A real-time probabilistic channel flood-forecasting model based on the Bayesian particle filter approach

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Abstract

Reliable real-time probabilistic flood forecasting is critical for effective water management and flood protection all over the world. In this study, we develop a real-time probabilistic channel flood-forecasting model by combining a channel hydraulic model with the Bayesian particle filter approach. The new model is tested in the upstream river reach of Three Gorges Dam (TGD) on the Yangtze River, China. Stage observations at seven hydrological stations are used simultaneously to adjust the Manning's roughness coefficients and to update discharges and stages along the river reach to attain reliable probabilistic flood forecasting. The synthetic experiments are applied to demonstrate the new model's correction and forecasting performances. The real-world experiments show that the new model can make accurate flood forecasting as well as derive reliable intervals for different confidence levels. The new probabilistic flood forecasting model not only outperforms the existing deterministic channel flood-forecasting models in accuracy, but also provides a more robust tool with which to incorporate uncertainty into flood-control efforts.

Highlights

- A real-time flood-forecasting model is proposed by assimilating real-time stage observations into a hydraulic model.

- Particle filter is adopted as the data assimilation method to update/correct stage, discharge, and Manning's roughness coefficient.
- Synthetic experiments are employed to explore model settings and evaluate model performance.
- Model performance is compared with previous studies using Kalman Filter based methods.
- Probabilistic predictions provided by the model are more accurate and reliable.

Keywords

Channel flood forecasting; probabilistic forecast; particle filter; data assimilation; Three Gorges Dam

Software availability

The probabilistic channel flood-forecasting model system is programmed in C#. The size of the program is 91 Kb, and the program has been tested in windows systems (7 and above) with a minimum RAM of 512 Mb. The code of the program is freely available by requesting a copy from the first author at xu-xy11@mails.tsinghua.edu.cn.

1 Introduction

Flood disaster is a serious threat to people and property all over the world. Flooding in the Yangtze River in China is a major concern as large economic and population centers sit along the river. For example, the catastrophic flood in 1998 resulted in 3704 deaths, 15 million people left homeless, and economic losses of US\$25 billion (Fang and Wang, 2000; Zong and Chen, 2000). The construction of dams has been adopted as an effective measure to regulate and mitigate flood damage. The Three Gorges Dam (TGD) located on the middle reaches of the Yangtze River is the largest flood-control and hydroelectric project in the world. Its operation

commenced in 2006 with a flood-control capacity of 22.15 billion cubic meters. Real-time flood forecasting provides essential information for real-time scheduling of dam operations. For example, the TGD can be operated to release water stored in the reservoir before the onset of a predicted flood event, enhancing its regulatory capacity (Fang et al., 2012). However, accurate and reliable flood forecasting in the Yangtze River remains a challenge (Minglei et al., 2010).

Currently, hydraulic models are being used to forecast discharges and stages at cross-sections along rivers and they have been used widely in channel flood forecasting (Chaudhry, 2007; Chow et al., 1988; Costabile and Macchione, 2015; Han et al., 2011; Lamberti and Pilati, 1996; Nguyen and Kawano, 1995; Saavedra et al., 2003). Although hydraulic models are able to simulate the physical processes of flood routing, their performances are highly dependent on the appropriate preparation of their inputs and parameterization and the assumptions of their governing equations (Balica et al., 2013; Costabile and Macchione, 2015). With recent advances in both automatic hydrological monitoring and information transmission technologies, real-time hydrological observations are available for incorporation into hydraulic models to improve their forecasting performance through data assimilation approaches (Costabile and Macchione, 2015; Madsen and Skotner, 2005; Merkuryeva et al., 2014; Schumann et al., 2009; Werner et al., 2013). Data assimilation approaches update model states and parameters against observations to obtain reliable initial conditions and model structures for the next time step's forecasting (Liu et al., 2012a; Liu and Gupta, 2007). One widely used sequential data assimilation methods is the Kalman Filter (KF). The traditional standard KF method can consider both observational and model errors, but is restricted to linear systems (Liu et al., 2016). Recently, the ensemble KF, which is capable of dealing efficiently with nonlinear models, has become a popular approach for assimilating observational data for improving hydraulic models in real-time flood forecasting (Andreadis et al., 2007; Lai et al., 2013; Neal et al., 2007, 2009; Paiva et al., 2013; Schumann et al., 2009).

The ensemble KF, as well as other variants of the KF, has an inherent assumption that the prior distribution of model states observes a Gaussian distribution so that the

posterior states are only determined by the first two moments of the prior density. This assumption rarely holds in hydraulic models (Pasetto et al., 2012; Weerts and El Serafy, 2006). Recent researches have allowed for relaxing the assumption of Gaussian priors in EnKF type filters (Anderson, 2010; Borup et al., 2015), but still can't obtain the full flexibility. By contrast, the particle filter (PF), a sequential Monte Carlo method based on the Bayesian theory, can relax the need for restrictive assumptions regarding the forms of the probability densities, i.e., it can handle the propagation of non-Gaussian distributions through nonlinear hydrological and hydraulic models (Bi et al., 2015; Liu et al., 2012b; Moradkhani, 2008; Moradkhani et al., 2005a; Noh et al., 2011; Noh et al., 2014; Noh et al., 2012; Seo et al., 2014; Thirel et al., 2013). The main drawback of the PF is that it is more computationally intensive than EnKF, requiring more ensemble members to represent the prior distributions at a reasonable level (Liu et al., 2012b). Recently, Matgen et al. (2010) and Giustarini et al. (2011) successfully used the PF method to assimilate remote-sensing derived water-level data into hydraulic models and achieved significant reductions in the uncertainties of water-level and discharge predictions. However, the Manning's roughness coefficients in their hydraulic models were set as constant values, ignoring the variation of the Manning's roughness coefficients through the course of a flooding event. Kim et al. (2013) examined the inflow and Manning's roughness coefficients of a small-river reach and highlighted the importance of being able to track dynamically the changes of these two variables.

