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Article

Grey Forecast Rainfall with Flow Updating Algorithm for Real-Time Flood Forecasting

Jui-Yi Ho [1] and Kwan Tun Lee [1,2,*]

[1] Hydrotech Division, Taiwan Typhoon and Flood Research Institute, National Applied Research Laboratories, 11F., No. 97, Sec. 1, Roosevelt Rd., Taipei City 10093, Taiwan; E-Mail: juiyiho@narlabs.org.tw

[2] Department of River and Harbor Engineering, National Taiwan Ocean University, No 2, Beining Rd., Keelung City 20224, Taiwan

* Author to whom correspondence should be addressed; E-Mail: ktlee@ntou.edu.tw; Tel.: +886-2-2462-2192 (ext. 6121); Fax: +886-2-2463-4122.

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Abstract: The dynamic relationship between watershed characteristics and rainfall-runoff has been widely studied in recent decades. Since watershed rainfall-runoff is a non-stationary process, most deterministic flood forecasting approaches are ineffective without the assistance of adaptive algorithms. The purpose of this paper is to propose an effective flow forecasting system that integrates a rainfall forecasting model, watershed runoff model, and real-time updating algorithm. This study adopted a grey rainfall forecasting technique, based on existing hourly rainfall data. A geomorphology-based runoff model can be used for simulating impacts of the changing geo-climatic conditions on the hydrologic response of unsteady and non-linear watershed system, and flow updating algorithm were combined to estimate watershed runoff according to measured flow data. The proposed flood forecasting system was applied to three watersheds; one in the United States and two in Northern Taiwan. Four sets of rainfall-runoff simulations were performed to test the accuracy of the proposed flow forecasting technique. The results indicated that the forecast and observed hydrographs are in good agreement for all three watersheds. The proposed flow forecasting system could assist authorities in minimizing loss of life and property during flood events.

Keywords: rainfall forecasting; flow forecasting; grey theory; geomorphology-based runoff model; flow updating algorithm

1. Introduction

Flood forecasting systems are nonstructural methods for reducing flood damage. An efficient forecasting system can assist with mitigating imminent disasters by providing information that can be disseminated rapidly to the flood-threatened areas. Standard practices in flood forecasting systems include hydrometeorological data transmission, database management, rainfall prediction, runoff estimation, and forecast information dissemination.

Brath *et al.* [1] indicated that quantitative rainfall forecasting plays a primary role in extending the lead time of river flow forecasting, which can improve the timeliness of flood control mechanisms. Because of improvements in the accuracy of weather radar systems, radar-based rainfall forecasting systems have superseded traditional rain gauges that provide measurements at only several locations for flood forecasting [2–4]. Toth *et al.* [5] indicated that radar detection is particularly difficult in mountainous regions because of the effect of ground occultation and altitude. Consequently, radar-based measurement techniques are limited under topographic conditions where radar reflectivity is poor [6,7]. Thus, hydrologists typically use probabilistic and stochastic methods for rainfall forecasting based on current and past rainfall measurements (e.g., [8–13]). Because these methods typically require large volumes of rainfall data for calibrating and training the model parameters, Deng [14] proposed a grey system theory-based model for future data prediction. Moreover, grey theory-based models require relatively few observations to predict outcomes [15–17]; thus, they are suitable for rainfall forecasting.

Rainfall forecasts are inputted into rainfall-runoff models to provide flood warning information for authorities. In recent decades, artificial neural networks (ANNs) have become a well-known tool for hydrologic forecasting [18–29]. However, ANNs require a large amount of hydrologic data to determine the adaptive weights, which are inadequate to be applied to data-sparse areas. Although fully distributed grid-based routing models can provide detailed information on flood wave transports, they may be unsuitable for real-time flood forecasting systems because the simulation process is typically time-consuming [30]. Hence, lumped and semi-distributed hydrological models are acceptable practical alternatives. For example, the Sacramento model was adopted by the National Weather Service River Forecast System in the United States [31,32], the tank model has been widely applied for runoff forecasting in Japan [33], the Hydrologiska Byråns Vattenbalansavdelning (HBV) model was adopted in Europe [34], and the Xinanjiang model was introduced in China [35]. To further minimize the requirement of observed flow data to develop semi-distributed models, hydrologists have adopted geomorphology-based runoff models [36–40].

Rodriguez-Iturbe and Valdes [35] proposed the geomorphologic instantaneous unit hydrograph (GIUH) model, which can be employed to derive the instantaneous unit hydrograph (IUH) of a watershed based on information from a topographic map or digital elevation data set. Subsequent studies have modified the GIUH model by incorporating kinematic-wave approximation, thereby providing reasonable estimations of flow velocity, which augments rainfall-runoff simulation used in both gauged and ungauged sites [41–43].

It is necessary to implement the effective data assimilation in the forecast process to bridge the immense gap between the theory and operational practice [44]. Comprehensive reviews of data assimilation approaches in operational hydrologic forecasting were presented by Liu *et al.* [45]. Since uncertainty is an inherent characteristic of watershed hydrodynamics, an ideal flood forecasting system should incorporate a real-time updating algorithm that revises the model state to improve the forecasting accuracy. Refsgaard [46] reported that techniques for updating real-time forecasting can be classified into the following four categories: (1) updating input variables; (2) updating state variables; (3) updating model parameters; and (4) updating output variables (*i.e.*, error prediction). Previous studies have developed updating techniques based on time-series analysis [47,48], statistical methods [17,49], multiple regression analysis [50], dimensional variational algorithms [51,52], and the filter approaches [53–58]. Selection of an appropriate updating algorithm depends on the availability of real-time feedback data and the structure of the rainfall-runoff model employed for flow forecasting.

The purpose of this study is to develop an effective flood forecasting system for midsize rural watersheds. We adopted the grey rainfall forecasting technique based on existing hourly rainfall data to avoid poor radar reflectivity in mountainous watersheds. In performing the watershed runoff simulation, a geomorphology-based runoff model which can account different geomorphologic and hydrological characteristics of the watershed was used in this study. Furthermore, a flow updating algorithm was linked to the runoff model to estimate watershed runoff in the next three hours. The proposed flow forecasting system can operate with high efficiency to meet the requirements of real-time flow forecasting. The system was applied to three watersheds; one in the United States (Goodwin Creek) and two in Northern Taiwan (Heng-Chi and San-Hsia). The results of the flood forecasting were compared with official records to confirm the validity of the proposed system. In the following sections, Section 2 describes the analytical methods including the short-term rainfall forecasting and the geomorphology-based runoff model with an updating algorithm. The application of the proposed methods and the forecast results are presented in Section 3. Section 4 summarizes the conclusions of this study.

2. Analytical Methods

The framework of the proposed flood forecasting system incorporates a grey rainfall forecasting model [14], kinematic-wave-based GIUH (KW-GIUH) model [36], and flow updating algorithm that is linked to the KW-GIUH model to improve the flow forecasting accuracy.

2.1. Short-Term Rainfall Forecasting

The grey rainfall forecasting is adopted herein for two reasons: (1) a short-term rainstorm system is too complex to be simulated by using deterministic approaches; (2) the grey system provides an efficient way for rainfall prediction using only small amount of past observed rainfall data. Consequently, the grey model proposed by Deng [14] is appropriate for the present system for rainfall forecasting.

Although hydrological time-series data typically exhibit random forms, a systematic trend can be observed after a repeatedly accumulated generating operations (AGO). According to the AGO concept, Deng [14] developed an effective method for predicting future data based on a limited number of observations. A series of raw rainfall data can be expressed as follows:

$$R^{(0)}(t) = \left[r^{(0)}(1),\ r^{(0)}(2),\ \ldots, r^{(0)}(k)\ ,\ldots,\ r^{(0)}(n) \right] \tag{1}$$

where $R^{(0)}(t)$ denotes the raw time-series rainfall data set, and $r^{(0)}(k)$ is the *k*th observed rainfall. The first-order AGO series can be defined as [14]:

$$R^{(1)}(t) = \sum_{k=1}^{t} r^{(0)}(k)\ ;\ t = 1,\ 2,\ 3,\ \ldots, n \tag{2}$$

where $R^{(1)}(t)$ is the first-order AGO rainfall time series, and $r^{(1)}(t)$ is the first-order AGO observed rainfall data at time *t*. A first-order differential equation is employed to fit the cumulative rainfall data, which can be expressed as:

$$\frac{dR^{(1)}(t)}{dt} + aR^{(1)}(t) = b \tag{3}$$

where a and b are the grey system model parameters. Deng [14] indicated that the whitening of the grey derivatives of discrete data with unit time intervals can be expressed as:

$$\left. \frac{dR^{(1)}(t)}{dt} \right|_{t=k} = r^{(1)}(k) - r^{(1)}(k-1) = R^{(0)}(k) \tag{4}$$

The whitening value of $R^{(1)}(t)\big|_{t=k}$ is defined as:

$$Z^{(1)}(k) = R^{(1)}(t)\big|_{t=k} \cong \frac{1}{2}\left(r^{(1)}(k) + r^{(1)}(k-1) \right), \quad \forall k = 2,\ 3,\ \ldots\ ,\ t \tag{5}$$

where $Z^{(1)}(k)$ denotes the whitening value of $R^{(1)}(t)\big|_{t=k}$. Next, Equations (4) and (5) are substituted into Equation (3) to obtain a grey discrete differential form as:

$$R^{(0)}(k) + a \cdot Z^{(1)}(k) = b \tag{6}$$

The grey parameters *a* and *b* can be estimated using the least square method. Thus, the solution of Equation (6) is expressed as:

$$\hat{r}^{(1)}(k + \Delta t) = \left(r^{(0)}(k) - \frac{b}{a} \right) e^{-ak} + \frac{b}{a} \tag{7}$$

where $\hat{r}^{(1)}(k+1)$ is the forecast value of the first-order AGO series. Consequently, the rainfall depth at the subsequent time step can be obtained from the equation:

$$\hat{r}^{(0)}(k + \Delta t) = \hat{r}^{(1)}(k + \Delta t) - \hat{r}^{(1)}(k),\ \ \forall k = 1,\ 2,\ 3,\ \ldots\ ,\ n \in N \tag{8}$$

where $\hat{r}^{(0)}(k + \Delta t)$ is the forecast rainfall depth at time $k + \Delta t$. The grey parameters in Equation (7) are updated when the new observed rainfall data are obtained. Yu *et al.* [17] indicated that the accuracy of rainfall forecasting decreases when the lead time is increased because the forecast error is cumulated from previous lead-time forecasting. Consequently, an algorithm called single-time-step forecasting proposed by Yu *et al.* [17] was used to overcome the shortcoming.

Several studies have successfully applied the first-order grey model for hydrological forecasting [14–17]. Because forecast errors are cumulative, grey forecasting models become less reliable as the forecast lead time increases. However, when a grey rainfall forecasting model is combined with a watershed rainfall-runoff model, the forecast lead time can be extended because of the time lag in the transporting of a flood wave from upstream to downstream.

This study adopted four criteria to evaluate the performance of the grey rainfall forecasting model. First, the error of total cumulative rainfall (*ETCR*) is defined as:

$$ETCR = \frac{\left| \sum_{t=1}^{n} r_t - \sum_{t=1}^{n} \hat{r}_t \right|}{\sum_{t=1}^{n} r_t} \tag{9}$$

where $\hat{r}_t$ is the forecast rainfall at time t; r_t denotes the observed rainfall at time t; and n represents the number of time steps to be estimated. A more accurate forecast can be obtained when *ETCR* is approximately zero. Second, the relative root mean square error (*RMSE*) is defined as:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} \left[\left(R_t - \hat{R}_t \right) / R_t \right]^2}{n}} \tag{10}$$

where R_t denotes the observed cumulative rainfall at time t; $\hat{R}_t$ is the forecast cumulative rainfall at time t. A more accurate forecast can be obtained when *RMSE* is approximately zero. Third, the coefficient of efficiency (*CE*) is defined as [56]:

$$CE = 1 - \frac{\sum_{t=1}^{n} \left(R_t - \hat{R}_t \right)^2}{\sum_{t=1}^{n} \left(R_t - \overline{R} \right)^2} \tag{11}$$

$\overline{R}$ represents the mean of the observed cumulative rainfall. A more accurate fit between the forecast rainfall and the observed rainfall can be obtained when *CE* is approximately one. Moreover, the coefficient of correlation (*CC*) is defined as:

$$CC = \frac{\sum_{t=1}^{n} \left(R_t - \hat{R}_t \right) \left(\hat{R}_t - \overline{\hat{R}} \right)}{\sqrt{\sum_{t=1}^{n} \left(R_t - \overline{R} \right)^2 \cdot \sum_{t=1}^{n} \left(\hat{R}_t - \overline{\hat{R}} \right)^2}} \tag{12}$$

where $\overline{\hat{R}}$ is the mean of the forecast cumulative rainfall at time t. A more accurate forecast can be obtained when the value of *CC* is approximately one. The *ETCR* and *RMSE* represent a quantitative judgment of model performance. The *CE* is used to measure the similarity between the predicted and observed accumulated rainfall. The *CC* is used to measure the correlative relationship between the predicted and observed accumulative rainfall.

