 which further indicated that the SCE-UA method has the ability to identify the parameters that can provide a good correspondence between the simulated and observed discharge. **Figs.3 a)**, **b)**, **c)**, and **d)** show the parameters k_1, p_1, k_3, and z respectively, and these are associated with all the considered models. **Fig.3 a)** shows that the Kimura's model has the lowest and

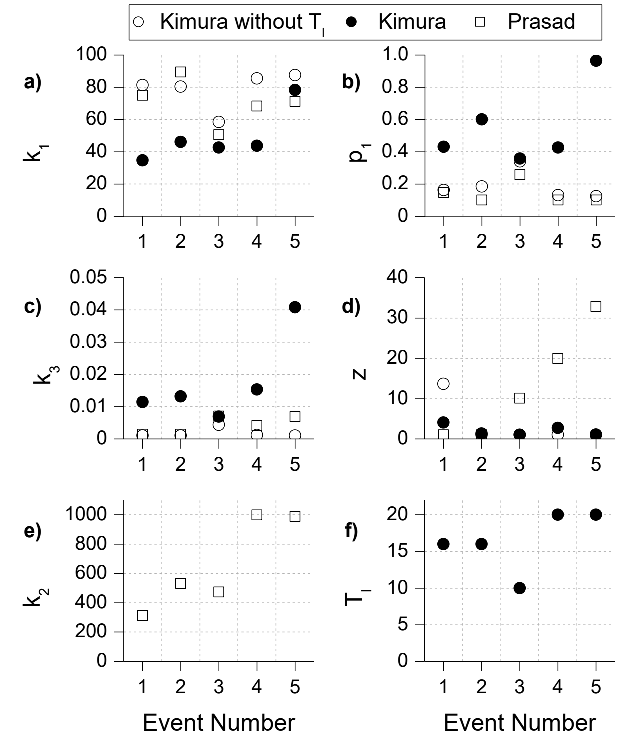

Fig.3 Event-based optimal parameters for the Kimura with and without lag time, and Prasad's models.

quite similar k_1 values compared with other models among all the events except event 5. The other two models, Kimura without lag time and Prasad, have quite near values of k_1 and they come closer to the values of Kimura's model during events 3 and 5. **Fig.3 b)** shows that the p_1 values of Kimura's model are highly fluctuating among the events and are far higher than other model parameter values. However, the p_1 value of all the three models meets at event 3, which is a multi-peak event. The other two models have alike p_1 values and are consistent with the events. The parameter k_3 exhibits the similar pattern of p_1 and all the model parameters coincide at event 3 as shown in **Fig.3 c)**. Kimura's model has higher values of k_3 compared with other models which are relatively stable. It can be clearly seen from **Fig.3 d)** that there is a gradual increase in the values of parameter z in Prasad's model from event 2 onwards, in contrast to the consistent values of z in Kimura's model. The Kimura's model without lag time was also able to generate z values analogous to Kimura's model except for event 1. The parameter k_2 depicted in **Fig.3 e)** is present only in Prasad's model and it ranges between 300 and 1000. The parameter, T_l depends on the hyetograph and is varying from event to event as shown in **Fig.3 f)**. The observed maximum and minimum T_l are 20 and 10 min respectively and conclusively we can say that the watershed response to a rainfall event is 16 min on an average. This shorter lag time depicts that the watershed can generate floods immediately after the rainfall.

(2) Hydrograph reproducibility

First and foremost, the effect of lag time (T_l) in Kimura's model was analyzed using the performance evaluation criteria of RMSE, NSE, PEP, PEV, and ETP for each event and are shown in **Fig.4**. The values corresponding to T_l=0 represent the Kimura's model without lag time and the values at optimized lag time represent Kimura's model and are tabulated in **Table 2**. It can be envisaged from **Fig.4 a)** that the

