応用水文 No.32 2020「部会報告編」
Applied Hydrology

Real-time Flood Forecasting Considering Probabilistic Distribution of Future Forecasted Rainfall
予測降雨の確率分布を考慮した洪水の実時間予測

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Abstract

Accurate and early flood forecasting is important for implementing safety measures, reducing flood damage, and ensuring effective flood rescue operations. In this study, the LST model was applied to hydrological data for 11 years in Kuroki Dam catchment (49.2 km^2) in Okayama Prefecture, Japan. The LST model was calibrated by the differential evolution technique. A system for real-time flood runoff forecasting was constructed by introducing the particle filter technique into the operation of the LST model. Using the LST model, the system for probabilistic flood runoff forecasting was developed. Pseudo forecasted rainfall data were generated by adding Gaussian noise to 1- and 2-h ahead future observations collected from gauge points in Kuroki Dam. The generated data were input to the LST model to calculate the distribution of forecasted discharges. The model performed well in the simulation of both flood (short-term) and long-term runoff. The results show that the distributions of 1- and 2-h ahead flood runoff predicted by the proposed forecasting system were accurate, compared with observed data. Therefore, it can provide useful information for efficient flood warning and protection planning.

Key words: Real-time flood forecasting, long- and short-term runoff (LST) model, Differential Evolution (DE) technique, Particle filter (PF), pseudo forecasted rainfall

要　旨

正確な早期の洪水予測は，洪水に対する安全対策，被害軽減，救助活動の実施のために重要である。本研究では，1991～2001 年の 11 年間に岡山県の黒木ダム流域（流域面積 49.2km^2）で観測された水文気象データを対象として LST モデルを適用し，洪水の実時間予測を行った。LST モデルのパラメータは，差分進化法により同定し，このモデルに粒子フィルターを導入して実時間洪水予測システムを構築した。さらに，1 時間および２時間先の地点観測雨量に正規ノイズを加えて擬似的な降雨の確率分布を生成し，これを同定した LST モデルに入力して将来の流量の確率分布を生成した。その結果，同定された LST モデルは対象流域の長期，短期（洪水期）いずれの降雨－流出関係も精度よく再現し，また，ここで提案した流量の分布予測システムは，１，２時間先の流出を精度よく予測した。以上の結果から，これらの情報は，効果的な洪水警報および洪水防御計画の策定に有用な情報を提供することが示された。

Key words: 実時間洪水予測，長短期流出両用モデル，差分進化法，粒子フィルタ，擬似将来降雨

1. INTRODUCTION

With increased frequency and intensity as well as irregular changes of natural disasters in the recent decades, climate change continues to be one of the key risks affecting natural and human systems across the world (Phuong, 2017; Pachauri & Meyer, 2014). Climate change has largely impacted social, economic, and environmental systems and shaped prospects for sustainable development in most countries (Munasinghe, 2007). In the last few decades, floods have without doubt become one of the most devastating manifestations of climate change on Earth, and every year, extreme floods have severe consequences for the society and mankind in terms of property destruction and loss of lives (Plaza Guingla et al., 2013). A recent increase in damages caused by floods has highlighted the need for significant measures to reduce damages and to protect lives. One of those most significant measures is issuing flood forecasting systems.

Timely and accurate flood forecasting can help in estimating the extent of the eventual flooding and allow safety measures to be taken at an earlier time, thereby reducing the destruction caused by extreme floods as well as assisting the authority in flood rescue operations. Additionally, the provision of flood forecasting and warning system is vital, practical, and promotes the mitigation of flood losses. It is, therefore, a requisite to develop flood forecasting systems that can make predictions as accurately and early as possible during real-time flooding events. To this end, a good forecasting system should be able to probabilistically estimate flood damage, such that effective flood warning and protection planning can be efficiently designed.

In this study, the long- and short-term runoff model (LST model) was applied to analyze flood runoff and long-term runoff successively and used to forecast flood in real-time. Parameters of the LST model were calibrated using the differential evolutionary (DE) technique, and the particle filter (PF) technique was introduced to improve the certainty of hydrological condition. Then, short-term rainfall prediction was conducted by creating pseudo forecasted rainfall with Gaussian distribution, and probabilistic 1- and 2-h ahead flood forecasting was finally performed in real-time using the LST model combined with PF.

2. RESEARCH CATCHMENT AND HYRDOLOGICAL DATA

The research was conducted in Kuroki Dam catchment, which covers an area of 49.2 km^2. The catchment is located upstream of Yoshii River Basin in the north of Okayama Prefecture in Japan. **Fig. 1** is a geographical map of the Kuroki Dam catchment showing the locations of hydro-meteorological stations.

In this study, hydrological data for 11 years from January 1991 to December 2001 were collected at Kuroki dam and five gauging stations (Kurami, Iwabuchi, Daigasen, Aba, and Tsuyama) in and around the catchment. The number of target flood is 22. The collected data include hourly and daily data of discharge and precipitation, and daily maximum and minimum temperature.