2.2. Geomorphology-Based Runoff Model with an Updating Algorithm

This study adopted an IUH model to provide an efficient method for estimating watershed runoff. The KW-GIUH model [36] was used because the IUH can be derived only by using watershed geomorphologic information obtained from a topographic map or digital elevation dataset. The hydrological response function of the watershed can be expressed analytically as follows [35]:

$$u(t) = \sum_{w \in W} \left[f_{x_{o_i}}(t) * f_{x_i}(t) * f_{x_j}(t) * \ldots * f_{x_\Omega}(t) \right]_w \cdot P(w) \tag{13}$$

where $u(t)$ is the IUH of the watershed; W is the flow path space, which is expressed as $W = \langle x_{o_i}, x_i, x_j, \ldots, x_\Omega \rangle$; $f_{x_{oi}}(t)$ denotes the travel time probability density function in state x_j with a mean value of T_{x_j}; $*$ denotes a convolution integral; and $P(w)$ represents the probability of a raindrop adopting a flow path w.

Kinematic-wave approximation can be employed to express the runoff travel time for the *i*th-order surface flow region as follows [59]:

$$T_{x_{o_i}} = \left(\frac{n_o \bar{L}_{o_i}}{\bar{S}_{o_i}^{1/2} i_e^{m-1}} \right)^{\frac{1}{m}} \tag{14}$$

where n_o is the overland-flow roughness coefficient; $\bar{L}_{o_i}$ denotes the mean *i*th-order overland length; $\bar{S}_{o_i}$ is the mean *i*th-order overland slope; i_e represents the effective rainfall intensity; and m is an exponent recognized as 5/3 in Manning's formula. The runoff travel time for the *i*th-other channel is expressed as follows [36]:

$$T_{x_i} = \frac{B_i}{2 i_e \bar{L}_{o_i}} \left[\left(h_{co_i}^m + \frac{2 i_e n_c \bar{L}_{o_i} \bar{L}_{c_i}}{\bar{S}_{c_i}^{1/2} B_i} \right)^{\frac{1}{m}} - h_{co_i} \right] \tag{15}$$

where B_i is the *i*th-order channel width; n_c represents the channel roughness coefficient; $\bar{L}_{c_i}$ is the mean *i*th-order channel length; $\bar{S}_{c_i}$ denotes the mean *i*th-order channel slope; and h_{co_i} is the inflow depth of the *i*th-order channel caused by water transporting from upstream reaches. Hence, the runoff travel times for different orders of overland-flow paths and channels can be estimated, and the watershed IUH can then be derived by using Equation (13). Consequently, the watershed runoff simulated by using KW-GIUH model can be expressed as:

$$Q_{sim,t} = \int_0^\tau i(\tau) u(t-\tau) d\tau \tag{16}$$

where $Q_{sim,t}$ is the simulated direct runoff at time *t*; $i(\tau)$ is the rainfall intensity; and $u(t-\tau)$ is the unit impulse response function derived from the KW-GIUH model.

Uncertainty is an inherent hydrodynamic characteristic of watershed; therefore, this study adopted a real-time updating algorithm to improve the accuracy of flow forecasting. The change in measured discharge between time *t* and $t + \Delta t$ can be expressed as:

$$\Delta Q_{rec} = Q_{rec,\ t+\Delta t} - Q_{rec,\ t} \tag{17}$$

where $Q_{rec,\ t}$ and $Q_{rec,\ t+\Delta t}$ denote the measured discharges at time *t* and $t+\Delta t$, respectively; and ΔQ_{rec} represents the change in measured discharge between time *t* and $t+\Delta t$. Assuming that a reliable runoff model is used and short-term rainfall forecasting data (*i.e.*, with a lead time of several hours) are available, the value of ΔQ_{rec} in Equation (17) is assumed equal to the change in simulated discharge between time *t* and $t+\Delta t$; this is illustrated as follows:

$$\Delta Q_{rec} = \Delta Q_{sim} = Q_{sim,\ t+\Delta t} - Q_{sim,\ t} \tag{18}$$

where $Q_{sim,\ t}$ and $Q_{sim,\ t+\Delta t}$ denote the simulated discharges at time *t* and $t+\Delta t$, respectively; and ΔQ_{sim} represents the change in simulated discharge between time *t* and $t+\Delta t$. Consequently, the forecast discharge at time *t* can be approximated by:

$$\begin{aligned} Q_{fore,\ t+\Delta t} &= Q_{rec,\ t} + \Delta Q_{rec} \\ &\cong Q_{rec,\ t} + \Delta Q_{sim} \end{aligned} \tag{19}$$

where $Q_{fore,\ t+\Delta t}$ is the forecast discharge at time $t+\Delta t$ and ΔQ_{sim} is obtained from Equation (18). The schematic of the updating algorithm is shown in Figure 1. In the case that the real-time measured discharge $Q_{rec,t}$ cannot be transmitted successfully through the telemetric system during the rainstorm, the forecast discharge at time $t+\Delta t$ ($Q_{fore,\ t+\Delta t}$) is replaced by the model generated runoff discharge ($Q_{\mathrm{sim},\ t+\Delta t}$) without using the updating techniques. Although the proposed updating algorithm is simple, it is an efficient method for watershed runoff forecasting.

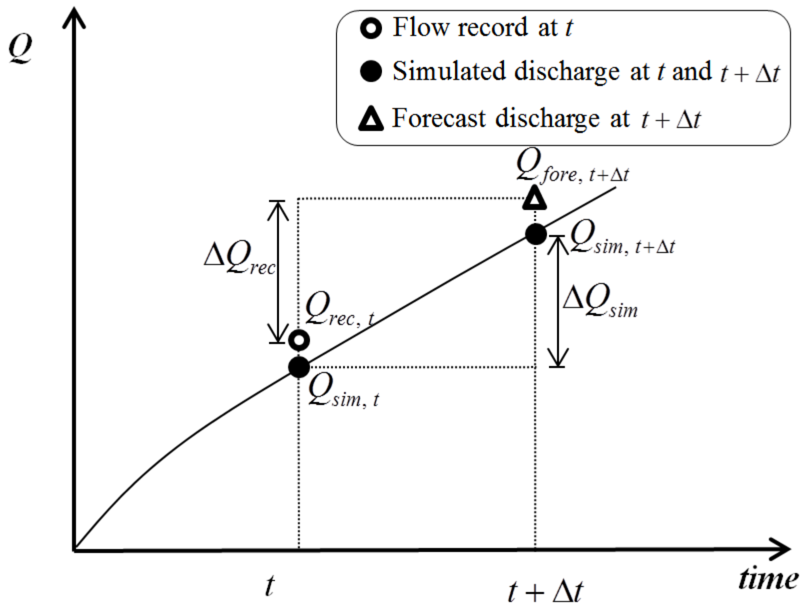


Figure 1. Schematic of the updating algorithm.

To evaluate the suitability of the KW-GIUH model, two criteria were chosen to determine the goodness-of-fit between the observed and simulated flow hydrographs. The coefficient of efficiency CE_Q is defined as follows [60]:

$$CE_Q = 1 - \frac{\sum_{t=1}^{n}\left(Q_{rec}(t) - Q_{fore}(t)\right)^2}{\sum_{t=1}^{n}\left(Q_{rec}(t) - \overline{Q}_{rec}\right)^2} \tag{20}$$

where $Q_{rec}(t)$ and $Q_{fore}(t)$ denote the recorded and forecast discharges at time *t*, respectively; $\overline{Q}_{rec}$ is the mean recorded discharge during a storm event, and *n* is the number of discharge records during the storm event. The CE_Q is used to measure the similarity between the predicted and observed discharge hydrographs. A more accurate fit is obtained when the value of CE_Q is approximately one. The peak discharge error is defined as follows:

$$EQ_P(\%) = \frac{\left|(Q_P)_{fore} - (Q_P)_{rec}\right|}{(Q_P)_{rec}} \times 100 \tag{21}$$

where $(Q_P)_{fore}$ is the forecast peak discharge, and $(Q_P)_{rec}$ denotes the recorded peak discharge. The EQ_P is used to measure the error of peak discharge directly. The error of time to peak discharge, ET_P, is defined as:

$$ET_P = (T_P)_{fore} - (T_P)_{rec} \tag{22}$$

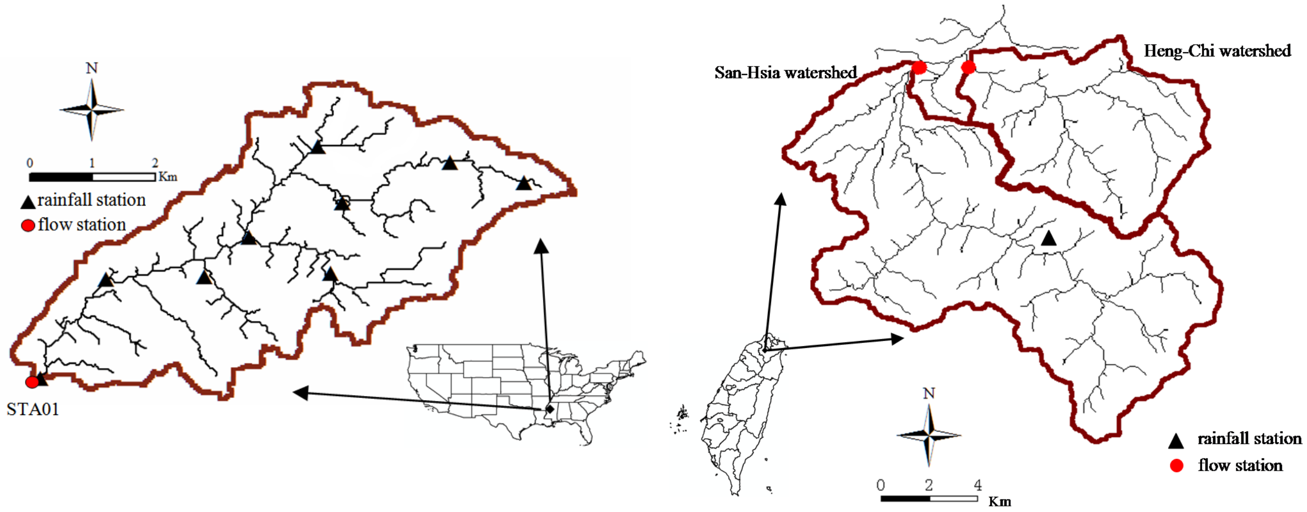
where $(T_P)_{fore}$ and $(T_P)_{rec}$ are the forecast and recorded time to peak discharge, respectively.

3. Model Applications

3.1. Description of Study Watersheds

Three watersheds were selected to investigate the applicability of the proposed model; one in the United States (Goodwin Creek) and two in Northern Taiwan (Heng-Chi and San-Hsia). Goodwin Creek is a tributary of Long Creek that flows into the Yocona River, which is one of the main rivers of the Yazoo River Basin. Figure 2a shows the watershed stream network and locations of hydrological gauging stations. The terrain elevation of the Goodwin Creek watershed ranges from 71 to 128 m above sea level (mean). The land area is composed of cultivated land (13.79%), forests (26.00%), pastures (59.80%), and water (0.41%). The climate of the Goodwin Creek watershed is humid with hot temperatures during summer and mild temperatures during winter. The mean annual temperature and rainfall are approximately 17 °C and 1399 mm, respectively. Most of the rainfall occurs during winter and spring. Hydrological data were obtained from the Agricultural Research Service of the United States Department of Agriculture. Among the 32 rain-gauging stations in the area, this study obtained rainfall records from nine stations. The Thiessen polygons method [61] was employed to calculate the hourly spatial-average rainfall intensities. Fourteen flow gauging stations were set up in the Goodwin Creek watershed area. The control areas of the flow gauging stations ranged from 0.06 to 21.39 km^2. In this study, Flow-gauging Station No.1 (STA01), which has a drainage area of 21.39 km^2, was selected as the test site to verify the model.