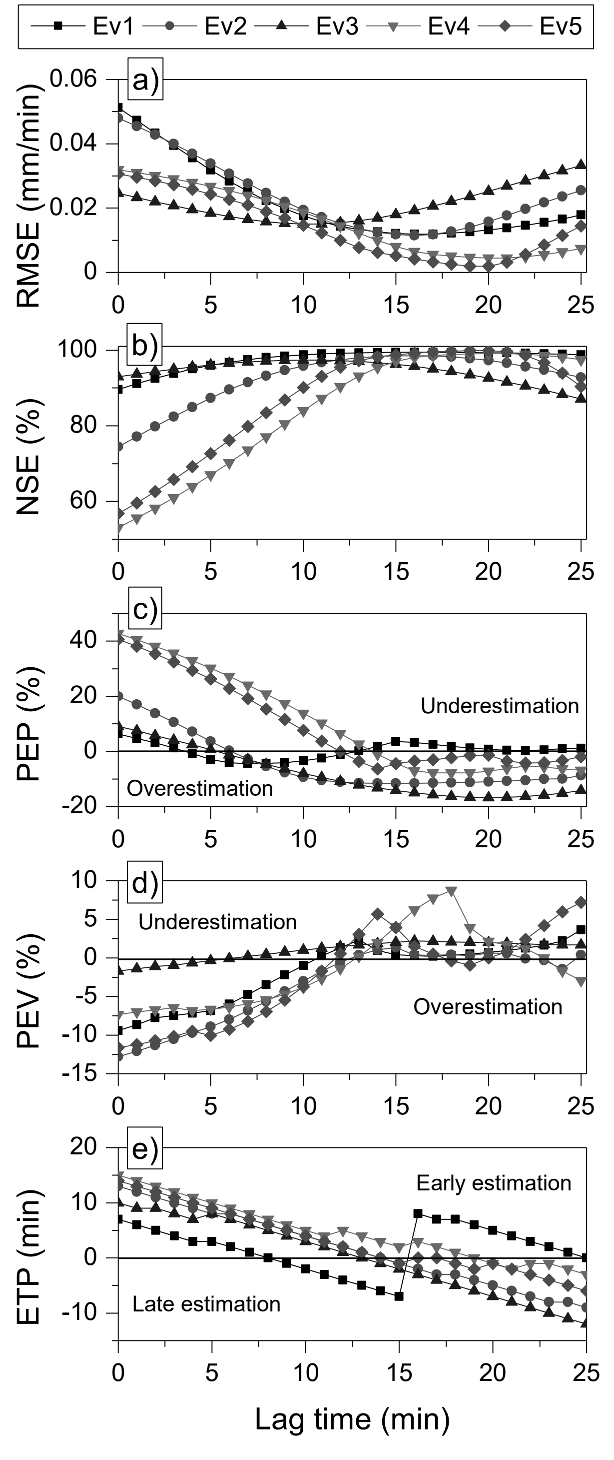

Fig.4 Effect of lag time on a) RMSE, b) NSE, c) PEP, d) PEV, and e) ETP by Kimura's model (Ev represents event).

Table 2 Comparison of RMSE, NSE, PEP, PEV, and ETP by the SF models (K represents Kimura's model).

Event No.	Model	RMSE (mm/min)	NSE (%)	PEP (%)	PEV (%)	ETP (min)
1	K(T_l=0)	0.051	89.6	6.4	-9.4	7
	K(T_l=16)	0.012	99.4	3.2	0.3	8
	Prasad	0.016	98.9	-0.5	-1.2	-1
2	K(T_l=0)	0.048	74.5	19.9	-12.8	13
	K(T_l=16)	0.012	98.5	-11.6	0.4	-2
	Prasad	0.014	97.8	7.9	1.6	-4
3	K(T_l=0)	0.025	92.9	9.1	-1.7	10
	K(T_l=10)	0.015	97.4	-8.0	1.0	3
	Prasad	0.013	98.1	3.2	0.4	-5
4	K(T_l=0)	0.032	53.1	42.8	-7.3	15
	K(T_l=20)	0.004	99.1	-7.2	2.1	-1
	Prasad	0.017	86.0	26.0	4.1	-2
5	K(T_l=0)	0.031	56.8	40.6	-11.6	14
	K(T_l=20)	0.002	99.8	-1.4	0.01	-1
	Prasad	0.017	86.9	28.0	0.9	-3