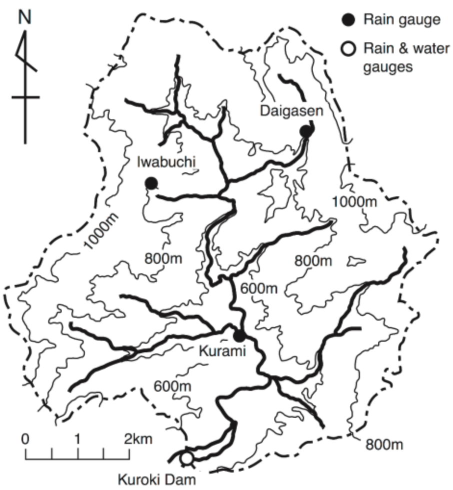

Fig. 1 Kuroki Dam catchment

3. RESEARCH METHODS

3.1 Long- and short-term runoff (LST) model

The LST model, developed by Kadoya and Nagai (1988), was applied to analyze long- and short-term runoff simultaneously and continuously. The LST model consists of three storage tanks arranged in vertical series, and the top tank is composed of upper and lower layers, as shown in **Fig. 2**.

The continuity equation of each tank is as follows:

$$\frac{dS_1}{dt} = r - E_1 - f - Q_1 - Q_2 \qquad \frac{dS_2}{dt} = f - Q_3 - g_1 \qquad (1)$$

$$\frac{dS_3}{dt} = g_1 - E_2 - Q_4 - g_2 \qquad \frac{dS_4}{dt} = g_2 - E_3 - Q_5$$

where S is the water storage depth; r is the rainfall intensity; f is the infiltration rate; g is the percolation rate; and Q is the runoff components in which Q_1 is the surface runoff, Q_2 is the prompt subsurface runoff, Q_3 is the delayed subsurface runoff, Q_4 is prompt groundwater runoff, and Q_5 is delayed groundwater runoff. $E_1 \sim E_3$ are the evapotranspiration rates from each tank, which are calculated as follows:

$$E_1 = \gamma\theta E \qquad E_2 = (1-\gamma)E \qquad E_3 = \gamma(1-\theta)E \qquad (2)$$

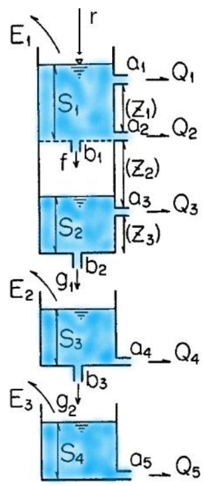

Fig. 2 LST Model

where γ is the separation ratio of evapotranspiration for the upper tank (γ = 0.6); $\theta = 1\ if\ S_1 > 0\ or\ S_2 \geq Z_3$, $\theta = S_2/Z_3\ if\ S_1 = 0$ and $S_2 < Z_3$; E is the actual evapotranspiration.
The actual evaporation, E, is estimated as the sum of the potential evaporation by the following equation:

$$E = \sum_{i=1}^{4} \omega_i\ .\ k_i\ .E_P \qquad (3)$$

where $E_p$is the potential evapotranspiration estimated by the Makkink equation; ω_i is the area ratio of the i-th zone of the four altitudinal zones in the Kuroki Dam catchment; k_i is a factor depending on weather conditions, in which k_i = 1.0 for $r_i = 0$ and $0 \leq k_i < 1.0$ for $r_i > 0$.

Runoff from each hole of the LST model is linearly related to the water storage depth in the respective tank, except for Q_1. The runoff Q_2, Q_3, Q_4, Q_5 and percolation g are calculated by the following equations by assuming that runoff occurs from the holes only when the storage depth of the tank, S, exceeds its corresponding height, Z, i.e., $S > Z$. The surface runoff, Q_1, is assumed to be expressed by Manning's law. Thus, $m = 5/3$ is used in Eq. (4). Each of the abovementioned relations is summarized as follows:

$$Q_1 = a_1(S_1 - Z_1)^m\ , m = 5/3 \qquad Q_2 = a_2 S_1 \qquad Q_3 = a_3(S_2 - Z_3)\ , g_1 = b_2 S_2 \qquad (4)$$

$$Q_4 = a_4 S_3\ , g_2 = b_3 S_3 \qquad Q_5 = a_5 S_4$$

where a_1 is the runoff coefficient; b_1 is the infiltration coefficient: b_2 and b_3 are percolation coefficients; and Z is the height of the runoff holes.

3.2 Differential Evolution (DE) technique

The DE technique, originally developed by Storn and Price (1995), is a very simple stochastic population-based global optimization technique. The DE-flow chart is pictorially represented in **Fig. 3**.

The selection and use of an appropriate and meaningful specific objective function, which is also considered as an efficiency criterion or indicator in this case, is a critical step as it strongly affects the success rate in hydrological modeling calibration using automatic optimization technique and in model performance assessment. In this study, the parameters of the LST model were calibrated using the DE method under the objective functions of mean absolute error (MAE) and Nash-Sutcliffe coefficient of efficiency (NSE), which are used to access the goodness-of-fit of the simulation model to the available observations. MAE and NSE are defined as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Q_{sim,i} - Q_{obs,i}\right| \qquad (5) \qquad\qquad NSE = 1 - \frac{\sum_{i=1}^{N}(Q_{sim,i} - Q_{obs,i})^2}{\sum_{i=1}^{N}(Q_{obs,i} - \overline{Q}_{obs})^2} \qquad (6)$$

MAE = 0 and NSE = 1 indicate that the simulated values completely correspond to observed values.