The Heng-Chi and San-Hsia watersheds are subwatersheds in Ta-Han Creek, which is one of the main rivers of the Tam-Sui River Basin in Northern Taiwan. Figure 2b shows the watershed stream networks and locations of the hydrological gauging stations. The elevation of the Heng-Chi (San-Hsia) watershed ranges from 20 to 970 m (30 to 1770 m), and the land is composed of 70% (75%) forest, 25% (20%) cultivated land, and 5% (5%) buildings/road. The mean annual precipitation in these areas is approximately 3000 mm. Most of the severe storm events are from typhoon activity between May and October, and intense rainfall (>50 mm/h) occurs every year.



(**a**) (**b**)

Figure 2. Watershed boundary and channel network of the study watersheds: (**a**) Goodwin Creek watershed; (**b**) Heng-Chi and San-Hsia watershed.

The geomorphologic factors were obtained from a digital elevation model [62] based on datasets of the Goodwin Creek watershed (30-m resolution) and the Heng-Chi and San-Hsia watersheds (40-m resolution). Table 1 shows the geomorphologic factors of the watersheds used in the KW-GIUH model.

Table 1. Geomorphologic factors of the study watersheds.

Watershed	i	N_i	$\overline{A}_i$ (km^2)	$\overline{L}_{c_i}$ (km)	$\overline{S}_{c_i}$ (m/m)	$\overline{S}_{o_i}$ (m/m)
Goodwin (STA01)	1	76	0.18	0.40	0.0128	0.0228
	2	16	0.75	0.76	0.0090	0.0257
	3	4	3.08	1.56	0.0060	0.0260
	4	1	21.38	7.53	0.0019	0.0213
Heng-Chi	1	29	1.07	0.80	0.1304	0.3028
	2	6	6.91	3.13	0.0580	0.2957
	3	2	19.81	1.79	0.0105	0.2468
	4	1	53.15	4.98	0.0078	0.1977
San-Hsia	1	69	1.15	0.92	0.1613	0.3138
	2	16	4.99	2.08	0.0924	0.3016
	3	3	18.15	3.88	0.0372	0.3644
	4	1	125.88	17.83	0.0131	0.2918

Notes: N_i is the number of ith-order streams; $\overline{A}_i$ is the mean ith-order subwatershed area; $\overline{L}_{c_i}$ is the mean ith-order channel length; $\overline{S}_{c_i}$ is the mean ith-order channel slope; $\overline{S}_{o_i}$ is the mean ith-order hillslope slope.

3.2. Rainfall Forecasting

Table 2 shows the details of storm events that occurred in the study watersheds; these details were used for parameter calibration and model verification. In performing the grey rainfall model, parameters *a* and *b* (Equation (7)) can be estimated by using a least square method only based on small amount of past observed rainfall data. The watershed geomorphological factors in performing the KW-GIUH model are shown in Table 1, which can be obtained by applying a digital elevation model. The calibrated model parameters of the KW-GIUH model for the Heng-Chi and San-Hsia watersheds are $n_o = 0.6$ and $n_c = 0.05$, and $n_o = 0.2$ and $n_c = 0.02$ for the Goodwin watershed. The values of model parameters were stable for the test storms in the watersheds. Sensitivity analysis for the model parameters of KW-GIUH can be found in Lee and Yen [42].

Table 2. Storm records analyzed in this study.

Watershed (Rain Station)	Event Date	Rainfall Peak (mm/h)	Total Rainfall (mm)	Rainfall Duration (h)	Flow Peak (m^3/s)
Goodwin (STA01)	10/07/1989	11.13	92	48	29.7
	02/03/1991	16.80	62	18	21.1
	14/02/1992	4.66	30	11	9.1
	04/08/1995	13.29	113	28	16.7
	29/11/1996	6.95	44	29	10.2
	23/12/1997	7.17	45	13	19.6
	15/02/1998	10.20	62	48	27.3
	13/03/1999	11.92	95	52	31.0
	01/04/2000	24.09	152	63	32.9
	17/01/2001	7.26	78	60	10.3
Heng-Chi (Ta-Pao)	17/08/1984	36.00	372	51	169.0
	16/09/1985	69.00	348	25	620.0
	17/09/1986	46.00	420	61	457.0
	27/07/1987	32.00	114	18	164.0
	08/09/1987	59.00	261	45	329.0
	18/08/1990	48.00	342	48	492.0
	05/06/1993	54.00	146	18	179.0
	10/07/1994	22.00	150	31	58.2
	30/07/1996	31.00	450	42	243.0
	31/10/2000	33.00	508	38	317.0
12125San-Hsia (Ta-Pao)	17/08/1984	36.00	372	51	214.0
	16/09/1985	69.00	348	25	620.0
	17/09/1986	46.00	420	61	404.0
	27/07/1987	32.00	114	18	349.0
	08/09/1987	59.00	261	45	379.0
	18/08/1990	48.00	342	48	1060.0
	05/06/1993	54.00	146	18	339.0
	10/07/1994	22.00	150	31	257.0
	30/07/1996	31.00	450	42	720.0
	31/10/2000	33.00	508	38	435.0

Table 3 and Figure 3 show the performance of the grey rainfall forecasting model for the three watersheds. The *ETCR* and RMSE from Equations (9) and (10) represent the quantitative evaluation of the model performance, and *CE* from Equation (11) indicates the performance of the model based on cumulative rainfall. The performance of the model was assessed qualitatively based on the value of *CC* (Equation (12)) relative to the correlation between the forecast and observed cumulative rainfall. The results showed that *ETCR* is less than 0.24, *RMSE* is less than 0.38, *CE* is greater than 0.85, and *CC* is greater than 0.90, indicating that the forecast and recorded hyetographs are in good agreement. The forecast and recorded hyetographs in Figures 4 and 5 show the performance of the grey rainfall forecasting model based on lead times ranging from 1 to 3 h. Although the accuracy of the forecast rainfall decreases as the lead time increased, the results indicate that the proposed grey model is suitable for rainfall forecasting.

Table 3. Results of grey forecast rainfall.

Watershed	Event Date	*ETCR*			*RMSE*			*CE*			*CC*		
		1-h Ahead	2-h Ahead	3-h Ahead	1-h Ahead	2-h Ahead	3-h Ahead	1-h Ahead	2-h Ahead	3-h Ahead	1-h Ahead	2-h Ahead	3-h Ahead
Goodwin Creek	10/07/1989	0.03	0.18	0.22	0.03	0.08	0.17	0.99	0.98	0.92	0.99	0.95	0.88
	02/03/1991	0.05	0.16	0.20	0.08	0.17	0.29	0.96	0.93	0.88	0.99	0.95	0.88
	14/02/1992	0.01	0.03	0.08	0.02	0.14	0.27	1.00	0.98	0.95	0.99	0.96	0.90
	04/08/1995	0.06	0.11	0.16	0.04	0.17	0.24	0.97	0.90	0.87	0.99	0.98	0.92
	29/11/1996	0.03	0.09	0.10	0.08	0.24	0.31	0.97	0.90	0.85	0.99	0.98	0.96
	23/12/1997	0.06	0.15	0.21	0.03	0.19	0.25	0.98	0.91	0.88	0.99	0.99	0.97
	15/02/1998	0.04	0.07	0.16	0.06	0.11	0.19	1.00	0.94	0.88	1.00	0.96	0.97
	13/03/1999	0.09	0.14	0.20	0.06	0.18	0.21	0.99	0.95	0.89	1.00	0.98	0.90
	01/04/2000	0.03	0.08	0.15	0.03	0.12	0.16	0.99	0.96	0.91	1.00	1.00	0.98
	17/01/2001	0.07	0.11	0.19	0.07	0.11	0.16	0.98	0.91	0.88	0.98	0.94	0.91
Heng-Chi and San-Hsia	17/08/1984	0.05	0.08	0.16	0.11	0.18	0.27	0.99	0.98	0.94	1.00	0.98	0.96
	16/09/1985	0.06	0.12	0.24	0.09	0.22	0.31	0.96	0.93	0.86	0.99	0.95	0.88
	17/09/1986	0.01	0.03	0.05	0.05	0.18	0.21	1.00	0.98	0.95	1.00	1.00	0.99
	27/07/1987	0.09	0.18	0.22	0.03	0.11	0.18	0.97	0.91	0.88	0.98	0.93	0.91
	08/09/1987	0.01	0.09	0.10	0.14	0.26	0.38	0.89	0.83	0.80	1.00	0.98	0.96
	18/08/1990	0.03	0.09	0.12	0.08	0.17	0.24	0.95	0.85	0.81	1.00	0.99	0.97
	05/06/1993	0.05	0.08	0.11	0.01	0.04	0.19	1.00	0.94	0.87	0.99	0.96	0.97
	10/07/1994	0.09	0.11	0.18	0.02	0.13	0.20	0.98	0.99	0.96	0.99	0.98	0.90
	30/07/1996	0.04	0.07	0.11	0.05	0.15	0.22	0.99	0.95	0.83	1.00	1.00	0.98
	31/10/2000	0.04	0.05	0.17	0.08	0.09	0.13	0.99	0.97	0.93	1.00	1.00	0.99
Average		0.05	0.10	0.16	0.06	0.16	0.23	0.98	0.93	0.89	1.00	0.98	0.94