RMSE have high value at T_l=0. It starts decreasing with increase in T_l until it reaches the minimum RMSE values at optimum T_l. Once it reaches the minimum RMSE, it begins to increase with further increase in T_l. The NSE also followed the same pattern of RMSE as shown in **Fig.4 b)**, but obviously in the opposite direction. Apart from RMSE and NSE, the PEP exhibited a different trend with changes in T_l as shown in **Fig.4 c)**. It starts to decrease with increase in T_l and the PEP values close to zero was obtained before reaching the optimum T_l in all the events. The changes in PEV values with changes in T_l of the model are shown in **Fig.4 d)** and are similar to the trend in PEP values. The minimum PEV value adjacent to zero was observed at a different T_l rather than the optimized value except for event 5. Generally, with the increase in T_l, the underestimated peak discharge progressively moved to overestimation and the overestimated volume gradually changed to underestimation. **Fig.4 e)** shows that the ETP gradually advances from early to late prediction with the increase in T_l and approaches zero at a particular lag time rather than the optimum one. The results revealed that the lag time has a higher impact on the hydrograph reproducibility characteristics. Hence, the estimation of optimum lag time which gives the best combination of evaluation criteria is essential to achieve a better performance.

Further, the hydrograph reproducibility in terms of the error functions by the three models (Kimura without lag time, Kimura with optimized lag time, and Prasad) for each event are shown in **Table 2** which include RMSE, NSE, PEP, PEV, and ETP. Additionally, **Fig.5** shows the visual representation of hydrograph reproducibility of the five selected

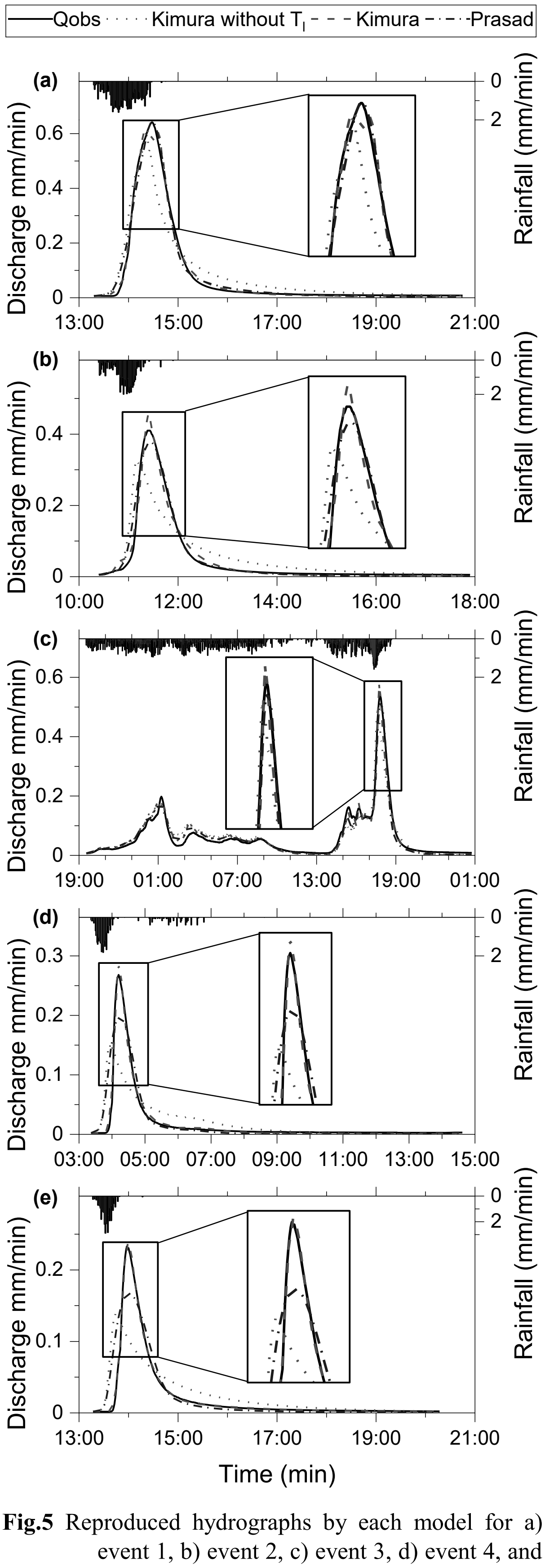

Fig.5 Reproduced hydrographs by each model for a) event 1, b) event 2, c) event 3, d) event 4, and e) event 5.