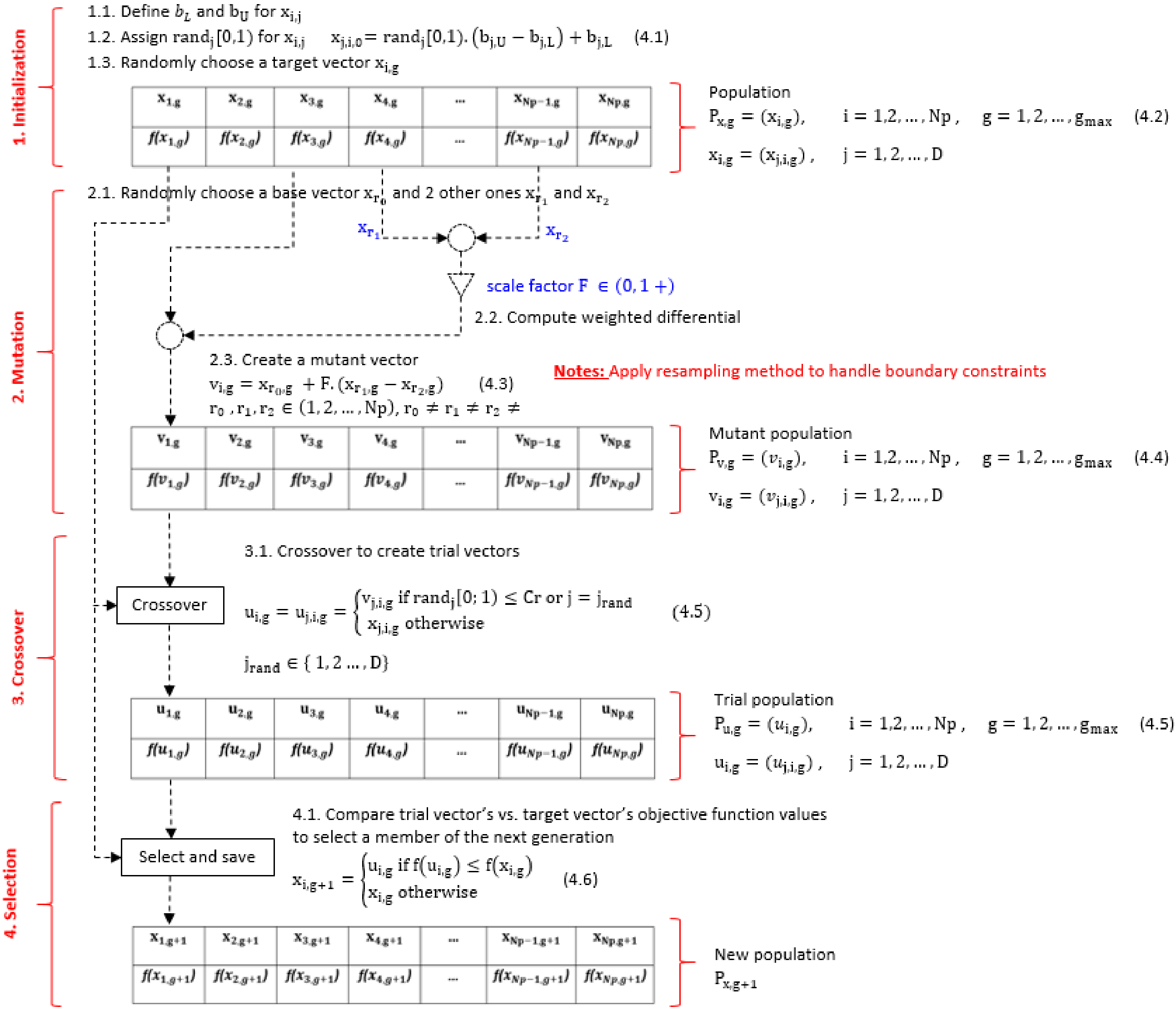

Fig. 3 A flow chart of DE's generate-and-test loop

3.3 Particle filter (PF) technique

A major problem that often occurs in real-time forecasting is the uncertainty quantification (Weerts & El Serafy, 2006). This uncertainty arises due to the oversimplification of the rainfall-runoff process, uncertainties of the model structure and/or model parameters, and the limit of the hydrological information (Nagai, 2003; Kadoya & Tanakaramu, 1989). This uncertainty problem can be efficiently solved by incorporating filtering techniques into a rainfall-runoff model, promoting accurate real-time flood forecasting (Chen et al., 2018, Plaza Guingla et al., 2013). In this research, the system for real-time 1- and 2-h ahead flood runoff forecasting was constructed using the LST model in combination with the PF technique (Gordon et al., 1993). Assuming x as a state variable and y as an observation variable, the procedure of the PF is outlined in the following steps:

Step 1: Randomly generate N initial particles $[x_t^{(i)}]_{i=1}^{N}$ based on the proposed distribution $\pi(x_t|x_{t-1}^{(i)}, y_{0:t})$. The number of particles is selected by the user as a tradeoff between computational effort and estimation accuracy.

Step 2: Prediction: Perform step (2.1) and (2.2) for each particle i

Step 2.1. Obtain the system noise u_t from a known prior density function $p(u_t)$.

Step 2.2. $x_{t-1}|x_{t-1}^{(i)}$ is evolved over time by the state evolutional model $x_{t|t-1} = f_t(x_{t-1}, u_t)$ and $x_t|x_{t-1}^{(i)}$ is obtained.