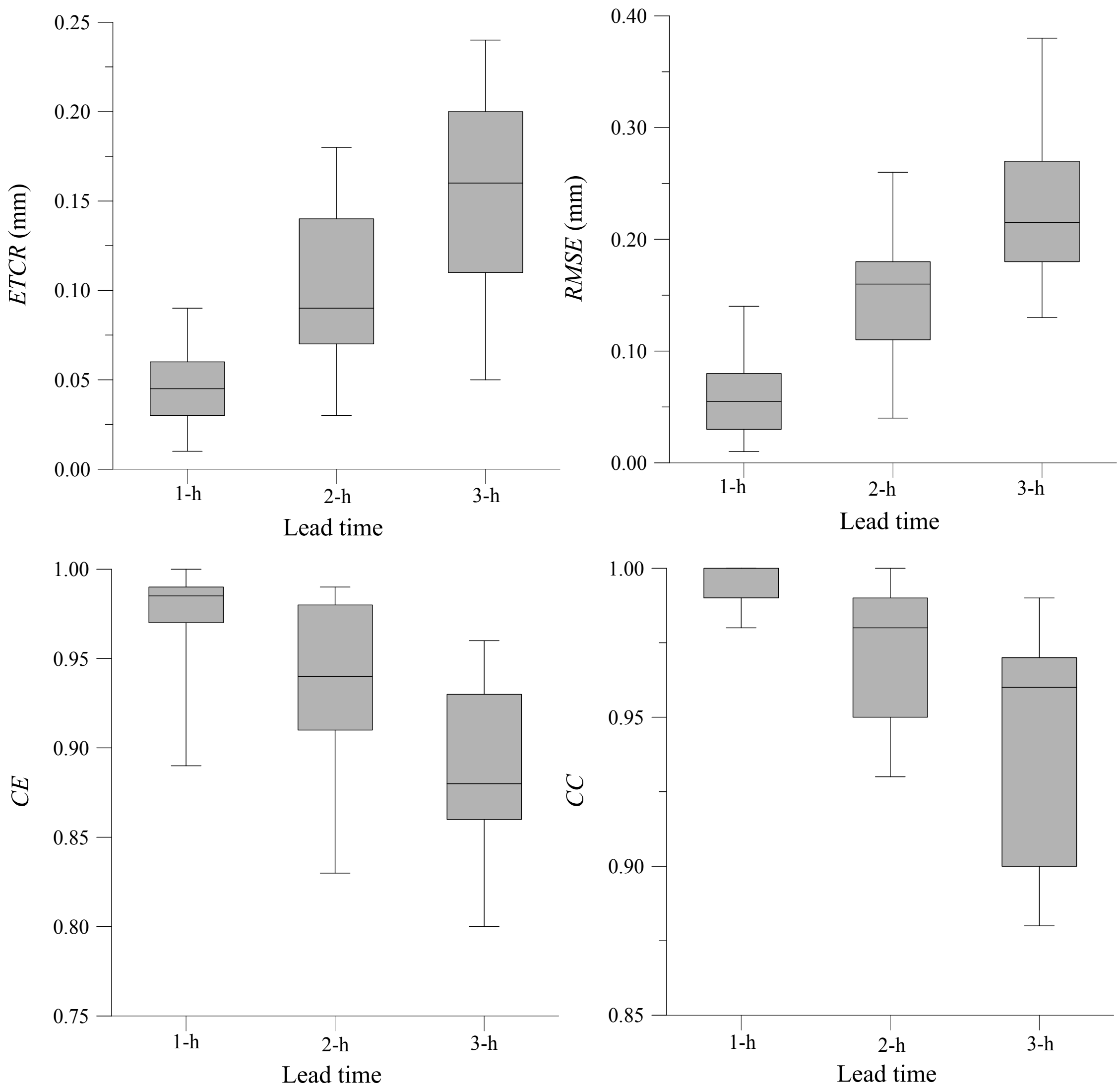
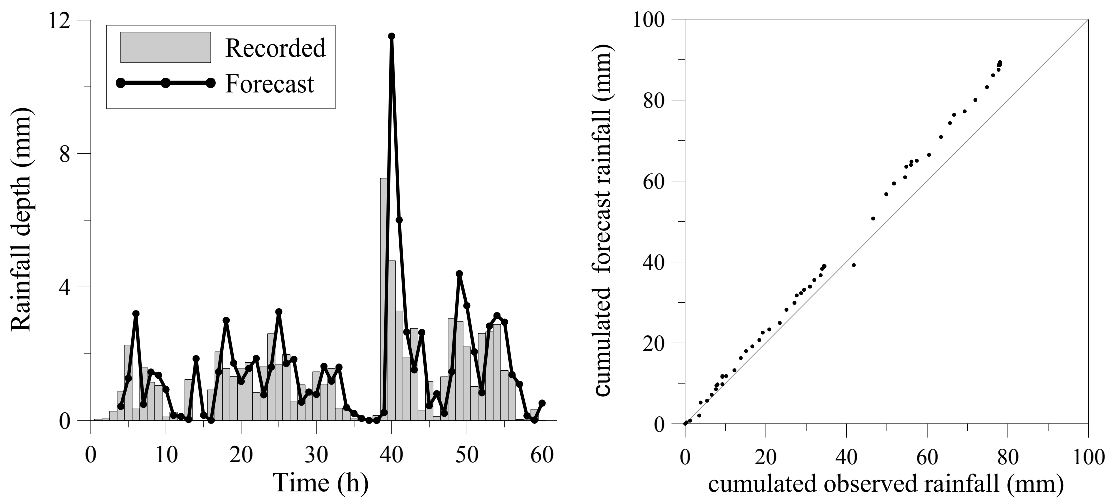
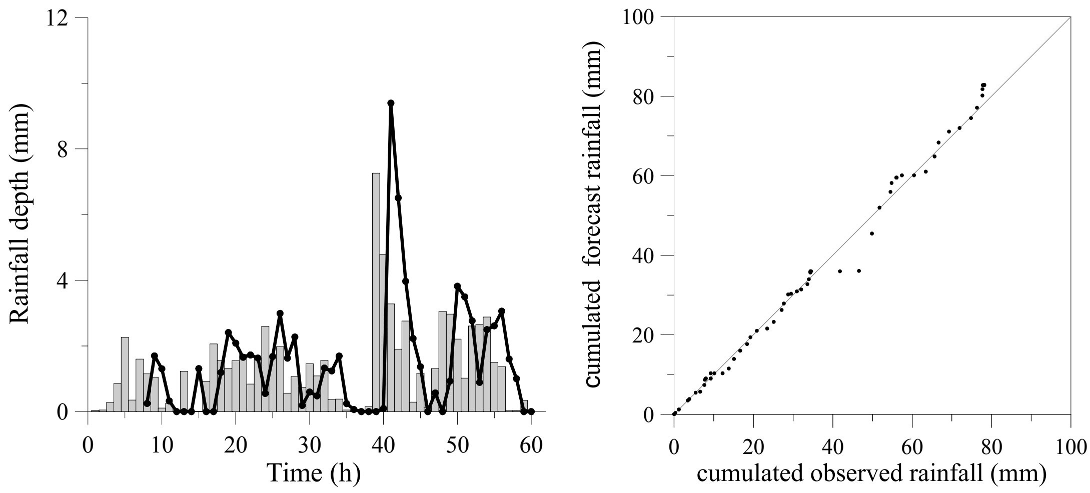


Figure 3. Results of evaluated criteria for grey forecast rainfall.

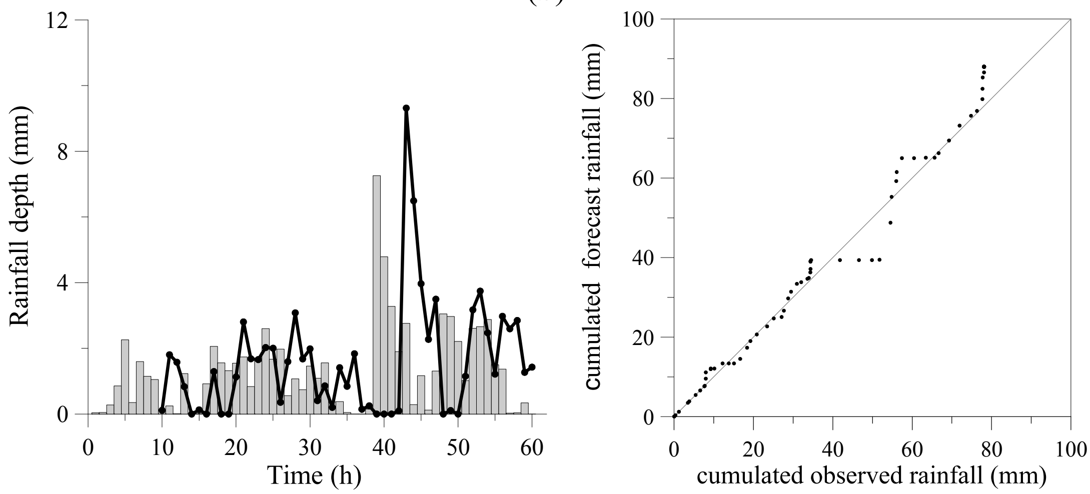


(a)

Figure 4. *Cont.*

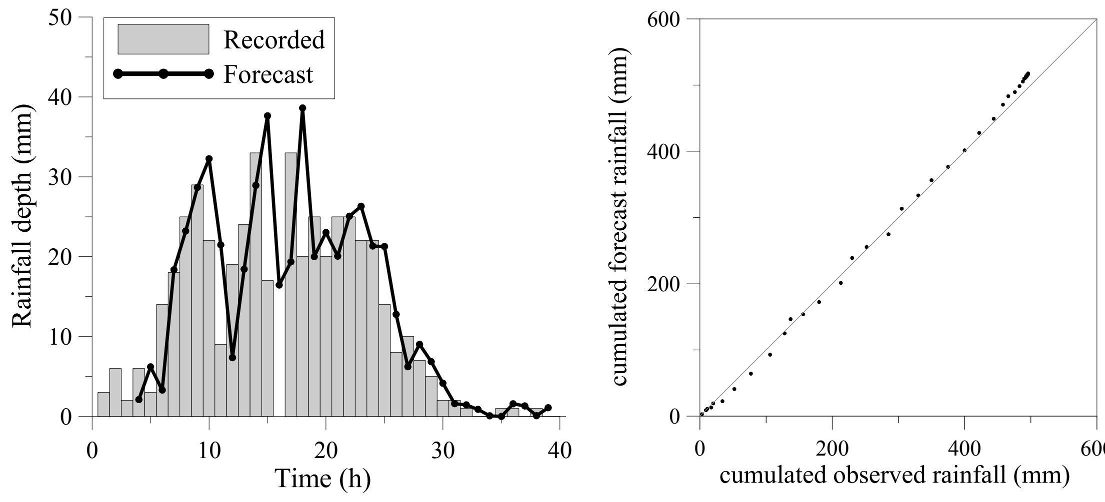


(**b**)



(**c**)

Figure 4. Grey model for rainfall forecasting in Goodwin Creek watershed: (**a**) 1-h ahead; (**b**) 2-h ahead; (**c**) 3-h ahead.



(**a**)

Figure 5. *Cont.*

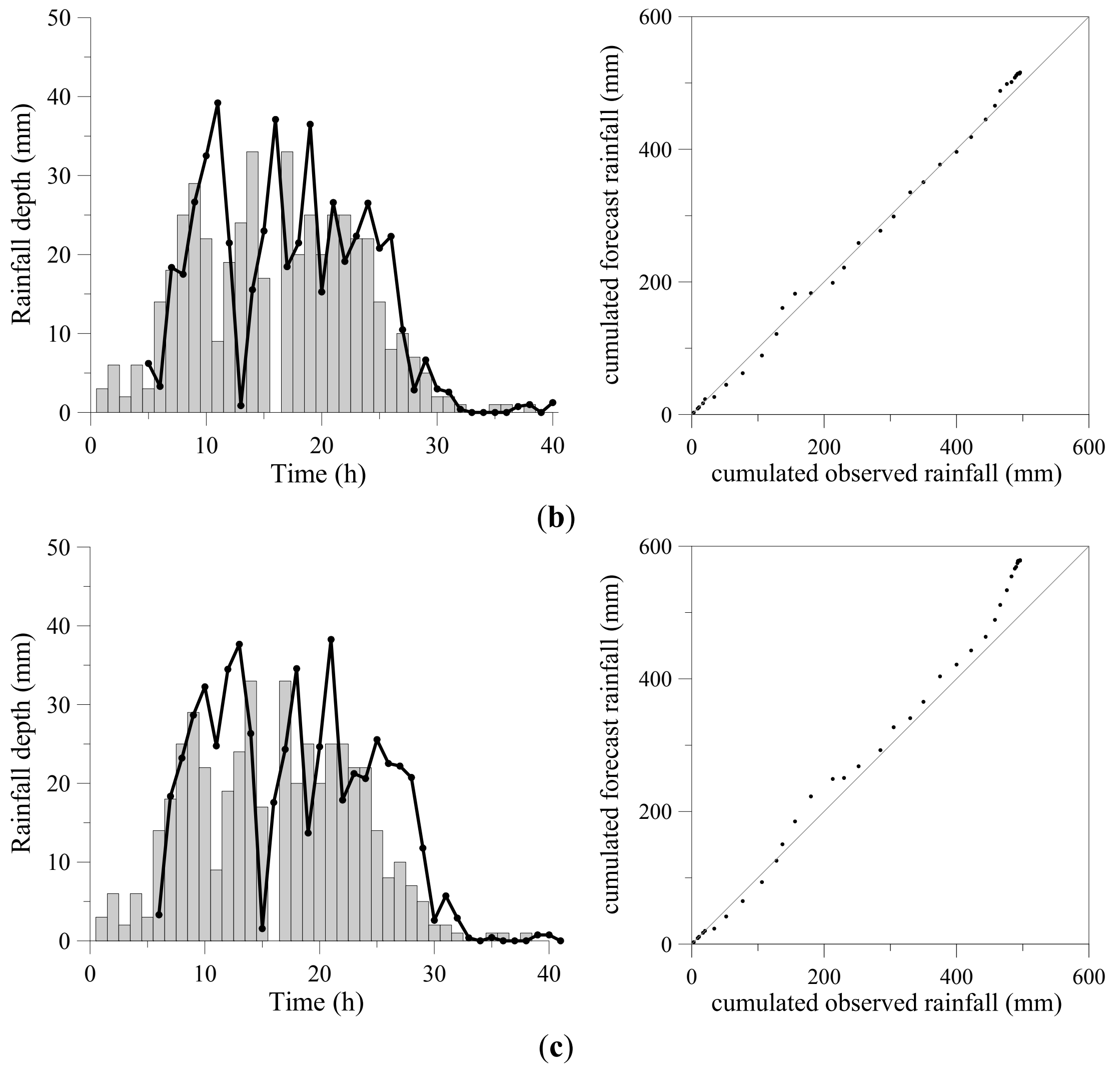


Figure 5. Grey model for rainfall forecasting in San-Hsia watershed: (**a**) 1-h ahead; (**b**) 2-h ahead; (**c**) 3-h ahead.

3.3. Flow Forecasting

Four sets of tests were performed to evaluate the applicability of the proposed system for real-time flood prediction. The simulation results are detailed shown as follows.