Currently, data assimilation based on the KF method has been applied in several studies to improve real-time channel flood forecasting in the Yangtze River. Ge et al. (2005) constructed a comprehensive state variable vector for the KF method to update a hydraulic model. Wu and Wang (2008) applied the KF method to update the Manning's roughness coefficients dynamically. Wu et al. (2013) developed an alternative coupled method to compute stages and discharges alternately using the KF. In all of the above studies, either the state variables or the parameters in the hydraulic model were updated, but not simultaneously.

To improve flood forecasting for the TGD, we aim to develop a new modeling

approach using the PF to derive probabilistic ensemble flood forecasts. In this study, a real-time probabilistic channel flood-forecasting model is developed for the river reach from Cuntan to the TGD, by assimilating real-time observed stages at multiple hydrological stations along the river channel using the PF. This approach not only updates model state variables (i.e., discharge and stage), but also corrects model parameters (i.e., Manning's roughness coefficient).

The rest of this paper is organized as follows. In the methodology section, the real-time channel flood-forecasting model is formulated by coupling a hydraulic model with the PF. Next, the coupled modeling approach is examined against synthetic data to test the validity of the developed modeling approach. In the real-world experiment section, we evaluate and verify the new model's applicability to three observed flooding events. In the discussion section, we compare the proposed modeling approach with other models applied previously to the Three Gorges river reach, and we highlight both its novel capability in achieving improved deterministic predictions and its reliability in quantifying forecasting uncertainties.

2 Materials & Methods

2.1 Study area

The study channel extends from the upstream boundary at the Cuntan hydrological station to the downstream boundary at the TGD on the upper Yangtze River (shown in Figure 1). The flow from the upstream of the Cuntan station accounts for approximately 90% of the total TGD reservoir inflow. The channel length from Cuntan to the TGD is about 604 km with an average channel gradient of 0.22%. Due to the constraint by the rocky hills along the river side, the mountainous river channel has a low sinuosity. As the geometry of the surveyed typical cross-sections and the typical water levels (100-year return period flood level, 20-year return period flood level and annual averaged level) shown in Figure 2, the river channels are characterized by U-shaped or V-shaped cross profiles with narrow and confined floodplains. The river bed mainly consists of sand and gravels, and the river bank

mainly consists of boulders and rough rock. The climate of the study area is a subtropical monsoon climate. The annual mean flow rate at the TGD is 14,300 m³/s. In May to October, torrential rain falling on the steep mountains of the Three Gorges region leads to fast-flowing damaging floods that can be developed within a period as short as 3–6 hours. The peak flow rate of the flood of 100-year return period is 83,700 m³/s (Fang and Rodi, 2003). After the TGD started to impound water in 2003, the upstream rivers of the TGD is affected by backwater in varying degrees, which makes the propagation of flood wave more complicated. Flood control is the top priority for the operation of the TGD, rather than hydropower generation, navigation, and water recharge. During flooding season, water level of the TGD reservoir will be kept low so as to ensure an adequate flood storage capacity (Wang and Chunhong, 2009). The reservoir release schedule is adapted based on real-time flood forecasting information. Hydrometric data are measured at seven hydrological stations along the mainstream channel. In addition to the Cuntan and TGD hydrological stations at the upstream and downstream boundaries, there are five additional hydrological stations on the mainstream channel, including Changshou, Qingxichang, Zhongxian, Wanxian, and Fengjie. Due to the importance of the TGD, gauge stations are also set on the main tributaries to measure the flow diverted into the mainstream channel. The real-time observations at these hydrological stations on the mainstream channel and tributaries are transmitted to the flood-control center every hour.

Fig. 1. River reach of the Yangtze River from Cuntan to the Three Gorges Dam.

Fig. 2. Typical cross-sections of the study channel with typical water level at six hydrological stations.

2.2 Hydraulic model

Although the 2-D modelling approach for flood propagation can provide more comprehensive and detailed flooding results, such as flood inundation, the 1-D modelling approach is still widely used in engineering practice due to its ease of implementation, reduced computational time and high real-time operational efficiency (Costabile et al., 2015). For this study, considering the long channel length, limited floodplain, and low sinuosity, as well as our flood forecasting is mainly focused on discharge and stage at cross-sections rather than flood inundation, the 1-D modelling approach is adopted to achieve real-time flood forecasting efficiently and sufficiently. So, the hydraulic model employed here is the classic 1D unsteady open-channel flow model represented with Saint-Venant formulation as (Chow et al., 1988):

$$\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial l} = q_l \quad (1)$$

$$\frac{\partial Q}{\partial t} + \frac{\partial}{\partial l} \left(\frac{\alpha Q^2}{A} \right) + gA \frac{\partial Z}{\partial l} + g \frac{Q|Q|n^2}{AR^{4/3}} = 0 \quad (2)$$

where t is the time, l is the space distance along the channel, Q is the discharge, Z is the stage, α is the momentum correction factor, A is the cross-section area, R is the hydraulic radius and q_l is the lateral discharge, and n is the Manning's roughness

coefficient. There are two flow state variables (i.e. discharge Q and stage Z) and one parameter (i.e. Manning's roughness coefficient n) in the Saint-Venant formulation.

Eqs. (1) and (2) are hyperbolic partial differential equations without analytical solution. The equations can be numerically solved with the four-point implicit finite-difference approximation with appropriate initial and boundary conditions (Castellarin et al., 2009). The advantages of the four-point implicit finite-difference scheme are that it is unconditionally stable, extremely robust and fast computation. The main drawback of the scheme is that it can't work well when the river topography is very complex, which is not the case in the current work. The upstream and lateral boundary conditions are inflow discharges and the downstream boundary conditions are outflow stages.