Step 3: Updating: Assume that observation data y_t is obtained, performing step (3.1) to (3.3) for each particle i

Step 3.1. Compute the likelihood $p(y_t|x_t)$ from $x_t|x_{t-1}^{(i)}$

$$p\left(y_t \middle| x_t | x_{t-1}^{(i)}\right) = \frac{1}{\sqrt{2\pi\sigma_y}} \exp\left(-\frac{E_q^2}{2\sigma_y^2}\right)$$
$$E_q = |Q_{obs,j} - Q_{cal,j}^{(i)}|$$
$$\sigma_y = 0.1 Q_{cal,j}^{(i)}$$

Step 3.2. Use the likelihood density to determine the corresponding importance weight of each particle $w_t^{(i)} = p(y_t | x_t^{(i)})$.

Calculate the total weight $T_w = \sum_{i=1}^{N} w_t^{(i)}$ and then normalize the particle weights as $w_t^{(i)} = T_w^{-1} w_t^{(i)}$

Step 3.3. Resample each particle based on $w_t^{(i)}$ to obtain $[x_{t|t}^{(i)}]_{i=1}^{N}$

Step 3.3.1. Construct the cumulative sum of weights (CSW) by computing $c_i = c_{i-1} + w_t^{(i)}$ with $c_1 = 0$.

Step 3.3.2. Let $i = 1$ and draw a starting point u_i from the uniform distribution $U[0, N^{-1}]$.

Step 3.3.3. For $j = 1,2, \ldots, N$

- Move along the CSW by making $u_j = u_1 + N^{-1}(j-1)$
- While $u_j > c_i$ make $i = i + 1$
- Assign samples: $x_t^j = x_t^i$
- Assign weights: $w_t^j = N^{-1}$
- Assign parents: $i^j = i$

Step 4: Return to step 2 as $t = t + 1$

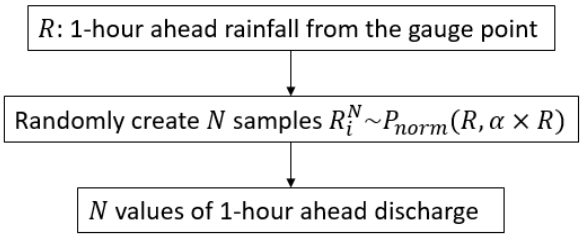

Fig. 4 Formulation of pseudo forecasted rainfall

3.4 Formulation of pseudo forecasted rainfall data

Systems for flood runoff forecasting require short-term prediction of rainfall. A few hours to days ahead online forecasts of rainfall are expected to improve flood forecasting accuracy. However, the Japan Meteorological Agency (JMA) only started providing 1 h to a few days ahead of rainfall forecasting information since June 2019. The record length of online rainfall forecasting by the JMA is not sufficient for assessing the influence of future rainfall prediction uncertainty on the runoff forecast. Additionally, reliable forecasted rainfall information is difficult to acquire. To account for the missing data, we used pseudo forecasted rainfall data created by adding Gaussian noise to 1- and 2-h ahead rainfall data collected from the gauge points in the research catchment instead of real forecasted rainfall information. **Fig. 4** presents a brief description of creating pseudo forecasted rainfall.

Table 1 Optimal model parameters (Kuroki Dam catchment)

PARAMETERS	LOWER BOUND	UPPER BOUND	OPTIMAL PARAMETERS
a1	0.001	0.05	0.0482
a2	0.01	0.1	0.0999
a3	0.001	0.1	0.0263
a4	0.0005	0.02	0.0199
a5	0.00001	0.001	0.0001
b1	0.01	0.02	0.0200
b2	0.001	0.04	0.0399
b3	0.001	0.01	0.0083
Z1	5	200	149.1574
Z2	5	500	499.6221
Z3	5	200	198.4917
S1	0	20	3.8738
S2	0	200	124.7907
S3	0	1000	204.1633
S4	0	1000	970.3223

Table 2 Accuracy of runoff simulation using LST model with and without particle filter

	MAE		NSE (%)	
	LT (mm/d)	ST (m3/s)	LT	ST
LST	3.93	4.17	75.40	71.34
LST + Particle filter	0.59	0.33	99.36	99.54

4. RESULTS AND DISCUSSION

4.1 Runoff simulation by LST model

The unknown parameters of the LST model were calibrated via DE to optimize the objective function. MAE and the NSE were used as objective functions for minimization and maximization, respectively. Optimal parameters of the LST model and the error of daily and flood runoff are shown in **Table 1**. When the LST model was optimized by minimizing MAE, the daily runoff error was 3.93 mm/d on average for 11 years. When optimized by maximizing NSE, it was 75.40% (see **Table 2**). Two examples of simulated daily runoff are presented in **Fig. 5**. The simulated hydrographs and results of MAE and NSE indicate that the calculated daily runoff well agrees with the observed one. Hence, the optimized LST models can be considered to show good performance in long-term runoff simulation.