(1) Flow forecasting by using measured rainfall and without flow updating

This set of tests was conducted to evaluate the performance of the KW-GIUH model for simulating rainfall-runoff. Observed rainfall data were inputted into the KW-GIUH model and the flow updating algorithm was not used in the simulation. Figure 6 shows the results of runoff simulations for the Goodwin Creek and San-Hsia watersheds. As shown in Table 4, the simulated and observed hydrographs are in relatively good agreement in the study watersheds. The CE_Q values of the simulated hydrographs for all storm events are greater than 0.82, and most of the EQ_P and ET_P are lesser than 10% and 2 h, respectively. The results indicate that the KW-GIUH model is reliable for rainfall-runoff simulation in these two watersheds. Figure 6a shows that the temporal distributions of the observed rainfall hyetograph and flow hydrograph were inconsistent; specifically, the rainfall peak occurred at 45 h, whereas the flow peak occurred at 57 h. The reason for this inconsistency is unknown. However, this unusual hydrological record could be used to test the effectiveness of the proposed flow updating algorithm.

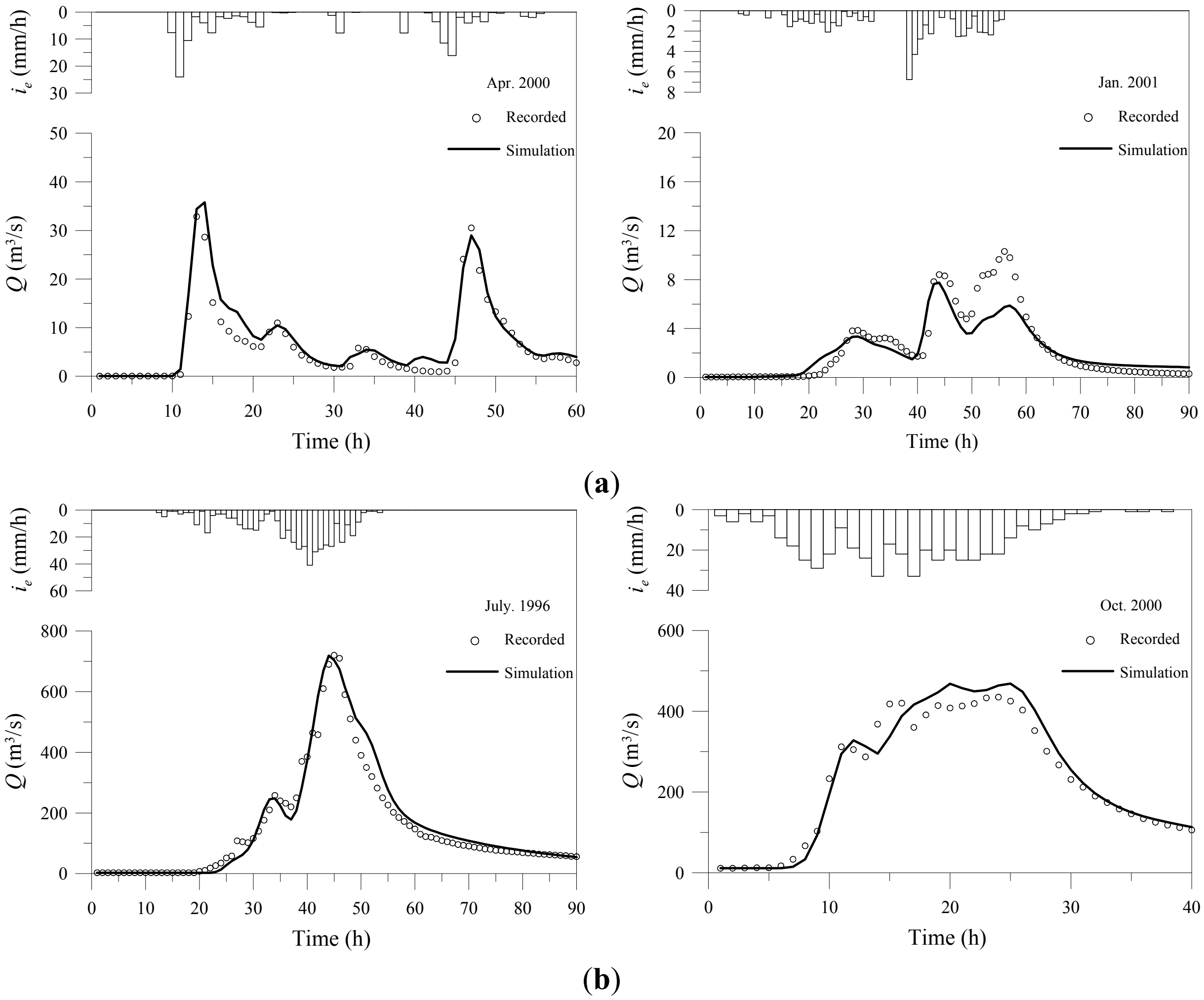


Figure 6. Flow forecasting using measured rainfall data and without flow updating in Goodwin Creek and San-Hsia watersheds: (**a**) Goodwin Creek watershed (STA 01); (**b**) San-Hsia watershed.

Table 4. Results of flow forecasting using measured rainfall and without flow updating technique.

Watershed	Event Date	CE_Q	EQ_p (%)	ET_p (h)
	10/07/1989	0.83	6.29	1
	02/03/1991	0.92	2.56	0
	14/02/1992	0.88	4.33	1
	04/08/1995	0.86	7.81	−1
Goodwin (SAT01)	29/11/1996	0.93	2.08	0
	23/12/1997	0.89	3.54	0
	15/02/1998	0.88	4.28	0
	13/03/1999	0.84	3.07	0
	01/04/2000	0.90	0.09	1
	17/01/2001	0.82	25.00	12

Table 4. *Cont.*

Watershed	Event Date	CE_Q	EQ_p (%)	ET_p (h)
Heng-Chi	17/08/1984	0.92	2.00	−1
	16/09/1985	0.88	0.24	−1
	17/09/1986	0.85	1.82	0
	27/07/1987	0.86	4.16	0
	08/09/1987	0.92	3.46	0
	18/08/1990	0.85	4.52	−1
	05/06/1993	0.97	2.01	−1
	10/07/1994	0.86	1.25	−1
	30/07/1996	0.94	3.54	−1
	31/10/2000	0.95	3.01	−2
San-Hsia	17/08/1984	0.90	6.54	0
	16/09/1985	0.89	3.33	0
	17/09/1986	0.86	6.29	1
	27/07/1987	0.84	5.54	1
	08/09/1987	0.88	5.19	0
	18/08/1990	0.83	2.24	0
	05/06/1993	0.87	5.64	−1
	10/07/1994	0.95	2.13	0
	30/07/1996	0.96	1.32	−1
	31/10/2000	0.95	7.65	−3
Average		0.89	4.36	0.10

(2) Flow forecasting by using forecast rainfall and without flow updating

For the second set of tests, flow forecasting was performed by inputting the forecast rainfall (obtained from the grey model) into the KW-GIUH model. Table 5 and Figure 7 show that the flow forecasting accuracy decreased as the lead time increased from 1 to 3 h. For the $t + 1$ forecast, the forecast flow is in good agreement with the observed flow. For the $t + 2$ and $t + 3$ forecasts, the temporal variation of the flow hydrograph is adequately represented in the simulation although the simulated flow peak is higher than the observed flow peak because the forecast peak rainfall was overestimated in the hyetograph. Regarding the storm event at the Goodwin Creek watershed on 17 January 2001, the results shown in Figure 7a indicate that the KW-GIUH model forecast the first flow peak accurately. However, the second flow peak is underestimated because of the inconsistency between the rainfall hyetograph and flow hydrograph as mentioned.

Table 5. Results of flow forecasting using forecast rainfall and without flow updating technique.

Watershed	Event Date	CE_Q 1-h Ahead	CE_Q 2-h Ahead	CE_Q 3-h Ahead	EQ_p (%) 1-h Ahead	EQ_p (%) 2-h Ahead	EQ_p (%) 3-h Ahead	ET_p (h) 1-h Ahead	ET_p (h) 2-h Ahead	ET_p (h) 3-h Ahead
Goodwin (SAT01)	10/07/1989	0.82	0.49	0.31	14.41	37.91	51.18	1	2	3
	02/03/1991	0.92	0.84	0.81	9.88	27.41	39.42	1	2	3
	14/02/1992	0.87	0.86	0.77	12.48	19.88	32.77	0	1	2
	04/08/1995	0.86	0.83	0.77	11.82	20.43	28.91	1	2	3
	29/11/1996	0.92	0.85	0.83	8.97	14.81	17.94	0	1	2
	23/12/1997	0.89	0.86	0.83	18.13	29.87	41.09	1	1	2
	15/02/1998	0.87	0.81	0.69	14.30	28.99	45.17	1	2	3
	13/03/1999	0.82	0.74	0.70	7.69	12.90	18.09	0	1	2
	01/04/2000	0.90	0.55	0.03	8.95	45.27	62.98	1	2	3
	17/01/2001	0.82	0.81	0.80	24.75	1.27	30.97	12	12	12
Heng-Chi	17/08/1984	0.90	0.86	0.81	4.81	11.85	19.28	1	2	2
	16/09/1985	0.87	0.81	0.74	3.29	8.74	20.32	1	1	2
	17/09/1986	0.83	0.79	0.71	10.93	24.31	31.88	1	2	3
	27/07/1987	0.85	0.83	0.78	8.49	18.41	24.31	1	2	2
	08/09/1987	0.92	0.90	0.86	7.96	16.19	19.22	1	2	2
	18/08/1990	0.75	0.43	0.09	14.41	19.84	31.03	1	2	3
	05/06/1993	0.95	0.94	0.88	2.09	7.31	9.08	0	1	2
	10/07/1994	0.85	0.81	0.70	1.09	8.54	11.72	0	1	1
	30/07/1996	0.93	0.91	0.82	9.75	14.32	18.97	−1	0	0
	31/10/2000	0.95	0.94	0.86	4.71	5.47	7.93	−3	−2	−1
San-Hsia	17/08/1984	0.90	0.81	0.79	8.49	14.55	21.09	1	2	2
	16/09/1985	0.88	0.80	0.74	6.39	11.52	17.92	1	1	2
	17/09/1986	0.86	0.83	0.52	9.31	18.45	37.01	1	2	3
	27/07/1987	0.84	0.83	0.67	4.09	11.12	14.17	1	2	2
	08/09/1987	0.87	0.81	0.63	4.41	9.18	22.97	1	2	2
	18/08/1990	0.81	0.62	0.31	6.31	11.48	18.02	1	2	3
	05/06/1993	0.85	0.81	0.76	7.31	9.52	16.55	0	1	2
	10/07/1994	0.95	0.91	0.85	4.86	7.59	16.31	0	1	1
	30/07/1996	0.95	0.94	0.89	1.96	4.48	12.05	−1	0	0
	31/10/2000	0.94	0.92	0.80	8.67	13.71	16.58	−3	−2	−1
Average		0.88	0.80	0.69	8.69	16.18	25.16	0.73	1.60	2.23