It's worth noting that the form of the above basic governing equations implicates the assumption of uniform velocity distribution in whole cross-section. When the out-of-bank flow occurs in compound channels, the difference in water depth and flow resistance between main channel and floodplains will lead to a difference in the flow velocity between these subsections. The division of cross-section should be considered in the governing equations to simulate the different flow characteristics in subsections by introducing larger momentum correction factor, transversal variations of Manning's roughness coefficient and the momentum transfer between main channel and floodplains (Costabile and Macchione, 2012). Considering the geometry of the cross-sections in the study channel and the floodplains are narrow or not developed in the mountain valleys, we simplify all cross-sections as simple channels ignoring the influence of floodplains. So the basic governing equations of the 1D hydraulic model remains the classic form with an overall Manning's roughness coefficient for each cross-section. The other advantage of using an overall Manning's roughness coefficient in hydraulic models is the ease of updating it in the assimilation step, which will be clarified in the following paragraphs.

The Manning's roughness coefficient reflects the aggregate resistance to the open-channel flow. Its value is not only controlled by physical conditions, such as bed geology and cross-sectional geometry, but is also affected by flow conditions, such as

the extent of submerged vegetation and flow turbulence intensity. The overall Manning's roughness coefficient for a cross-section is a composite value including the flow resistance contributions by all factors, which can be calibrated by comparing with hydrological observations. Given the longitudinal variation of the physical characteristics of a channel and the unsteady flooding flow, the Manning's roughness coefficients in the flood-forecasting model should be allowed to vary both spatially and temporally. Hsu et al. (2006) described a method for dividing a river reach into multiple segments, in which each segment is defined by two adjacent hydrological stations along the river and a series of spatially discrete cross-sections. Each river segment is assigned an independent Manning's roughness coefficient, while the cross-sections within a river segment share the same Manning's roughness coefficient. The Manning's roughness coefficient values are initially calibrated according to historical flow data using a trial-and-error method, and subsequently updated according to real-time stage observations from the hydrological stations to reflect the instantaneous changes in flow resistance resulting from the unsteady flood. According to previous studies (Wu et al., 2008; Wu et al., 2013), the initial calibrated Manning's roughness coefficients along the channel for each river reach are 0.036 from Cuntan to Changshou, 0.04 from Changshou to Qingxichang, 0.035 from Qingxichang to Zhongxian, 0.038 from Zhongxian to Wanxian, 0.045 from Wanxian to Fengjie and 0.07 from Fengjie to TGD, respectively.

To build the topography of the study channel for hydraulic model, we collected data of 86 surveyed cross-sections perpendicular to the flow direction and further supplemented the surveyed cross-sections by dividing the river reach into 296 cross-sections at a horizontal resolution of about 2km. There are no man-made structures in the study channel except for few suspension bridges with long spans and piers close to the river banks. In the model calculation, we deducted the area of bridge piers under the water to derive the actual cross-section area.

2.3 Particle filter

The PF is a sequential data assimilation algorithm that utilizes Monte Carlo simulation based on the Bayesian theory. One advantage of the PF, as compared with other data assimilation algorithms, is its capability to deal with non-linear and non-Gaussian modeling systems. For a non-linear stochastic model system, the dynamic state-space formulation can be described by the state transition equation and the observation equation as follows:

$$x_t = f(x_{t-1}, \theta_t, u_t) + v_t \quad v_t \sim N(0, V_t) \quad (3)$$

$$y_t = e(x_t, \theta_t) + w_t \quad w_t \sim N(0, W_t) \quad (4)$$

where f is the non-linear operator expressing the system transition from time $t-1$ to t in response to the model forcing data u_t , N is the symbol of normal distribution, x_t is the system state variable vector at time t , θ_t is the time-variant model parameter vector, v_t is the white noise random sequence in the discrete-time domain with mean zero and variance V_t in state transition equation, e is the non-linear operator mapping model prediction of variables of interest from both model state variables and parameters, y_t is the observation of variables of interest at time t , w_t is the white noise random sequence in the discrete-time domain with mean zero and variance W_t in the observation equation. To consider the stochastic character of the state-space formulation, the state variables and the parameters are represented by probability distribution to consider their uncertainties.

The state-space formulation is recursive so that it can be applied to sequentially assimilate observational data when it becomes available. The relationship between the model outputs and observational data from time $t-1$ to t can be represented by conditional probability recursive equation as:

$$p(x_t, \theta_t | y_{1:t}) = \frac{p(y_t | x_t, \theta_t)}{p(y_t | y_{1:t-1})} p(x_t, \theta_t | y_{1:t-1}) \quad (5)$$

where $p(x_t, \theta_t | y_{1:t})$ is the posterior probability distribution of model state variables and parameters at time t , $p(x_t, \theta_t | y_{1:t-1})$ is the prior probability distribution at time t which

can be obtained from the posterior probability distribution at time $t-1$ by the state transition equation, $p(y_t | x_t, \theta_t)$ is the likelihood function at time t , and $p(y_t | y_{1:t-1})$ is the normalizing constant.

For complex systems it is difficult to obtain analytical functional expressions of the probability distributions of state variables and parameters. The PF employs an ensemble particles (i.e. sets of model state variables and parameters) to approximate the distributions. Particles generated by Monte Carlo simulation can approximate adequately to the true probability densities when the number of particles is large enough. With the ensemble of particles, the posterior probability distribution of model state variables and parameters at time t can be approximated as:

$$p(x_t, \theta_t | y_{1:t}) \approx \sum_{i=1}^{N_p} w_t^i \delta(x_t - x_t^i, \theta_t - \theta_t^i) \quad (6)$$

where (x_t^i, θ_t^i) and w_t^i is the i th particle and its weight respectively, $\delta(\cdot)$ is the Dirac delta function, N_p is the number of particles.

For a non-linear stochastic model system, like a hydraulic model, the particles used to approximate the posterior probabilities of state variables and parameters are updated by assimilating the information contained in new observations and recursively propagated through the model internal dynamics for next time steps. The recursive model procedures based on the PF can be divided into two phases: model forecast and filter correction. Figure 3 illustrates the evolution of particles in the recursive processes.

(1) Model forecast phase. The dynamic non-linear model is executed from time $t-1$ to t for each particle (i.e. each set of state variables and parameters). Before integration, each particle represents the posterior probability distribution of a set of state variables and model parameters at time $t-1$, while after integration each particle represents the prior probability distribution at time t .