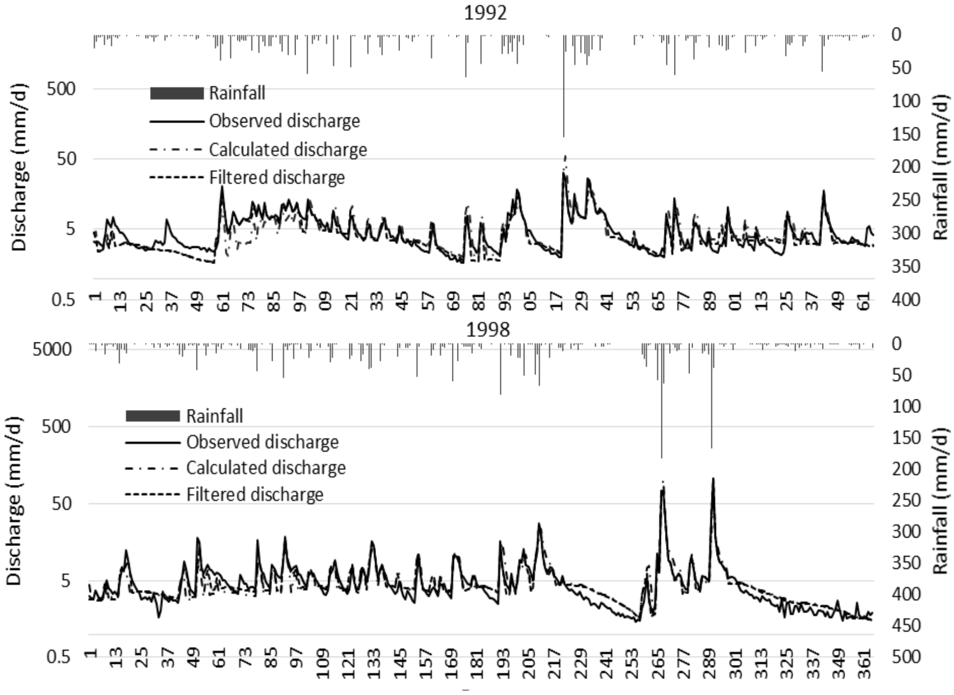

Fig. 5 Examples of simulated daily runoff by the LST model with particle filter

Fig. 6 shows that the calculated flood runoff hydrographs during four floods, which shows that the calculated runoff well simulates the observed runoff. The MAE and NSE in every 1-h discharge for 22 floods shown in **Table 2** were 4.17 m^3/s and 71.34%, respectively. Thus, the LST model also simulated the flood runoff suitably. The results clearly indicate that the LST model simulated both long- and short-term runoff with good accuracy.

4.2 Runoff simulation by LST model with updating by particle filter

As the abovementioned results show that the identified runoff model has good applicability in the Kuroki Dam catchment, the existing difference between the calculated and observed discharge can be mainly attributed to the estimation of the areal average rainfall. The rainfall estimation error is believed to influence the storage depth of the top tank, particularly the upper layer's storage, S_1, of the top tank that dominantly controls flood runoff. S_1, therefore, is considered to be the state variable in this research. With the application of the particle filter to storage depth in the upper layer of the top tank, the simulation accuracy of the model can be expected to be significantly improved in the short-term runoff. This improvement is shown in **Table 2,** in which MAE is decreased to 0.59 mm/d and NSE is increased to 99.36% in the case of the daily runoff, and 0.33 m^3/s and 99.54%, respectively, in the case of flood runoff.

Figs. 5 and **6** show the good agreement between calculated and observed discharge for both daily and flood runoff, which proves that the combination of the LST model and particle filter can be used for real-time flood forecasting.

4.3 Statistical forecast of discharge considering rainfall forecast uncertainty and updating by particle filter

While planning countermeasures against flood disasters, the uncertainty of discharge forecasting should be evaluated because it is strongly related to the security of our society. The uncertainty related to discharge forecasting is considered to mainly arise from the uncertainty in rainfall forecasting. The influence of rainfall-runoff modeling, which is another important factor in the uncertainty of discharge forecasting, has been already minimized by optimization of the rainfall-runoff model using the DE technique. The uncertainty is inevitable in forecasting, although the accuracy of the forecasted rainfall is essentially important for real-time flood forecasting. Therefore, we here discuss the influence of uncertainty in rainfall forecasting on discharge forecasting.