events by the models. From **Table 2**, we can see that Kimura's model without lag time received highest RMSE and least NSE in all the events which further reveals its low hydrograph reproducibility. It is evident from the table that the model always underestimated peak discharge (positive PEP) and overestimated the volume (negative PEV) with an early peak prediction (positive ETP) in all the events. It is also clear from **Fig.5** that the Kimura's model without lag time considerably underestimated the peak discharge with a highly deviated recession limb and lags behind the observed hydrograph with an early estimated peak. However, the introduction of lag time in Kimura's model drastically changed the RMSE to the least and NSE to the highest values except for event 3, a multi-peak event, as shown in **Table 2**. Also, the model started to slightly overestimate the peak discharge with a late peak prediction which was very close to the observed time to peak except for event 1. The model was able to reproduce the volume which was close to the observed volume even though it was consistently underestimated very slightly. It can also be envisaged from **Fig.5** that the Kimura's model slightly overestimated the peak discharge in all the events except for event 1 even though it fits well with the rising and recession limbs. Therefore, the results exhibited that the introduction of lag time in Kimura's model greatly improved its reproducibility.

On the contrary, the Prasad's model has the lowest RMSE and highest NSE for event 3 and having comparable RMSE and NSE values with Kimura's model during the rest of the events. The Prasad's model gives best PEP values in events 1, 2, and 3 among all the models as shown in **Table 2** even though it considerably underestimated the peak discharge during events 4 and 5 which is evident from **Fig.5**. Therefore, the Prasad's model can be considered as the good model in estimating the peak discharge for the single as well as multi-peak events compared with Kimura's model. The model was also able to reproduce the shape of the hydrograph in events 1, 2, and 3 although it depicted a deviated rising limb in the events 4 and 5 as shown in **Fig.5**. It is noticeable from the table that the Prasad's model received low PEV values close to zero throughout all the events. However, the model has got the least PEV value only during event 3, which further revealed that the model is good for the volume estimation of multi-peak events over the Kimura's model. On the other hand, Kimura's model was superior to Prasad's model in the volume estimation of single-peak events. The ETP values exhibited in **Table 2** revealed that the Kimura's model is good in estimating the time to peak discharge compared with Prasad's model during all the events, especially in multi-peak events. This is because of the presence of lag time in Kimura's model which can delay the time to peak discharge based on the rainfall.

The above results demonstrated that Kimura's model has high hydrograph reproducibility during the single-peak events. This can be attributed to the effect of incorporated lag time on the runoff response of the basin. The consideration of single lag time for the multiple peaks in a multi-peak event may be insufficient to achieve a higher reproducibility. Therefore, the Prasad's model can be contemplated as the good model for reproducibility of multi-peak events. Additionally, hydrograph characteristics of Kimura's model without lag time revealed that the model is not appropriate for both single and multi-peak events which additionally showed the relevance of lag time in Kimura's SF model.