(2) Filter correction phase. There are three steps during filter correction: likelihood calculation, resampling and perturbation. The aim of likelihood calculation is to update the weight of each particle based on available observations. The

likelihood value of each particle can be calculated by Gaussian likelihood function as:

$$w_t^i = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x_t^i - y_t)^2}{2\sigma^2}\right) \quad (7)$$

where x_t^i is the prior state variables of i th particle at time t , y_t is the observation of state variables at time t , and σ is the standard deviation associated with the observation noise.

The weight of each particle is determined by normalizing its likelihood value by the sum of the likelihood value of all particles:

$$W_t^i = w_t^i / \sum_{i=1}^{N_p} w_t^i \quad (8)$$

where W_t^i is the normalized weight of the i th particle at time t . N_p is the number of particles.

Resampling is performed after calculating the normalized weights. It is possible that most particles obtain negligible weights and only a few particles are effective in the filter, which is called “particle degeneracy” (Snyder et al., 2008). In order to reduce the meaningless calculation and estimate current time step’s state more accurately, it is essential to resample the particles, which is a process to eliminate the low weighted particles and generate promising new particles based on the high weighted particles.

Here we used the multinomial resampling algorithm (Gordon et al., 1993). First, it divides the interval $[0, 1]$ into N_p sub-intervals based on the N_p normalized weights of the current pool of particles. The i th interval is represented by $[\sum_{j=1}^{i-1} W_t^j, \sum_{j=1}^i W_t^j]$. Next, N_p random numbers are generated following the uniform distribution $r_k \sim U[0,1]$. If r_k belongs to the i th interval, then duplicate the i th particle. After N_p times duplicating, all the particles are assigned with same weight $1/N_p$.

Perturbation is introduced to maintain the diversity of particles. Although resampling can alleviate degeneracy, the diversity of particles may deteriorate given that some individual particles with large weights are duplicated many times leading to “sample impoverishment” (Moradkhani et al., 2012). Repeating model runs with the same particles is a waste. The perturbed particles can move in the space stochastically

in order to track the possible evolution over time. The particles can be perturbed by incorporating a random noise to the model parameter:

$$\theta_{t+1} = \theta_t + \zeta, \quad \zeta \sim N(0, \sigma_p^2) \quad (9)$$

where ζ is the random noise from the Gaussian distribution with mean zero and standard variance σ_p .

Fig. 3. Schematic diagram of the recursive model forecasting and filter correction procedures with the PF.

2.4 Real-time probabilistic flood forecasting model

The real-time probabilistic flood-forecasting model from Cuntan to the TGD is built by integrating the 1D hydraulic model and the PF data assimilation method. With the seven hydrological stations, we assigned the total 296 cross-sections into six river segments. From upstream to downstream, six Manning's roughness coefficients (i.e. n_1 – n_6) are assigned to the Cuntun–Changshou, Changshou–Qingxichang, Qingxichang–Zhongxian, Zhongxian–Wanxian, Wanxian–Fengjie, and Fengjie–TGD segments, respectively. The upstream and lateral boundary conditions are the inflow discharges at Cuntan and confluences of tributaries, which can be predicted using a

rainfall–runoff hydrological model. The downstream boundary condition is the stages at the TGD, which can be derived in advance from the scheduling plan of the TGD reservoir. In this study, both the upstream, lateral and downstream conditions are determined using observed data to minimize uncertainty of the boundary conditions. Here, discharge observations in 17 main tributaries (shown in Fig.1) are added at the confluences to mainstream flow as the lateral inflow boundary conditions. The combination of the discharges, stages, and Manning’s roughness coefficients at all cross-sections along the river determines the behavior of the hydraulic model and comprises a particle. A basic particle represents a realization of stochastic flow along the channel. The ensemble of all particles is used to approximate the probability distribution of the flood flow and provide a means for measuring the uncertainty of the predicted flood stage.

The i -th basic particle in the ensemble at time t , $\bar{P}_i(i) = (\bar{x}_i(i), \bar{\theta}_i(i))$ can be described as:

$$\bar{P}_i(i) = (\bar{Q}_i(i), \bar{Z}_i(i), \bar{n}_i(i)) \quad (10)$$

$$\bar{Q}_i(i) = (Q_i^1(i), Q_i^2(i), \dots, Q_i^j(i), \dots, Q_i^m(i)) \quad (11)$$

$$\bar{Z}_i(i) = (Z_i^1(i), Z_i^2(i), \dots, Z_i^j(i), \dots, Z_i^m(i)) \quad (12)$$

$$\bar{n}_i(i) = (n_i^1(i), n_i^2(i), \dots, n_i^j(i), \dots, n_i^m(i)) \quad (13)$$

where Q_i^j , Z_i^j , and n_i^j are the discharge, stage, and Manning’s roughness coefficient at the j -th cross-section at time t , and m is the total number of cross-section sections.

It’s worth noting that the new flood-forecasting model system consisting of the swarm of individual model particles updates the states and parameters of the model system by adjusting particle weights instead of updating the states and parameters in the individual models explicitly. For simplicity, we specify the new flood-forecasting model system with the PF as “new model” in the rest part. Because the observed stage data are more accurate than the discharge observations and the discharge observational data are limited at some hydrological stations (e.g., Changshou, Zhongxian, and Fengjie), we only assimilate real-time stage observations into the new model. The observed stage at the TGD is already used as the downstream boundary,

leaving the real-time stage observations at the other six hydrological stations available as assimilation data. Each stage observation is used to evaluate the model simulation at the corresponding cross-section by generating a sub-likelihood:

$$w_t^{i,j} = \frac{1}{\sqrt{2\pi}\sigma_t^j} \exp\left(-\frac{(Z_t^{i,j} - Y_t^j)^2}{2\sigma_t^{j2}}\right) \quad (14)$$

where $w_t^{i,j}$ is the sub-likelihood at the j -th hydrological station for particle i at time t , $Z_t^{i,j}$ is the model-simulated stage, Y_t^j is the observed stage, and σ_t^j is the standard deviation of the likelihood function, which is assumed constant along the river at every assimilation time step for the sake of simplicity (Matgen et al., 2010).