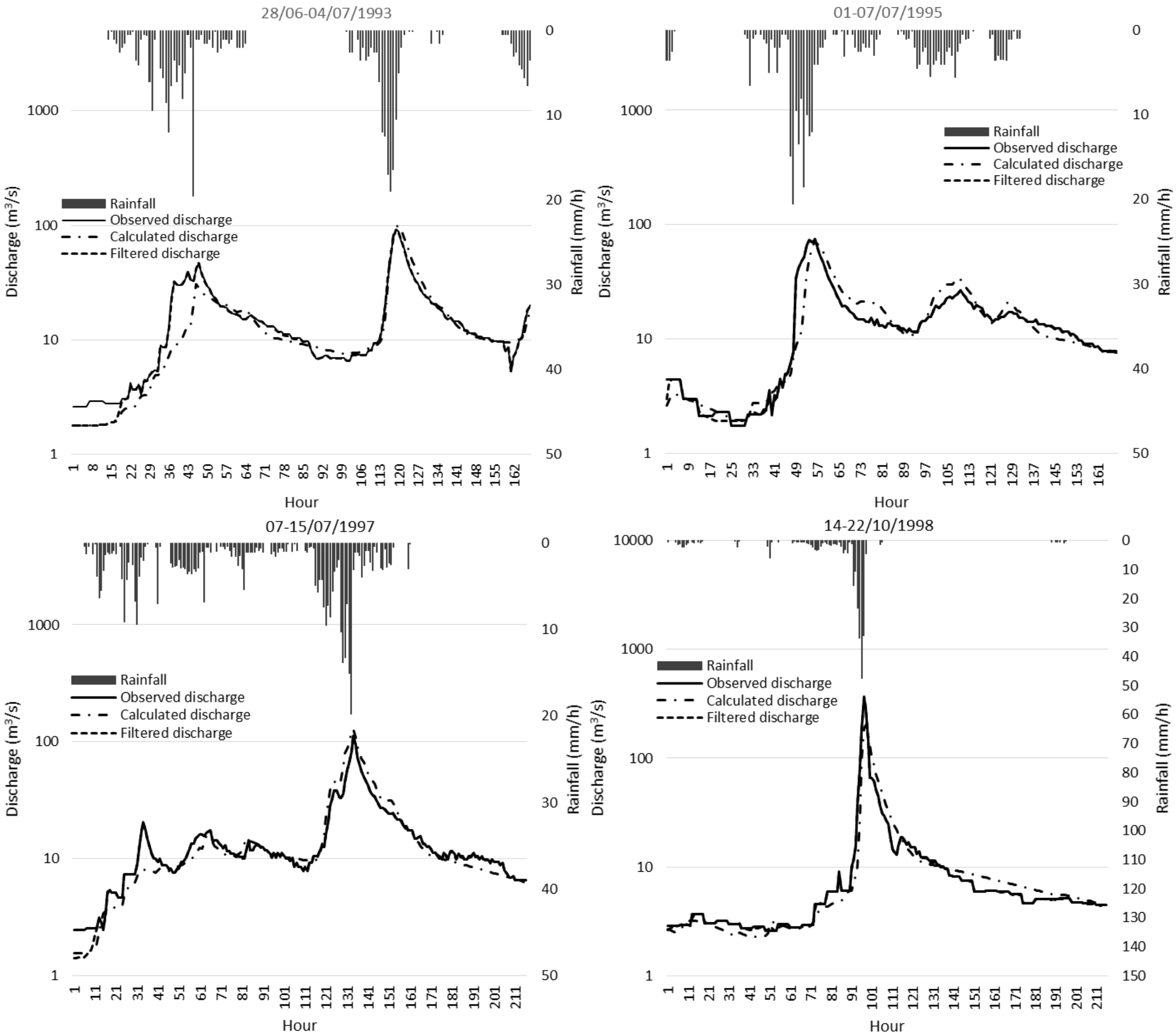

Fig. 6 Examples of simulated flood runoff by the LST with particle filter

The JMA started to deliver 1 h to a few days ahead of rainfall forecasting information in June 2019. This record length is not yet sufficient for use and it is not easy to obtain a reliable record of real-time rainfall information. Additionally, if reliable probabilistic information of future discharge is available, the alert level of flood can be set by considering the exceedance probability of forecasted water levels, which is expected to be used as valuable information for effective flood management. A method for creating pseudo forecasted rainfall data was, therefore, applied to overcome this issue. Instead of using real forecasted rainfall information, we used pseudo forecasted rainfall data created by adding Gaussian noise to the 1- and 2-h ahead future rainfall data collected from gauge points in and around the research catchment. In this research the standard deviation of the rainfall noise was selected as 10% of the future observed rainfall values and all the negative pseudo forecasted rainfall generated from this method were replaced by 0. An example of the distribution of the pseudo forecasted rainfall and the corresponding forecasted discharges are depicted in **Fig. 7**. With the method of creating pseudo forecasted rainfall, a corresponding distribution of forecasted discharges could be obtained. The distribution of forecasted discharge is a significant solution to deal with the problem of forecast uncertainty. It can be used to probabilistically estimate flood risk, thereby supporting efficient real-time flood warning and protection plans.

Next, the mean of all the forecasted discharges was selected as the output for the flood forecasting and compared with the observed discharge obtained from Kuroki dam to assess the accuracy of the proposed forecasting system. **Fig. 8** presents examples of the results for 1- and 2-h ahead flood forecasting in Kuroki Dam catchment. The hydrographs show that the proposed forecasting method provides remarkably accurate estimations of flood runoff forecasting. The accuracy of flood forecasting is expressed by the Normalized Root-Mean-Squared Error (NRMSE) (given by Eq. 7), which is a measure of errors widely used to assess the forecasting accuracy when comparing with observed values.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(Q_{obs}-Q_{forcasted})^2}{T}} \qquad NRMSE = \frac{RMSE}{Q_{obs}^{max}-Q_{obs}^{min}} \tag{7}$$