(3) Storage hysteresis loop effect

Furthermore, the storage hysteresis loop effect was analyzed by computing the storage estimated by the models. **Fig.6** shows the storage hysteresis loops reproduced by the models for all the events. The continuity Eq. (3) was used to compute the storage which requires the estimation of the outflow component q_l , that represents the groundwater related loss. However, the quantification of q_l further needs two parameters k_3 and z as shown in Eq. (4) which is not known for the actual watershed. Consequently, we have computed the storage estimated by the models and compared the storage loops among the models. It can be envisaged from **Fig.6** that Kimura's model without lag time generated a bivalent storage loop and the storage is increasing with an increase in discharge. After the inflection point, the loop changed the direction and the storage started to decrease. We can see from **Figs.6 a)**, **b)**, **d)**, and **e)** that the model generated single loops during the single-peak events, while the produced loop had a complicated shape with multiple loops in multi-peak event 3 as shown in **Fig.6 c)**. However, it is clear from **Fig.6** that the storage loop produced by Kimura's model was very narrow and become close to a monovalent storage-discharge relationship in all the events even though the model has multiple loops during event 3. The narrow loop was arisen due to the incorporation of the lag time which was 16, 16, 10, 20, and 20 min during events 1, 2, 3, 4, and 5 respectively as shown in **Fig.3 f)**. The storage estimated by the model was very low compared with the Kimura's model without lag time. On the other hand, Prasad's model exhibited a clear bivalent storage-discharge relationship as shown in **Fig.6**. The storage by Prasad's model during the rising limb portion was close to that of Kimura's model without lag time while the storage during recession limb portion was lower than the Kimura's model without lag time in all events except for event 5. This difference in the storage loop behavior

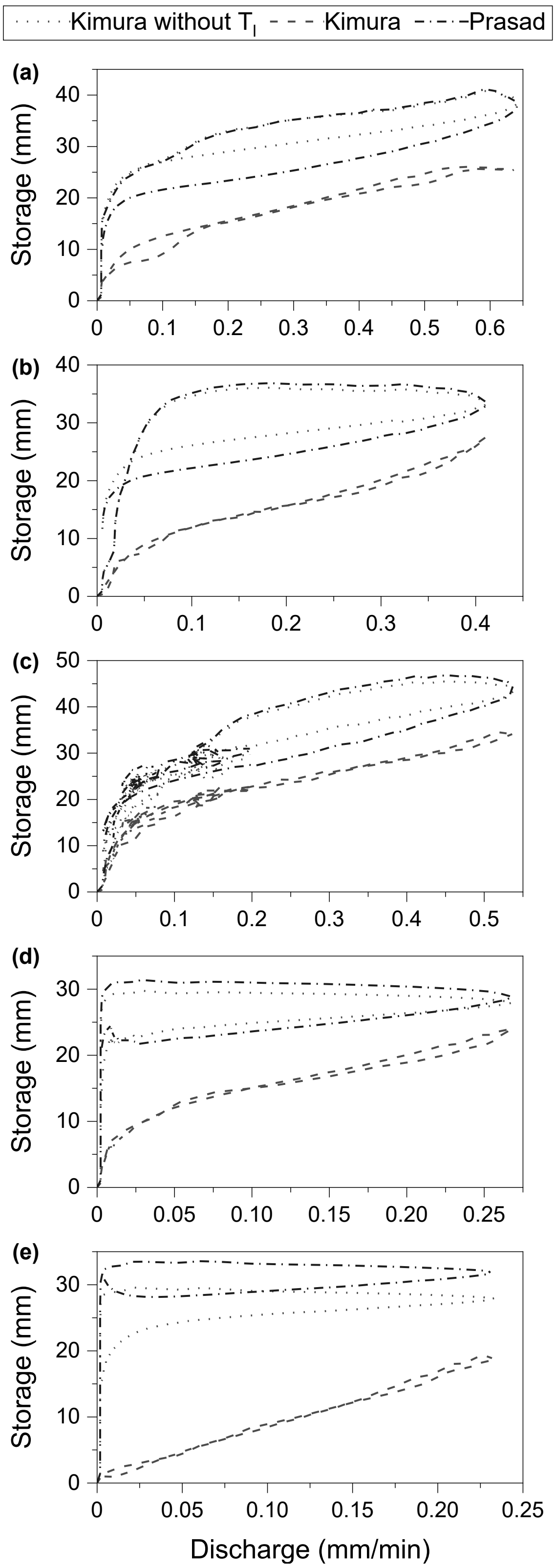

Fig.6 Storage hysteresis loop reproduced by each model for a) event 1, b) event 2, c) event 3, d) event 4, and e) event 5.

between the models during event 5 can be possibly ascribed to the higher *z* value of the model as shown in **Fig.3 d)**. The estimated storage by Prasad's model was far higher with a relatively wide loop when compared with the storage loop of Kimura's model.

Table 3 The summary of AIC results for the five events.