The overall likelihood of a particle is calculated by applying the joint probability theory for independent variables:

$$w_t^i = \prod_{j=1}^{N_o} w_t^{i,j} \quad (15)$$

where N_o is the number of stage observations.

Subsequently, the weighting of each particle can be derived by normalizing the overall likelihood:

$$W_t^i = w_t^i / \sum_{i=1}^{N_p} w_t^i \quad (16)$$

The multinomial resampling algorithm is used to resample particles. As perturbations of the stages and discharges may cause imbalances in the mass conservation in the hydraulic model, the perturbation procedure is only applied to the Manning's roughness coefficients (Hsu et al., 2006).

With the pre-conditioned boundary conditions, the hydraulic model was implemented with each particle to forecast the probabilistic distribution of the incoming flood flow into the TGD. When new real-time stage observations are available, the particles are updated using the PF.

The following illustrates the procedures of the implementation of the real-time probabilistic flood-forecasting model using the PF (Figure 4):

- (1) Model Initialization. Sample N_p initial particles $\vec{P}_0 = (\vec{Q}_0, \vec{Z}_0, \vec{n}_0)$ from prior probability distributions and assign the particle weights uniformly with $W_0^i = 1 / N_p$.

Here, the initial discharges $\bar{Q}_0$, stages $\bar{Z}_0$, and Manning's roughness coefficients $\bar{n}_0$ of each particle are derived by adding noises drawn from uniform distributions at each cross-section as follows:

$$\hat{Q}_0^m = Q_0^m + \varepsilon_Q^m \quad \varepsilon_Q^m \sim U[-0.1Q_0^m, 0.1Q_0^m] \quad (17)$$

$$\hat{Z}_0^m = Z_0^m + \varepsilon_Z^m \quad \varepsilon_Z^m \sim U[-0.05, 0.05] \quad (18)$$

$$\hat{n}_0^m = n_0^m + \varepsilon_n^m \quad \varepsilon_n^m \sim U[-0.005, 0.005] \quad (19)$$

where m is the index of the cross-section and hat symbols indicate variables perturbed by noise. As the Manning's roughness coefficients of all cross-sections in a river segment are assumed to be uniform, the same noises for perturbing Manning's roughness coefficients are applied in a river segment.

(2) Likelihood Estimation. Use the real-time stage observations at the hydrological stations from Cuntan to Fengjie at time t to update the particle weights. The weight of each particle can be estimated using Eqs. (14)–(16).

(3) Particle Resampling. Employ the polynomial resampling algorithm to resample the particles, removing those particles with low weights and duplicating particles with high weights to map the unequally weighted set of particles into an equally weighted set.

(4) Particle Perturbation. Perturb the particles by adding random noise to the Manning's roughness coefficients to reduce the risk of sample impoverishment:

$\bar{n}_t = \bar{n}_{t-1} + \zeta$, $\zeta \sim N(0, \sigma_p^2)$. Considering that the varying gradients of Manning's roughness coefficients with time are varying from upstream to downstream along the river, we assign different variances for the normal random noises in different river segments as follows:

For the first two river segments Cuntan to Changshou and Changshou- Qingxichang:

$$\bar{n}_t = \bar{n}_{t-1}^{resample} + \zeta_1, \quad \zeta_1 \sim N(0, 0.004^2) \quad (20)$$

For the second two river segments Qingxichang to Zhongxian and Zhongxian to Wanxian:

$$\bar{n}_t = \bar{n}_{t-1}^{resample} + \zeta_2, \quad \zeta_2 \sim N(0, 0.003^2) \quad (21)$$

For the last two river segments Wanxian to Fengjie and Fengjie to TGD:

$$\bar{n}_t = \bar{n}_{t-1}^{resample} + \zeta_3, \quad \zeta_3 \sim N(0, 0.002^2) \quad (22)$$

(5) Forecasting Calculation. Calculate discharge and stage predictions with each updated particle $\bar{P}_t(i) = (\bar{Q}_t(i), \bar{Z}_t(i), \bar{n}_t(i))$ at time t using the hydraulic model to provide the probabilistic forecasting of $\bar{Q}_{t+LT}$ and $\bar{Z}_{t+LT}$ at the lead-time LT . For each particle, the discharges at upstream and lateral boundaries are derived by perturbing the observed discharge data, and the stages at downstream boundary are derived by perturbing the observed stage data as follows:

$$\hat{Q}_t^{up} = Q_t^{up} + \xi_1, \quad \xi_1 \sim N(0, 0.05Q_t^{up}) \quad (23)$$

$$\hat{Q}_t^{lateral} = Q_t^{lateral} + \xi_2, \quad \xi_2 \sim N(0, 0.05Q_t^{lateral}) \quad (24)$$

$$\hat{Z}_t^{down} = Z_t^{down} + \eta, \quad \eta \sim N(0, 0.03) \quad (25)$$

Two points need to be explained to get deeper understanding of the developed model approach. One is that the uncertainty of forcing data (inputs) is reduced by using the observational data with small noises as the boundary conditions, and the uncertainty of model structure is not considered. In this setting, the model uncertainty is more associated with the uncertainty of model parameter (i.e. Manning's roughness coefficient). So, by assimilating the stage observations into the hydraulic model sequentially, the dynamic estimation of the uncertainty of Manning's roughness coefficients can be achieved. The other is that, we also add small random perturbations to resampled parameter particles artificially to avoid sample impoverishment, but the parameter augmentation method will not result in possibly diffusive distributions and unstable inference, deteriorating the parameter identifiability as shown in the previous study (Moradkhani et al., 2005b). Here, the Manning's roughness coefficient as an inherently time-varying model parameter evolves over the course of a flood event. When real-time stage observations are available, the Manning's roughness coefficients will be updated as part of a particle

454 along with state variables. The resampling step narrows down the range of Manning's
455 roughness coefficients towards the "true value". Therefore, the general evolving trend
456 of Manning's roughness coefficients remains stable and consistent in repeated
457 simulation runs, which show a satisfactory identifiability in parameter estimation.