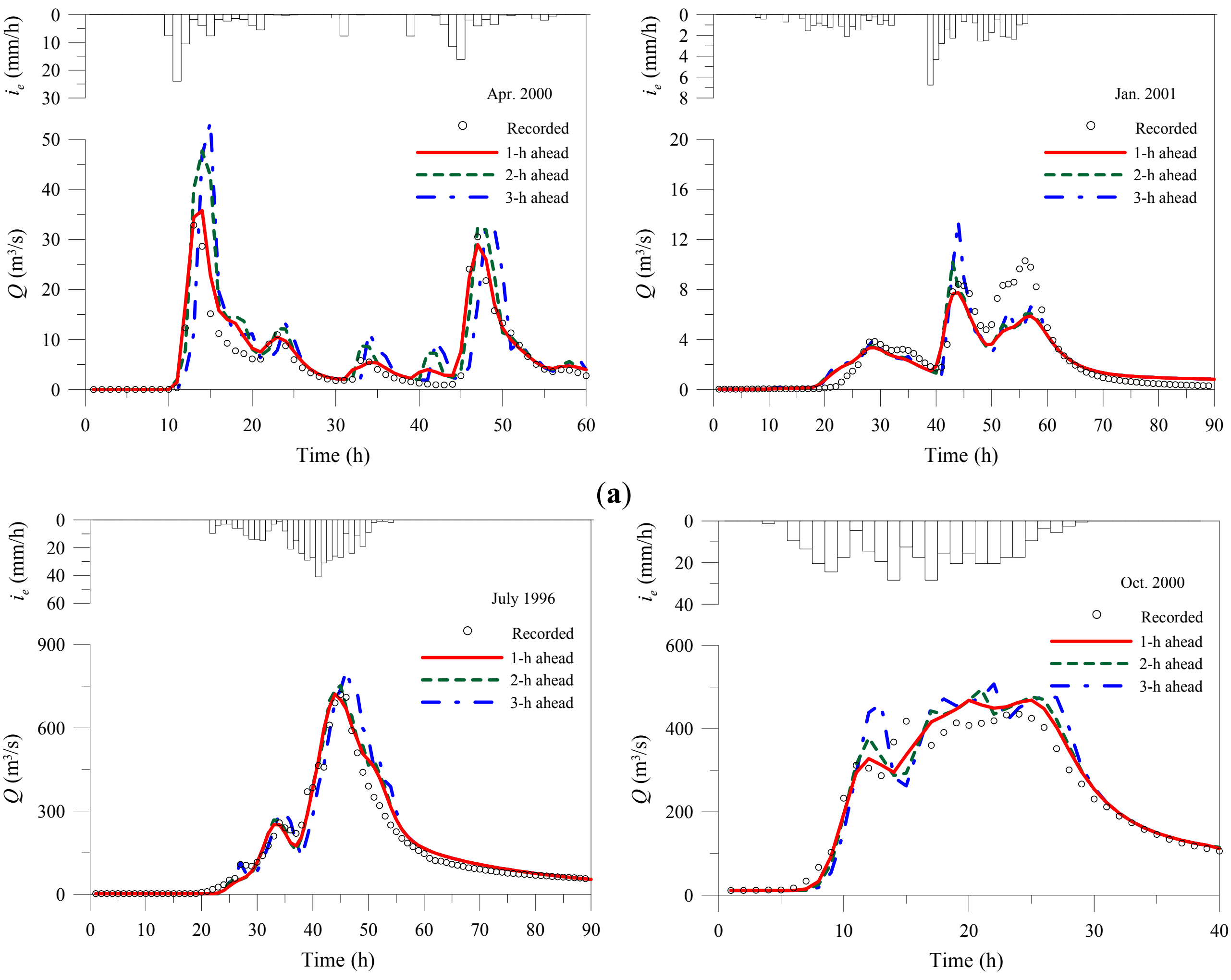


Figure 7. Flow forecasting using forecast rainfall and without flow updating in Goodwin Creek and San-Hsia watersheds: (**a**) Goodwin Creek watershed (STA 01); (**b**) San-Hsia watershed.

(3) Flow forecasting by using measured rainfall and flow updating technique

The third set of tests was conducted to evaluate the performance of the KW-GIUH model when the flow updating algorithm was used in the rainfall-runoff simulation, as shown in Equation (18). The measured rainfall at $t + 1$, $t + 2$, and $t + 3$ was inputted into the KW-GIUH model. Table 6 and Figure 8 show the simulation results, which were evaluated based on the coefficient of efficiency CE_Q, error of peak discharge EQ_P, and error of time to peak discharge ET_P. When the value CE_Q is approximately one and EQ_P and ET_P are approximately zero, good agreement between the recorded and simulated hydrographs is anticipated. The results in Figure 8 show that the CE_Q values are higher than 0.96, the mean EQ_P is 2.73%, and the mean ET_P is 0.17 h for the $t + 1$ simulation. For the $t + 2$ simulation, the CE_Q values are higher than 0.87, the mean EQ_P is 4.40%, and the mean ET_P is 0.67 h. Finally, for the $t + 3$ simulation, the CE_Q values are higher than 0.81, the mean EQ_P is 7.92%, and the mean ET_P is 1.23 h. Figure 9 shows that the forecast and recorded hydrographs are in good agreement for all storm events in this test, indicating that the proposed flow updating algorithm combined with the KW-GIUH model simulated the watershed runoff more accurately than do the KW-GIUH model alone. Moreover, regarding the storm event at the Goodwin Creek watershed on 17 January 2001, the flow hydrographs in Figures 7a and 9a show that the second peak was accurately forecasted when the flow updating algorithm is used, despite the recorded flow peak appearing to be unreasonable. The results show that using a purely deterministic approach to simulate watershed rainfall runoff is difficult without the assistance of a real-time adaptive algorithm.

Table 6. Results of flow forecasting using measured rainfall and flow updating technique.

Watershed	Event Date	CE_Q			EQ_p (%)			ET_p (h)		
		1-h Update	2-h Update	3-h Update	1-h Update	2-h Update	3-h Update	1-h Update	2-h Update	3-h Update
Goodwin (SAT01)	10/07/1989	0.97	0.93	0.89	2.54	5.77	8.43	1	1	1
	02/03/1991	0.98	0.94	0.90	0.14	3.43	4.95	1	1	2
	14/02/1992	0.96	0.91	0.84	3.83	5.46	5.57	0	0	1
	04/08/1995	0.96	0.92	0.83	2.53	4.59	7.33	0	0	1
	29/11/1996	0.96	0.91	0.85	3.64	4.22	8.36	1	2	2
	23/12/1997	0.97	0.92	0.85	4.81	5.65	8.78	−1	0	1
	15/02/1998	0.96	0.92	0.86	0.19	3.19	3.97	−1	−1	0
	13/03/1999	0.96	0.91	0.83	3.71	0.13	9.80	0	1	1
	01/04/2000	0.97	0.93	0.85	1.94	0.97	8.11	−1	−1	0
	17/01/2001	0.97	0.87	0.81	0.84	0.53	2.05	1	1	1
Heng-Chi	17/08/1984	0.96	0.92	0.88	4.75	5.69	10.54	0	0	1
	16/09/1985	0.97	0.93	0.89	4.55	6.29	14.12	0	0	1
	17/09/1986	0.97	0.92	0.90	2.30	1.89	4.92	0	1	2
	27/07/1987	0.96	0.91	0.88	0.76	2.69	5.50	0	1	1
	08/09/1987	0.96	0.92	0.89	1.62	5.86	8.80	1	2	2
	18/08/1990	0.97	0.93	0.91	0.50	3.40	4.14	−1	0	0
	05/06/1993	0.98	0.93	0.91	2.75	0.68	8.15	1	2	2
	10/07/1994	0.97	0.93	0.90	3.03	4.42	9.09	1	1	2
	30/07/1996	0.96	0.91	0.89	3.16	2.19	2.09	0	0	1
	31/10/2000	0.98	0.93	0.91	3.17	10.78	14.44	0	1	1
San-Hsia	17/08/1984	0.96	0.92	0.87	2.95	5.69	12.86	1	1	2
	16/09/1985	0.96	0.91	0.88	1.21	8.33	13.23	0	1	1
	17/09/1986	0.97	0.92	0.89	1.53	1.64	3.23	0	1	1
	27/07/1987	0.97	0.92	0.88	3.76	3.24	4.18	0	0	1
	08/09/1987	0.97	0.91	0.86	1.64	6.24	10.8	0	1	2
	18/08/1990	0.96	0.91	0.88	1.69	3.23	3.15	0	0	1
	05/06/1993	0.97	0.94	0.91	2.42	4.89	9.33	1	2	2
	10/07/1994	0.96	0.91	0.88	1.72	3.09	11.56	0	0	1
	30/07/1996	0.98	0.98	0.93	3.84	3.28	4.34	−1	0	1
	31/10/2000	0.99	0.96	0.95	6.22	7.35	9.42	1	2	2
Average		0.97	0.92	0.88	2.73	4.40	7.92	0.17	0.67	1.23

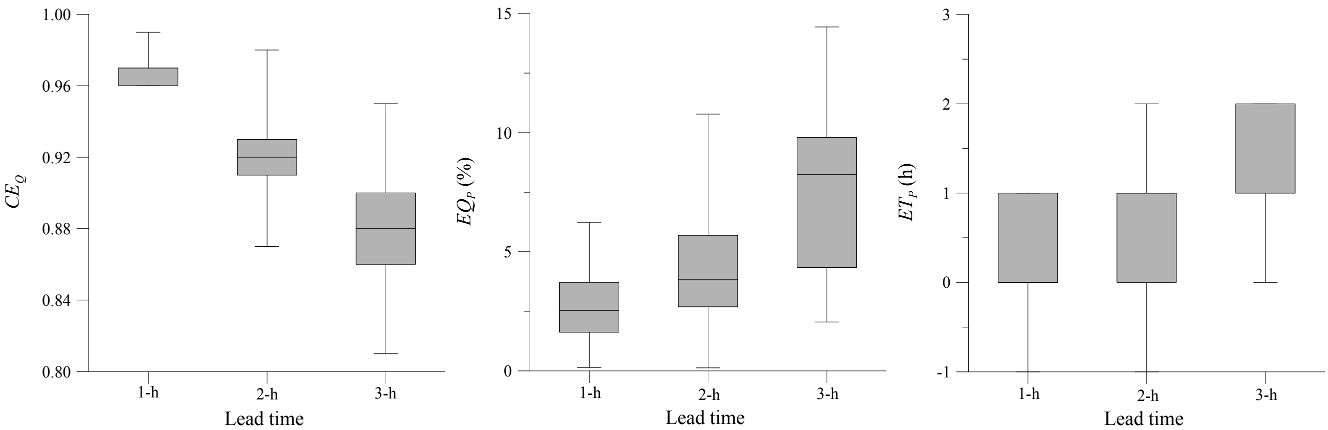


Figure 8. Results of evaluated criteria for flow forecasting using measured rainfall and flow updating technique.

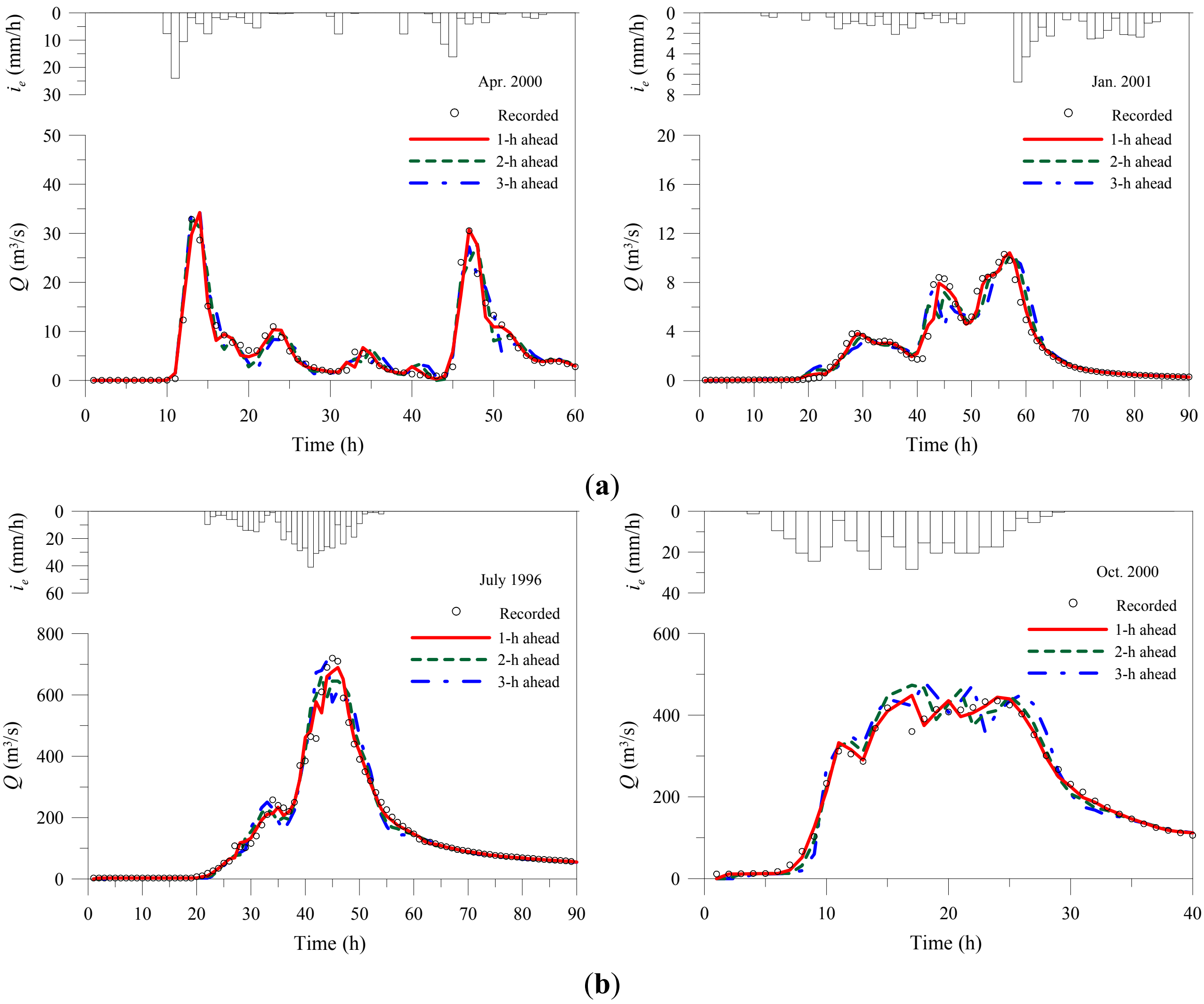


Figure 9. Flow forecasting using measured rainfall and flow updating algorithm in Goodwin Creek and San-Hsia watersheds: (**a**) Goodwin Creek watershed (STA 01); (**b**) San-Hsia watershed.