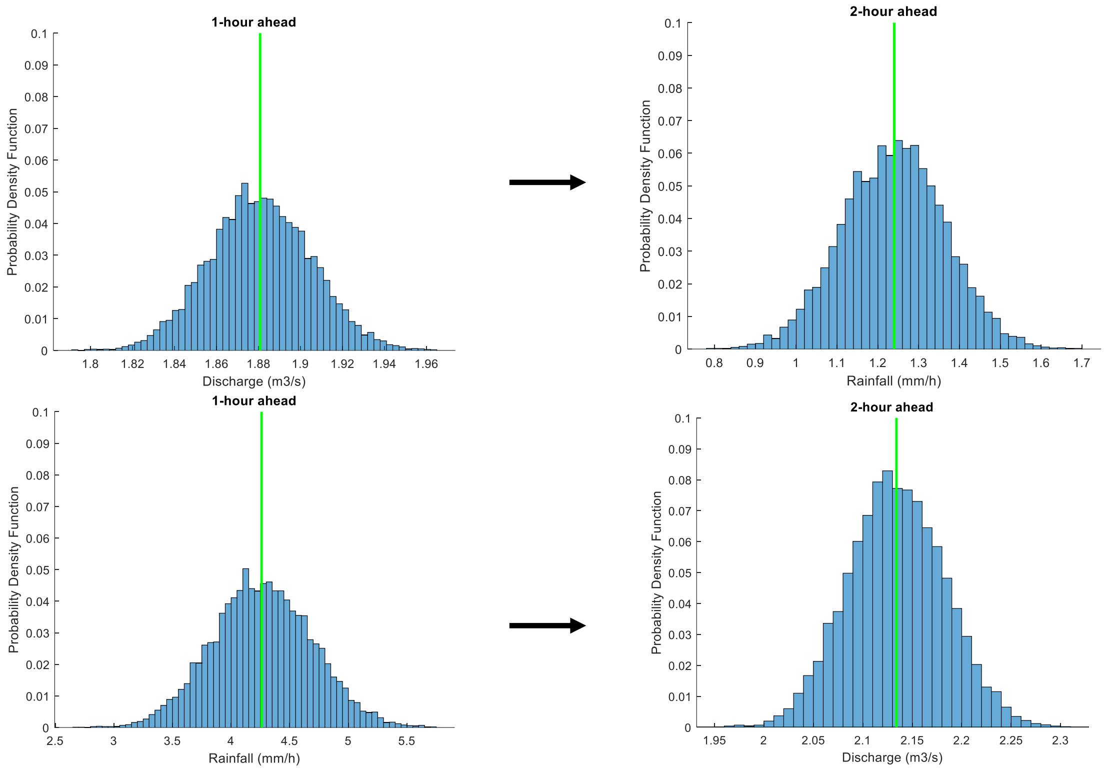

Fig. 7 Example of distribution of pseudo1-h and 2-h forecasted rainfall and corresponding forecasted runoff

Table 3 Improvement of forecasting accuracy by filtering

Forecasting method	NRMSE (%)	
	1-h ahead	2-h ahead
No filter	9.98	11.10
Particle filter	5.05	7.40

The comparison between observed and forecasted discharge is shown in **Fig. 9** for all floods, in which the errors of 1- and 2-h ahead forecasting are 5.05% and 7.40%, respectively. NRMSE appears to increase with increasing hours ahead of the flood forecasting, but it remained within an acceptable range. Flood runoff was also forecasted without updating (no filter) and the results are presented in **Table 3**. It can be seen that application of PF significantly improves the NRMSE. From the results, it is concluded that by introducing the filtering technique (particle filter) to the LST model and applying a suitable method of rainfall prediction, the 1-h and 2-h ahead flood can be accurately forecasted.

In this research, we used the pseudo probabilistic distribution of rainfall based on the observed rainfall to consider probabilistic forecasting of future discharge. If more reliable probabilistic information of future forecasted rainfall is available, real-time probabilistic discharge forecasting is expected to provide more valuable information to for reducing flood damage.