Fig. 4. Flow chart of the probabilistic flood-forecasting model.

2.5 Experimental setup and evaluation metrics

2.5.1 Synthetic experimental setup

To test the validity of the developed modeling approach to approximate true distributions of the state variables, parameters, and flood forecasting, numerical synthetic experiments are carried out to evaluate the model performance. Simplified linear relationships between the Manning's roughness coefficient and water depth are assumed to generate synthetic "true values." According to the field investigation of Yang and Liu (1991) in the study area, the river bank roughness is higher than the riverbed roughness, resulting in that Manning's roughness coefficients increase with the rise of water depth. Here, we simply assume that Manning's roughness coefficients are linearly proportional to water depth in each river segment, as shown in Figure 5. Based on this underlying assumption, the hydraulic model is executed in a free run using the boundary conditions of a real flood event that occurred from 00:00 June 27, 2009 to 00:00 July 09, 2009. The initial Manning's roughness coefficients are determined by the assumed relationship with initial water depth. The simulated time-varying stages, discharges, and Manning's roughness coefficients at all cross-sections are recorded as synthetic "true values."

After the free run, the synthetic "true" stages at the hydrological stations are used as "observations" to be assimilated into the new model every hour in an assimilation run with the PF. In the assimilation run, the initial Manning's roughness coefficients are set as the pre-calibrated values as described in Section 2.3. Some site-specific parameters in the PF algorithm that affect the PF assimilation performance are determined by sensitive experiments to get the optimal settings, which is detailed in the supplementary. With these considerations, the number of particles N_p is chosen as 200, which can balance model performance and calculation burden. And the standard deviation σ in the likelihood function is set to 0.1, which has optimal resampling effects at both upstream and downstream cross-sections. To reflect the improvement brought by the PF in model performance, another free run without assimilation using

the fixed pre-calibrated Manning's roughness coefficients, which is referred to as open-loop simulation, is also executed.

Fig. 5. Assumed linear relationships between water depth h and the Manning's roughness coefficient n for different river segments in the synthetic experiments.

2.5.2 Real-world case studies

The new model is also applied to three documented real flood events to test its applicability in real-world situations. These flood events are: flood event 1 from 00:00 on 27 June to 00:00 on 9 July, flood event 2 from 00:00 on 9 July to 00:00 on 24 July and flood event 3 from 00:00 on 1 August to 00:00 on 17 August. All three flood events occurred in 2009. As in synthetic experiments, the boundary conditions used in real-world experiments are the observed discharges at Cuntan and confluences of tributaries and stages at TGD to minimize the uncertainty of boundary conditions. The historical hourly water stages at hydrological stations are assimilated into the hydraulic model. Same as in the assimilation run of synthetic experiment, the initial Manning's roughness coefficients are set to the pre-calibrated values, and the number of particles and standard deviation in the likelihood function are set to 200 and 0.1, respectively. Open-loop simulations are also executed with the same fixed Manning's roughness coefficients for the three real flood events.

2.5.3 Model performance evaluation metrics

One deterministic metric, the root-mean-square error (RMSE), is used to evaluate the accuracy of model results. The RMSE represents the sample standard deviation of the differences between the mean values of predicted particle ensembles and observed values:

$$RMSE = \sqrt{1/N \left(\sum_{k=1}^{N_{obs}} \bar{p}^k - p_{true}^k \right)^2} \quad (26)$$

where $\bar{p}^k$ is the mean value of the particle ensemble simulated by the new model, p_{true}^k is the synthetic truth, p can be discharge, stage and Manning's roughness coefficient. N_{obs} is the total number of the assimilated observations.

Two probabilistic metrics, the percentage of observations within a certain confidence interval (PERCT) and the Quantile-Quantile (Q-Q) plot, are used to evaluate the probabilistic reliability of model results.

The PERCT can be used to examine the reliability of the certain predictive confidence interval quantitatively by comparing the namely confidence level with it (Vrugt et al., 2013):

$$PERCT = \frac{\sum_{k=1}^{N_{obs}} I_k}{N_{obs}} \times 100\% \quad (27)$$

where I_k is the function of p_{true}^k , $p_{downbound}^k$ and $p_{upbound}^k$: $I_k=1$ if $p_{downbound}^k \leq p_{true}^k \leq p_{upbound}^k$ and $I_k=0$ if $p_{true}^k < p_{downbound}^k$ or $p_{true}^k > p_{upbound}^k$. $p_{downbound}^k$ and $p_{upbound}^k$ are the lower boundary and upper boundary of the confidence interval. PERCT-66% and PERCT-95% are most commonly used corresponding to 66% and 95% confidence interval. The symmetric ranges of 66% and 95% confidence intervals are from 17th to 83rd percentiles and from 2.5th to 97.5th percentiles, respectively. Here, to facilitate the interpretation of PRERCT, we also calculate the normalized PRERCT. When the normalized PRERCT value equals one, it means the estimated confidence interval can perfectly represent its nominal uncertainty. When the normalized PRERCT value is larger than 1 or smaller than 1, the confidence interval is over-estimated or under-estimated, respectively.

The Q-Q plot is a visual method comparing the empirical cumulative density of p-values of observations in the predictive distribution on the y-axis and the uniform distribution on the x-axis to examine the reliability of the probabilistic distribution. If the plot follows a 1:1 line, it indicates that this probabilistic prediction is perfectly reliable. The advantage of Q-Q plot is that it can illustrate different aspects of probabilistic prediction including the under- or over-prediction and under- or over-estimated predictive uncertainty. The detailed description of the Q-Q plot can be found in Laio and Tamea (2007).