(4) Flow forecasting by using forecast rainfall and flow updating algorithm

The final set tests was conducted to confirm the performance of the proposed flood forecasting system. The forecast rainfall is generated by using the grey model, and the flow updating algorithm is included in the runoff simulation by using the KW-GIUH model to improve the forecasting accuracy. Table 7 and Figure 10 show that the mean CE_Q (EQ_P) values of the t + 1, t + 2, and t + 3 forecasts are 0.92 (4.50%), 0.80 (9.12%), and 0.72 (13.57%). The mean ET_P values of the t + 1, t + 2, and t + 3 forecasts are 0.70 h, 1.47 h, and 2.13 h, respectively. The results of the storm event simulations in Figure 11 shows that the recorded and simulated hydrographs are in good agreement for all the three watersheds under various geoclimate conditions, even as the lead time increases from 1 to 3 h.

Table 7. Results of flow forecasting using forecast rainfall and flow updating technique.

Watershed	Event Date	CE_Q			EQ_P (%)			ET_P (h)		
		1-h Ahead	2-h Ahead	3-h Ahead	1-h Ahead	2-h Ahead	3-h Ahead	1-h Ahead	2-h Ahead	3-h Ahead
Goodwin (SAT01)	10/07/1989	0.94	0.82	0.80	3.81	11.21	13.91	1	1	2
	02/03/1991	0.95	0.87	0.77	1.00	3.60	7.33	1	1	2
	14/02/1992	0.89	0.69	0.66	4.22	1.89	4.04	1	2	2
	04/08/1995	0.88	0.70	0.69	1.01	8.67	12.59	1	2	3
	29/11/1996	0.89	0.86	0.81	3.64	9.45	16.24	1	1	2
	23/12/1997	0.91	0.69	0.65	7.28	8.15	14.89	0	1	2
	15/02/1998	0.93	0.85	0.79	9.56	10.69	11.28	0	1	2
	13/03/1999	0.91	0.79	0.78	3.70	8.91	7.28	0	1	1
	01/04/2000	0.95	0.72	0.61	4.13	12.34	18.75	1	2	3
	17/01/2001	0.97	0.94	0.91	1.07	0.39	4.20	0	1	1
Heng-Chi	17/08/1984	0.95	0.76	0.62	8.42	11.21	3.71	1	1	2
	16/09/1985	0.89	0.71	0.61	4.88	13.77	5.66	1	1	2
	17/09/1986	0.90	0.84	0.79	1.52	8.15	19.10	1	2	3
	27/07/1987	0.96	0.76	0.61	6.79	9.97	11.52	1	2	2
	08/09/1987	0.89	0.75	0.62	0.04	7.44	16.60	1	2	3
	18/08/1990	0.91	0.78	0.66	3.21	0.22	9.67	0	1	1
	05/06/1993	0.88	0.77	0.61	7.93	12.73	19.02	1	2	3
	10/07/1994	0.92	0.74	0.64	3.28	11.82	23.11	1	1	2
	30/07/1996	0.96	0.90	0.83	1.70	3.62	6.61	1	2	2
	31/10/2000	0.95	0.89	0.82	3.68	5.03	10.02	1	2	2
San-Hsia	17/08/1984	0.93	0.76	0.63	9.31	11.59	17.42	1	2	3
	16/09/1985	0.89	0.74	0.61	5.81	14.60	19.88	1	2	2
	17/09/1986	0.91	0.91	0.78	8.44	18.00	22.30	0	1	2
	27/07/1987	0.89	0.72	0.59	7.32	11.52	15.39	1	2	3
	08/09/1987	0.96	0.83	0.74	1.75	5.47	14.50	0	1	1
	18/08/1990	0.91	0.75	0.65	1.68	3.13	9.50	1	2	2
	05/06/1993	0.88	0.71	0.63	6.03	22.14	27.56	1	2	3
	10/07/1994	0.92	0.78	0.69	1.32	13.36	28.36	0	1	2
	30/07/1996	0.98	0.97	0.92	4.60	4.83	5.03	1	1	2
	31/10/2000	0.98	0.95	0.94	7.75	9.65	11.62	0	1	2
Average		0.92	0.80	0.72	4.50	9.12	13.57	0.70	1.47	2.13

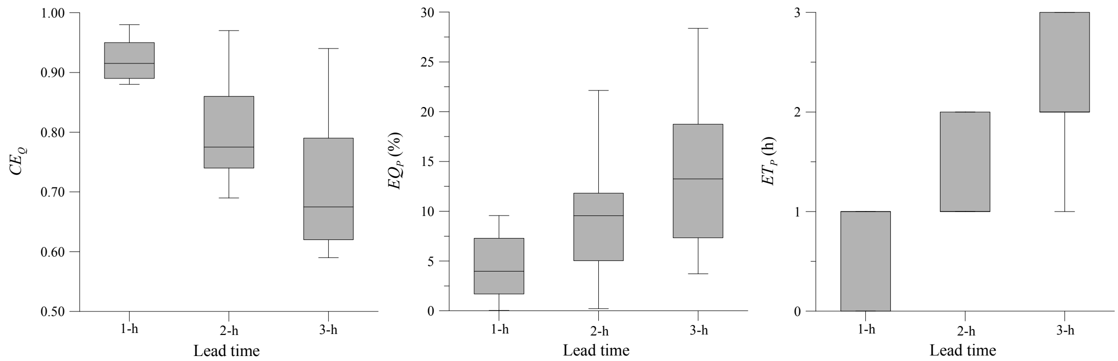


Figure 10. Results of evaluated criteria for flow forecasting using forecast rainfall and flow updating technique.

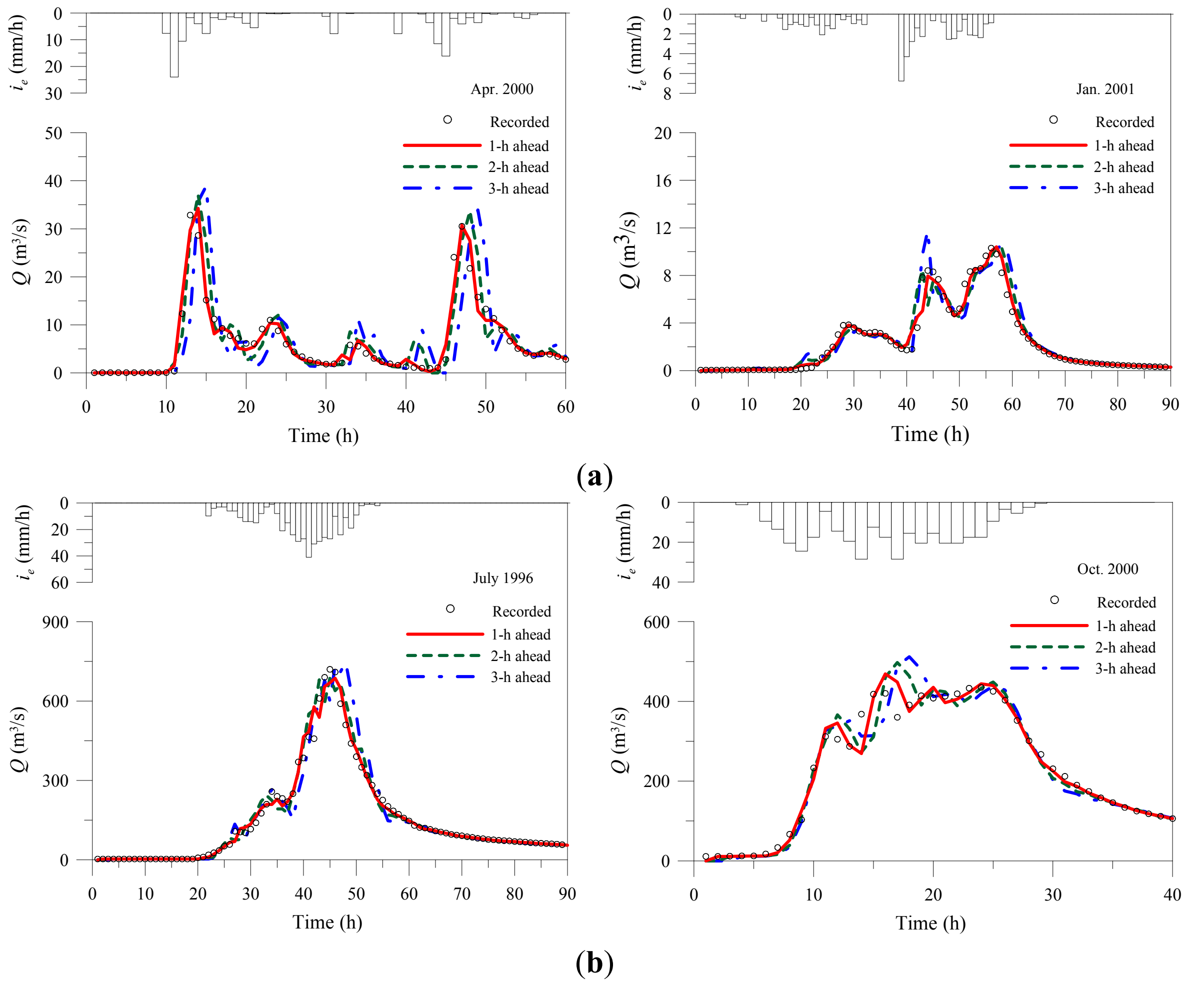


Figure 11. Flow forecasting using forecast rainfall and flow updating algorithm in Goodwin Creek and San-Hsia watersheds: (**a**) Goodwin Creek watershed (STA 01); (**b**) San-Hsia watershed.

4. Conclusions

This study developed an integrated framework for flood forecasting by using a rainfall forecasting model, watershed rainfall-runoff model, and real-time flow updating algorithm. Considering that current numerical meteorological models used in Taiwan cannot provide a 3-h prediction of the temporal distribution of rainfall, this study adopted a grey rainfall forecasting model. Using the KW-GIUH model for runoff simulation is advantageous because it can be developed based on only geomorphologic factors of the watershed. Moreover, a real-time flow updating algorithm was incorporated into the KW-GIUH structure to account for the uncertainty of watershed runoff processes. The proposed flood forecasting system was tested based on hydrological records from three watersheds under different geomorphological and hydrological conditions. For the 1-h, 2-h, and 3-h ahead forecast cases, the simulated mean coefficient of efficiency (error of peak discharge) is 0.92 (4.5%), 0.80 (9.12%), and 0.72 (13.57%). The mean ET_P values of the $t + 1$, $t + 2$, and $t + 3$ forecast cases are 0.70 h, 1.47 h, and 2.13 h, respectively. These results indicate that the proposed flood forecasting system can provide credible warning information for authorities. Furthermore, the proposed flow forecasting system can operate with high efficiency to meet the requirements of real-time flow forecasting. Nevertheless, in considering that the forecast rainfall is assumed to have the same tendency as previous rainfall; hence, only short-term prediction is applicable for this rainfall forecasting system. Since spatially-uniform rainfall is used in the KW-GIUH model, the proposed flow forecasting may be not used in a large watershed. Further validations to account for watersheds with various hydrological and geomorphologic characteristics are still required in future research.

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Author Contributions

Jui-Yi Ho was validated proposed model. Kwan Tun Lee was designed and performed the model. Both authors contributed about equally to compose this paper, discussed the results, and commented on the manuscript at all stages.