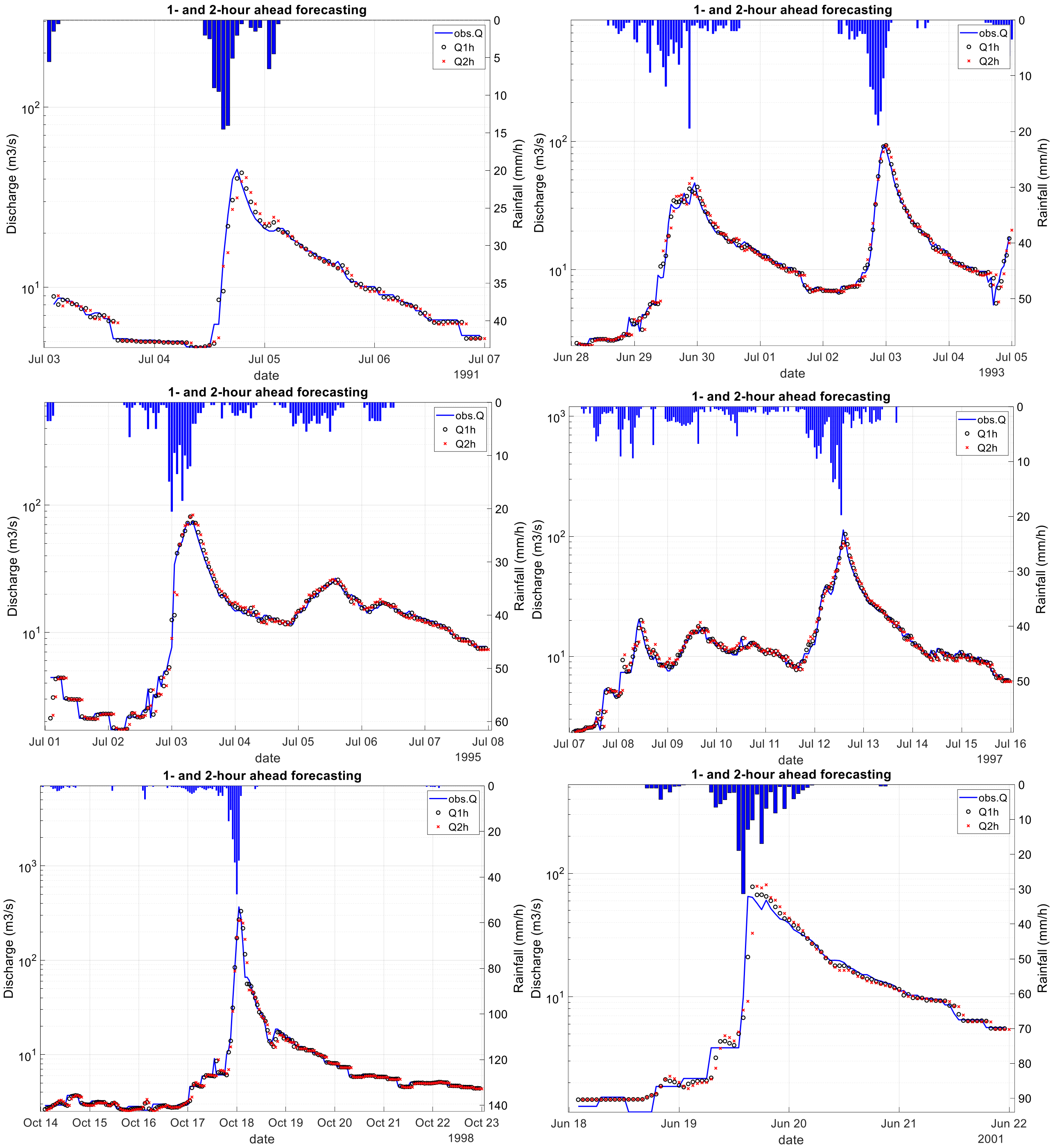

Fig. 8 Examples of real-time flood forecasting (1- and 2-h ahead)

5. CONCLUSION

In this study, the LST model was applied to hydrological data (1991–2001) in the Kuroki Dam catchment (49.2 km^2). Some conclusions can be drawn as follows:

(1) The LST model calibrated by the differential evolution technique can simulate both long-term and flood runoff (short-term runoff) successively with good accuracy. The applicability of the model was tested through continuous simulation for 11 years and for 22 floods.

(2) Using the method of creating pseudo forecasted rainfall, a distribution of forecasted discharge values can be obtained. It can be used for probabilistic estimation of flood risk that is expected for application to real-time flood warning and protection planning.

(3) The proposed forecasting system including the LST model combined with particle filter and using the method of creating pseudo forecasted rainfall provided accurate 1- and 2-h ahead flood runoff forecasts.

More reliable probabilistic information of future forecasted rainfall can be obtained, more valuable information for mitigating flood damage can be acquired by using generated real-time probabilistic discharge forecasting. Hence, future research on efficient methods to probabilistically forecast rainfall data is expected.

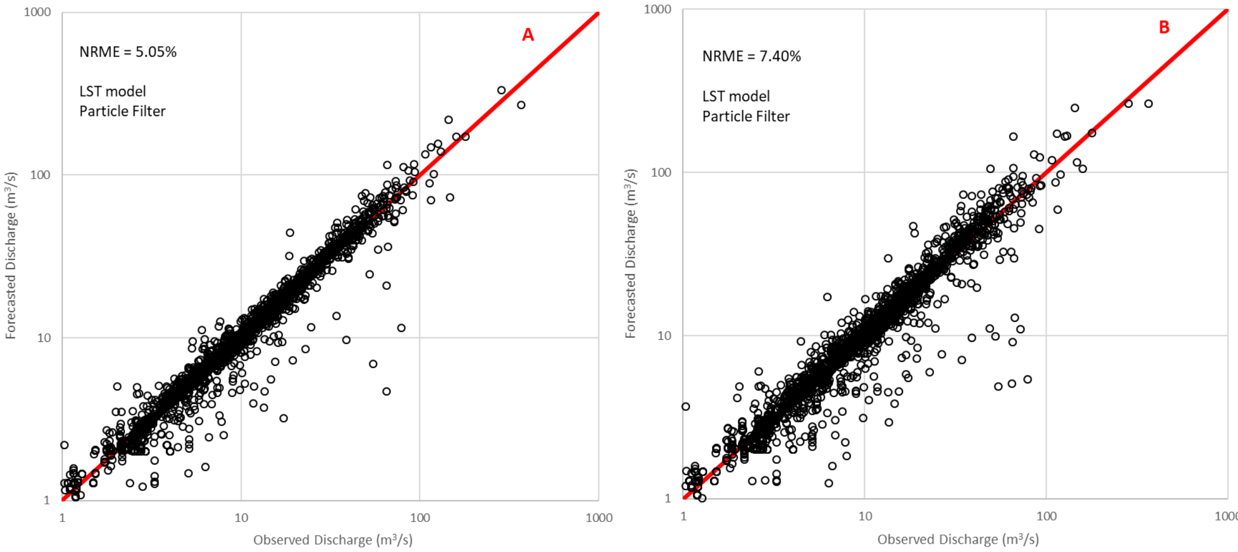

Fig. 9 Comparison between observed and forecasted discharge for all floods (1- and 2-h ahead forecasting)

ACKNOWLEDGEMENTS: The authors gratefully acknowledge the support of the management office in Kuroki Dam (Okayama Prefecture, Japan) for collecting the research data.

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