3 Results & Discussion

3.1 Synthetic experiments

3.1.1 Correction performance

A good data assimilation algorithm must have the capability of incorporating observations into the new model to update model states and parameters effectively. The quality of the correction performance will have a direct influence on the subsequent forecasting performance. The synthetic experiments are used to evaluate the correction performance. Figure 6 shows the corrected discharges, stages, and Manning's roughness coefficients against the synthetic truths. Clearly, the discharges, stages, and Manning's roughness coefficients are progressively corrected to track the synthetic truths throughout the course of the flood event, indicating the usefulness of the PF. Although we only used the observed stages for assimilation into the new model, the discharges and Manning's roughness coefficients can also be corrected indirectly because they are coupled with stages as part of the particles. As shown in Table 1, the RMSE values of the corrected discharges, stages, and Manning's roughness coefficients against the synthetic truths in the PF assimilation run are significantly lower than those in the open-loop simulation. Figure 7 shows the histograms of the simulated and corrected discharges, stages, and Manning's roughness coefficients at 02:00 June 29 ($t = 50$ h) for the synthetic flood event. This

instance is chosen because it is located in the rising limb of the flood event. We can observe differences between the prior and posterior probability distributions of discharges, stages, and Manning's roughness coefficients, and a clear shift toward the synthetic truth. This illustrates a typical correction process whereby the prior probability distributions are effectively updated to the posterior probability distributions via the assimilation of information contained in the observations with the PF.

Values of PERCT-66% and PERCT-95% are also listed in Table 1 and the Q-Q plots are shown in Figure 8 (for legibility, only results at Qingxichang and Wanxian are shown) to evaluate the probabilistic reliability of the posteriori probability distributions of discharges, stages, and Manning's roughness coefficients. Generally, PERCT-66% and PERCT-95% are consistent with the corresponding confidence intervals and the Q-Q plots are close to the 1:1 uniform line, indicating that the ensemble of updated particles can reliably derive probabilistic simulations of the synthetic truths.

Fig. 6. Corrected probabilistic distributions of the Manning's roughness coefficients, stages, and discharges for the synthetic experiments with default settings. (The dot line represents the synthetic truths. The solid line represents the ensemble mean of particles. The dash line represents

581 the open-loop results. The shaded areas correspond to 66% (lighter shading) and 95% (darker
 582 shading) confidence intervals.)

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Fig. 7. Histograms of prior (gray) and posterior (dashed) distributions of discharges, stages and Manning's roughness coefficients at $t = 50$ h of the synthetic experimental flood event. The synthetic truths are indicated as stars. The vertical dash line is the prior histogram centroid and the vertical solid line is the posterior histogram centroid.

Table 1 Correction performance for the synthetic experiment.

Stage				Manning's roughness coefficient						Discharge				
RMSE(m)		PERCT(%)		RMSE(unitless)		PERCT(%)		RMSE (m³/s)		PERCT(%)				
		(Normalized)				(Normalized)				(Normalized)				
Open	PF	-66	-95	Open	PF	-66	-95	Open	PF	-66	-95			
-loop				-loop				-loop						
CT	0.284	0.117	72.2 (1.08)	87.3 (0.92)	CT-CS	8.40E-03	6.80E-04	83.3 (1.25)	94.4 (0.99)	CS	784.2	193.1	72.2 (1.08)	92.7 (0.98)
CS	0.234	0.077	83.3 (1.25)	94.4 (0.99)	CS-QXC	7.20E-03	8.50E-04	77.8 (1.17)	94.4 (0.99)	QXC	698.1	232.1	61.1 (0.92)	88.9 (0.94)
QXC	0.175	0.038	83.3 (1.25)	94.4 (0.99)	QXC-ZX	9.30E-03	5.40E-04	72.2 (1.08)	100.0 (1.05)	ZX	684.3	218.4	66.7 (1.00)	88.9 (0.94)
ZX	0.156	0.031	72.2 (1.08)	87.3 (0.92)	ZX-WX	1.05E-02	9.70E-04	66.6 (1.00)	94.4 (0.99)	WX	623.4	206.4	72.2 (1.08)	88.9 (0.94)
WX	0.102	0.016	72.2 (1.08)	94.4 (0.99)	WX-FJ	6.80E-03	1.04E-03	66.6 (1.00)	100.0 (1.05)	FJ	658.1	199.9	72.7 (1.09)	83.3 (0.88)
FJ	0.115	0.014	83.3 (1.25)	100.0 (1.05)	FJ-TGD	1.21E-02	8.60E-04	72.2 (1.08)	88.9 (0.94)	TGD	715.7	196.4	66.7 (1.00)	77.8 (0.82)

Fig. 8. Q-Q plot visualizing the correction performance for the synthetic experiment.

3.1.2 Forecasting performance

The developed modeling approach is intended to provide more accurate and reliable forecasting of incoming floods. In the synthetic experiments, the RMSEs of discharge and stage predictions for a lead time up to 12 hours are shown in Figure 9 for the Qingxichang and Wanxian stations. With increase in lead time, the accuracy of discharge and stage prediction decreases. One reason is that the Manning's roughness coefficients obtained for the current time step do not adequately represent the hydraulic conditions several hours later. This emphasizes the importance of keeping track of the changing flood flow to adjust Manning's roughness coefficients in flood forecasting. Figure 10 shows Q-Q plots of discharge and stage predictions at the lead times of 3 h, 6 h, 9 h, and 12 h at Qingxichang and Wanxian, respectively. In general, with increase in lead time, the probabilistic predictions deteriorate slightly, but still represent well the uncertainty of simulated stages and discharges.

Fig. 9. RMSEs of predicted discharges and stages at different lead times at Qingxichang and Wanxian for the synthetic experiments.

Fig. 10. Q-Q plots of predicted discharges and stages at different lead times at Qingxichang and Wanxian for the synthetic experiments.

3.2 Real-world Experiments

3.2.1 Correction Performance

The new model's correction performance is evaluated to verify the correction ability of the PF for real flood events. The Qixichang and Wanxian hydrological stations observe both stages and discharges, and therefore the corrected discharges, stages, and Manning's roughness coefficients at these two stations are selected to illustrate the model correction performance, as shown in Figure 11.