Conflicts of Interest

The authors declare no conflict of interest

References

1. Brath, A.; Burlando, P.; Rosso, R. Sensitivity analysis of real-time flood forecasting to on-line rainfall predictions. In *Selected Papers from the Workshop on Natural Disasters in European-Mediterranean Countries*; Siccardi, F., Bras, R.L., Eds.; National Research Council: Perugia, Italy, 1998; pp. 469–488.
2. Borga, M.; Anagnostou, E.N.; Frank, E. On the use of real-time radar rainfall estimates for flood prediction in mountainous basins. *J. Geophys. Res.* **2000**, *105*, 2269–2280.
3. Plessis, L.D. A review of effective flood forecasting, warning and response system for application in South Africa. *Water SA* **2002**, *28*, 129–137.

4. Walser, A.; Schär, C. Convection-resolving precipitation forecasting and its predictability in Alpine river catchments. *J. Hydrol*. **2004**, *288*, 57–73.
5. Toth, E.; Brath, A.; Montnari, A. Comparison of short-term rainfall prediction models for real-time flood forecasting. *J. Hydrol*. **2000**, *239*, 132–147.
6. Garbrecht, J.; Ogden, F.L.; DeBarry, P.A.; Maidment, D.R. GIS and distributed watershed models. I: Data converges and sources. *J. Hydrol. Eng.* **2001**, *6*, 506–514.
7. Moore, R.J.; Bell, V.A.; Jones, D.A. Forecasting for flood warning. *Comptes Rendus Geosci.* **2005**, *337*, 203–217.
8. French, M.N.; Krajewski, W.F.; Cuykendall, R.R. Rainfall forecasting in space and time using a neural network. *J. Hydrol.* **1992**, *137*, 1–31.
9. Burlando, P.; Rosso, R.; Gadavid, L.G.; Salas, J.D. Forecasting of short-term rainfall using ARMA models. *J. Hydrol.* **1993**, *144*, 193–211.
10. Lardet, P.; Obled, C. Real time flood forecasting using a stochastic rainfall generator. *J. Hydrol.* **1994**, *162*, 391–408.
11. Kelly, K.S.; Krzysztofowicz, R. Precipitation uncertainty processor for probabilistic river stage forecasting. *Water Resour. Res.* **2000**, *36*, 2643–2654.
12. Krzysztofowicz, R. Integrator of uncertainties for probabilistic river stage forecasting: Precipitation-dependent model. *J. Hydrol.* **2001**, *249*, 69–85.
13. Lin, G.F.; Wu, M.C. A hybrid neural network for typhoon-rainfall forecasting. *J. Hydrol.* **2009**, *375*, 450–458.
14. Deng, J.L. Introduction to grey system theory. *J. Grey Syst.* **1989**, *1*, 1–24.
15. Xia, J. Research and application of grey system theorem to hydrology. *J. Grey Syst.* **1989**, *1,* 43–52.
16. Huang, Y.P.; Huang, C.C. The integration and application of fuzzy and grey modeling methods. *Fuzzy Sets Syst.* **1996**, *78,* 107–119.
17. Yu, P.-S.; Chen, C.-J.; Chen, S.-C.; Lin, S.-C. Application of grey method toward runoff forecasting. *J. Am. Water Resour. Assoc.* **2001**, *37*, 151–166.
18. ASCE Task Committee on Application of Artificial Neural Networks in Hydrology. Artificial Neural Networks in Hydrology, part I: Preliminary concepts. *J. Hydrol. Eng.* **2000**, *5*, 115–123.
19. ASCE Task Committee on Application of Artificial Neural Networks in Hydrology. Artificial Neural Networks in Hydrology, part II: Hydrologic applications. *J. Hydrol. Eng.* **2000**, *5*, 124–137.
20. Xu, Z.X.; Li, J.Y. Short-term inflow forecasting using an artificial neural network model. *Hydrol. Process.* **2002**, *16*, 2423–2439.
21. Lin, G.F.; Chen, L.H. A non-linear rainfall-runoff model using radial basis function network. *J. Hydrol.* **2004**, *289*, 1–8.
22. Chetan, M.; Sudheer, K.P. A hybrid linear-neural model for river flow forecasting. *Water Resour. Res.* **2006**, *42*, doi:10.1029/2005WR004072.
23. Chen, W.; Chau, K.W. Intelligent manipulation and calibration of parameters for hydrological models. *Int. J. Environ. Pollut.* **2006**, *28*, 432–447.
24. Muttil, N.; Chau, K.-W. Neural network and genetic programming for modelling coastal algal blooms. *Int. J. Environ. Pollut.* **2006**, *28*, 223–238.
25. Chau, K.W. An ontology-based knowledge management system for flow and water quality modeling. *Adv. Eng. Softw.* **2007**, *38*, 172–181.

26. Toth, E.; Brath, A. Multistep ahead streamflow forecasting: Role of calibration data in conceptual and neural network modeling. *Water Resour. Res.* **2007**, *43*, W11405.
27. Taormina, R.; Chau, K.W. Neural network river forecasting with multi-objective fully informed particle swarm optimization. *J. Hydroinform.* **2015**, *17*, 99–113.
28. Wu, C.L.; Chau, K.W.; Li, Y.S. River stage prediction based on a distributed support vector regression. *J. Hydrol.* **2008**, *358*, 96–111.
29. Cheng, C.T.; Chau, K.W.; Sun, Y.; Lin, J. Long-term prediction of discharges in Manwan Reservoir using artificial neural network models. *Lecture Notes Comput. Sci.* **2005**, *3498*, 1040–1045.
30. Hapuarachchi, H.A.P.; Wang, Q.J. *A Review of Methods and Systems Available for Flash Flood Forecasting*; Report for the Bureau of Meteorology, Australia; Commonwealth Scientific and Industrial Research Organisation (CSIRO): Dickson, Austrilia, July 2008.
31. Burnash, R.J.C.; Ferral, R.L.; McGuire, R.A. *A Generalized Streamflow Simulation System: Conceptual Modeling for Digital Computers*; U.S. Department of Commerce: Washington, DC, USA, 1973.
32. Burnash, R.J.C. The NWS river forecast system-catchment modeling. In *Computer Models of Watershed Hydrology*; Singh, V.P., Ed.; Water Resources Publications: Highlands Ranch, CO, USA, 1995; pp. 311–366.
33. Sugawara, M. Automatic calibration of the tank model. *Hydrol. Sci. Bull.* **1979**, *24*, 375–388.
34. Bergstrom, S. The HBV model. In *Computer Models of Watershed Hydrology*; Singh, V.P., Ed.; Water Resources Publications: Highlands Ranch, CO, USA, 1995; pp. 443–476.
35. Zhao, R.J. The Xinanjiang model applied in China. *J. Hydrol.* **1992**, *135*, 371–381.
36. Jain, V.; Sinha, R. Derivation of unit hydrograph from GIUH analysis for a Himalayan river. *Water Resour. Manag.* **2003**, *17*, 355–375.
37. Zhang, B.; Govindaraju, R.S. Geomorphology-based artificial neural networks (GANNs) for estimation of direct runoff over watersheds. *J. Hydrol.* **2003**, *273*, 18–34.
38. Shadeed, S.; Shaheen, H.; Jayyousi, A. GIS-based KW-GIUH hydrological model of semiarid catchments: the case of Faria Catchment, Palestine. *Arabian J. Sci. Eng.* **2007**, *32*, 3–16.
39. Chiang, S.; Tachikawa, Y.; Takara, K. Hydrological model performance comparison through uncertainty recognition and quantification. *Hydrol. Process.* **2007**, *21*, 1179–1195.
40. Kumar, A.; Kumar, D. Predicting direct runoff from hilly watershed using geomorphology and stream-order-law ratios: Case Study. *J. Hydrol. Eng.* **2008**, *13*, 570–576.
41. Rodriguez-Iturbe, I.; Valdes, J.B. The geomorphologic structure of hydrologic response. *Water Resour. Res.* **1979**, *15*, 1409–1420.
42. Lee, K.T.; Yen, B.C. Geomorphology and kinematic-wave based hydrograph deviation. *J. Hydraul. Eng.* **1997**, *123*, 73–80.
43. Yen, B.C.; Lee, K.T. Unit hydrograph derivation for ungauged watersheds by stream order laws. *J. Hydrol. Eng.* **1997**, *2*, 1–9.
44. Clark, M.P.; Rupp, D.E.; Woods, R.A.; Zheng, X.; Ibbit, R. P.; Slater, A.G.; Schmidt, J.; Uddstrom, M.L. Hydrological data assimilation with the ensemble Kalman filter: Use of streamflow observation to update states in a distributed hydrological model. *Adv. Water Resour.* **2008**, *31*, 1309–1324.
45. Liu, Y.Q.; Weerts, A.H.; Clark, M.; Hendricks Franssen, H.J.; Kumar, S.; Moradkhani, H.; Seo, D.-J.; Schwanenberg, D.; Smith, P.; van Dijk, A.I.J.M.; *et al*. Advancing data assimilation in operational

hydrologic forecasting: Progresses, challenges, and emerging opportunities. *Hydrol. Earth Syst. Sci.* **2012**, *16*, 3863–3887.
46. Refsgaard, J.C. Validation and intercomparison of different updating procedures for real-time forecasting. *Nordic Hydrol.* **1997**, *28*, 65–84.
47. Reed, D.W. *A Review of British Flood Forecasting Practice*; Report 90; Institute of Hydrology: Wellington, UK, 1984.
48. Bobinski, E.; Mierkiewicz, M. Recent developments in simple adaptive flow forecasting models in Poland. *Hydrol. Sci. J.* **1986**, *31*, 297–320.
49. Nayak, P.C.; Sudheer, K.P.; Ramasastri, K.S. Fuzzy computing based rainfall-runoff model for real time flood forecasting. *Hydrol. Process.* **2005**, *19*, 955–968.
50. Chatfield, C. *The Analysis of Time Series an Introduction*; Chapman and Hall: London, UK, 1989.
51. Seo, D.J.; Koren, V.; Cajina, N. Real-time variational assimilation of hydrologic and hydrometeorological data into operational hydrologic forecasting. *J. Hydrometeorol.* **2003**, *4*, 627–641.
52. Valstar, J.R.; McLaughlin, D.B.; te Stroet, C.B.M.; van Geer, F.C. A representer-based inverse method for groundwater flow and transport applications. *Water Resour. Res.* **2004**, *40*, doi:10.1029/2003WR002922.
53. Da Ros, D.; Borga, M. Adaptive use of a conceptual model for real time flood forecasting. *Nordic Hydrol.* **1997**, *28*, 169–188.
54. Madsen, H.; Skotner, C. Adaptive state updating in real-time river flow forecasting-a combined filtering and error forecasting procedure. *J. Hydrol.* **2005**, *308*, 302–312.
55. Weerts, A.H.; el Serafy, G.Y.E. Particle filtering and ensemble Kalman filtering for state updating with hydrological conceptual rainfall-runoff models. *Water Resour. Res.* **2006**, *42*, doi:10.1029/2005WR004093.
56. Wang, D.; Cai, X. Robust data assimilation in hydrological modeling-a comparison of Kalman and H-infinity filters. *Adv. Water Resour.* **2008**, *31*, 455–472.
57. Matgen, P.; Montanari, M.; Hostache, R.; Pfister, L.; Hoffmann, L.; Plaza, D.; Pauwels, V.R.N.; de Lannoy, G.J.M.; de Keyser, R.; Savenije, H.H.G. Towards the sequential assimilation of SAR-derived water stages into hydraulic models using the Particle Filter: proof of concept. *Hydrol. Earth Syst. Sci.* **2010**, *14*, 1773–1785.
58. DeChant, C.M.; Moradkhani, H. Examining the effectiveness and robustness of data assimilation methods for calibration and quantification of uncertainty in hydrologic forecasting. *Water Resour. Res.* **2012**, *48*, doi:10.1029/2011WR011011.
59. Nash, J.E.; Sutcliffe, J.V. River flow forecasting through conceptual models part I—A discussion of principles. *J. Hydrol.* **1970**, *10*, 282–290.
60. Henderson, F.M.; Wooding, R.A. Overland flow and groundwater flow from a steady rainfall of finite duration. *J. Geophys. Res*. **1964**, *69*, 1531–1540.
61. Thiessen, A.H. Precipitation averages for large areas. *Mon. Weather Rev.* **1911**, *39*, 1082–1084.
62. Lee, K.T. Generating design hydrographs by DEM assisted geomorphic runoff simulation: A case study. *J. Am. Water Resour. Assoc.* **1998**, *34*, 375–384.