Event No.	Model	Kimura without T_l	Kimura	Prasad
1	AIC	552.0	389.4	395.2
	AICc	552.1	389.6	395.3
2	AIC	1103.0	859.3	854.7
	AICc	1103.2	859.4	854.8
3	AIC	4128.1	3877.6	3842.4
	AICc	4128.2	3877.6	3842.4
4	AIC	2802.2	2240.3	2299.5
	AICc	2802.3	2240.4	2299.6
5	AIC	1729.9	1398.2	1444.6
	AICc	1730.0	1398.3	1444.7

(4) AIC aspect

The best model for each selected event was determined by using the AIC aspect and are shown in **Table 3**. The best model is the one with the lowest AIC score. The results show that the Kimura's model without lag time could not succeed to achieve lower AIC values in any of the events and was far higher compared with other model values. The addition of lag time parameter in the Kimura's model substantially reduced the AIC values and made it comparable with the Prasad's model values during all the events. The Kimura's model with optimized lag time has the lowest AIC values in events 1, 4, and 5 which are single-peak events. Concurrently, Prasad's model received lowest AIC values in events 2 and 3 in which event 3 is a multi-peak event. The corrected AIC (AICc) values computed for each event was almost equal to the AIC values which indicate that the dataset used is long enough to consider for the AIC analysis[13]. The AIC values highly depend on the number of parameters to be optimized and it is evident that the models with the same number of parameters may have almost the same AIC values. However, the Kimura and Prasad's models have the same number of optimized parameters and yet the Kimura's model received lowest AIC values during most of the single-peak events which make it the best model for the single-peak events compared with Prasad's model. This higher performance exhibited by Kimura's model can be attributed to the presence of lag time parameter which can effectively constitute the hydrograph lagging. On the other hand, Prasad's model received the lowest AIC value during the multi-peak event which makes it suitable for multi-peak events. The higher AIC score generated by Kimura's model without lag time specifies that the incorporation of lag time is indispensable in order to achieve better performance in urban watersheds.

4. CONCLUSIONS

The Kimura's model with and without lag time and Prasad's model with optimal parameters were applied to five selected flood events in an urban watershed in Japan in order to evaluate the hydrograph reproducibility. The major findings of this study can be summarised as follows:

1. The differences in performance between the Kimura's model with and without lag time can be attributed to the differences in the values of parameters k_1, p_1, k_3, and T_l. This further indicated that the SCE-UA method succeeded in locating the global optimum with an additional parameter.
2. The effect of lag time in Kimura's model has not yet reported and the results of our current study revealed that the inclusion of optimized lag time can considerably enhance the performance of Kimura's model and its incorporation is inevitable.
3. The notable difference between the storage-hysteresis loops estimated by Kimura with and without lag time models revealed the effect of lag time on the storage characteristics of an urban watershed. The inclusion of lag time converted the bivalent storage-discharge relationship into a nearly monovalent relationship.
4. The inability of Kimura's model to truly reproduce the observed hydrograph of multi-peak events can be ascribed to the consideration of single lag time for the multiple peaks in the model which makes the model parsimonious only for the single-peak events.
5. The flexibility of the SCE-UA method to incorporate the structural modification of models enhanced the performance of Prasad's model by the competitive evolution of model parameters in multi-peak events. It also confirmed that the modification of the model framework in order to accommodate all the possible inflows and outflows of an urban watershed can portray the model structure in a more successful way.
6. It was noted that the models with the same number of optimized parameters produced quite different AIC values. This strengthens the argument raised by Gan et al.[14] that the structure of the model is of critical importance for the model performance rather than the number of optimized parameters.

This study successfully demonstrated the effect of lag time in Kimura's SF model and compared it with Prasad's model for an urban watershed. The results obtained from this study can be further used to formulate a basic idea on how different the performance of SF models. This accumulated knowledge is applicable not only in the Kanda river basin but also in any other urban watersheds around the world because the Kanda river basin has all the typical urban watershed characteristics. Therefore, this study put forwards an important need for the planning of future studies in order to check the applicability of the proposed model frameworks for the better flood prediction in other urban watersheds.

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