The Manning's roughness coefficients are effectively corrected from the initial pre-calibrated values and updated to accommodate changes in the hydraulic conditions over the course of the flood events. According to the results, the relationship between the Manning's roughness coefficients and stages in real flood events is quite complex. Generally, the Manning's roughness coefficients increase

nonlinearly with the increase of stages. This is mainly due to the roughness of the river bank is larger than the roughness of the riverbed. When the stage rises from a low level, the Manning's roughness coefficients increase with increase of water depth for the flow resistance is more influenced by the rough bank than before. When the stage reaches a certain level and continues to rise, the Manning's roughness coefficients may increase or decrease, or remain constant, depending on the complex interplay of many factors, like flow condition, bed form, and composition of river bank. For example, in flood event 3, the Manning's roughness coefficients in the Wanxian–Fengjie segment decreased as the stage increased.

The correction results for stages and discharges are shown in Figure 11 against the real observations. Discrepancies between the corrected and observed stages (as well as between corrected and observed discharges) are noticeable at the beginning for all three flood events, indicating that the initializations of the model state variables and parameters are not optimal. However, as the data assimilation process proceeds, these discrepancies gradually decrease over time.

The averaged metric values for the three flood events (excluding the beginning 20 hours that are affected by the model initialization errors) are used to describe the model performance in the real-world experiments. The comparison of averaged RMSEs of the stages and discharges between the open-loop and PF runs, as shown in Table 2, demonstrates the advantage of the PF in correcting model states. The uncertainty associated with the corrected stage and discharge is also well estimated as indicated by the probabilistic metrics of PERCT-66% and 95% (shown in Table 2) and Q-Q plots (shown in Figure 12).

Table 2 Averaged correction performance for the three real-world flood events.

Stage					Discharge				
RMSE(m)			PERCT(%)		RMSE (m ³ /s)			PERCT(%)	
			(Normalized)					(Nomalized)	
	Open-loop	PF	-66	-95		Open-loop	PF	-66	-95
CT	0.462	0.145	78.7	91.1	QXC	2658.2	536.4	62.5	80.4
			(1.18)	(0.96)				(0.94)	(0.85)
CS	0.388	0.155	66.1	80.4					

			(0.99)	(0.85)					
			78.5	93.6					
QXC	0.342	0.128	(1.18)	(0.99)					
			76.6	80.4					
ZX	0.298	0.107	(1.15)	(0.85)					
			64.3	89.4					
WX	0.228	0.088	(0.97)	(0.94)	WX	3432.5	682.4	58.9	84.0
			63.8	78.7				(0.88)	(0.88)
FJ	0.186	0.057	(0.96)	(0.83)					

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Fig. 11. Corrected probabilistic distributions of the Manning's roughness coefficients, stages, and discharges at Qingxichang and Wanxian for the three real flood events. (The dot line represents the real observations. The solid line represents the ensemble mean of the particles. The dash line represents the open-loop results. The shaded areas correspond to 66% (lighter shading) and 95%

(darker shading) confidence intervals. The three columns from left to right are for flood events 1, 2 and 3, respectively.)

Fig. 12. Q-Q plot visualizing averaged model correction performances for the three real-world flood events.

3.2.2 Forecasting Performance

Stages and discharges are predicted at lead times up to 12 hours for the three real flood events. Figure 13 shows the probabilistic predictions of stages and discharges at the lead time of 3 h against observations at Qixichang and Wanxian hydrological stations. The model forecasting performance is highly dependent on the correction performance obtained by the PF. Similar to the assessments of correction performance reported in the previous section, we also observed larger discrepancy between the forecasted and observed stages at the beginning than the later phases of the flood events. This is also true for discharge prediction. These findings highlight the role of progressively assimilating real-time observations for improving flood forecasting over time.

Figure 14 shows the averaged RMSE of predictions of stages and discharges for three flood events at lead times up to 12 hours. Similar to the results in the synthetic experiments, the accuracy of discharge and stage predictions decreases with increase in lead time due to the fixed Manning's roughness coefficients.

Figure 15 shows Q-Q plots of discharge and stage predictions at lead times of 3 h,

679 6 h, 9 h, and 12 h at Qingxichang and Wanxian, respectively. In general, the reliability
680 of the probabilistic predictions in the real-world experiments at both sites is lower
681 than that in the synthetic experiments due to the involvement of the uncertainty
682 associated with model structure in the real-world experiments, but still acceptable.
683 The predictive uncertainty of stage is over-estimated, while the predictive uncertainty
684 of discharge is under-estimated. The stage predictions are more reliable than the
685 discharge predictions. This can be attributed to that we only assimilated the stage
686 observations into the hydraulic model. There is also a trend of slight deterioration in
687 predictive reliability with increase of lead time in both stage and discharge
688 predictions.

689 Many factors, such as flood magnitude, stage rising rate and the operational water
690 level at the TGD, may influence the flood travel time. So the flood travel time varies
691 in different flood events at different locations. In common, according to the three real
692 flood events we simulated, the averaged flood travel time from Cuntan to TGD is
693 about 22 hours, which includes about 6 h from Cuntan to Changshou, about 4 h from
694 Changshou to Qingxichang, about 4 h from Qingxichang to Zhongxian, about 4 h
695 from Zhongxian to Wanxian, about 2 h from Wanxian to Fengjie and about 2 h from
696 Fengjie to TGD.

Fig. 13. Probabilistic forecasting of stages and discharges at a lead time of 3 h at Qingxichang and Wanxian for the three real-world flood events. (The dot line represents the real observations. The solid line represents the ensemble mean of the particles. The dash line represents the open-loop results. The shaded areas correspond to 66% (lighter shading) and 95% (darker shading) confidence intervals. The three columns from left to right represent flood events 1, 2 and 3, respectively.)

Fig. 14. RMSEs of predicted discharges and stages for different lead times at Qingxichang and Wanxian in the real-world experiments.

Fig. 15. Q-Q plots of predicted discharges and stages for different lead times at Qingxichang and Wanxian in real-world experiment.

3.3 Comparison with previous studies in the Three Georges Reach

Fig. 16. Comparison of forecasting performance in terms of RMSE between this study and previously used models.

To put the performance of the new modeling approach developed in this study into perspective, we compared the new model with several models that have been applied previously for real-time channel flood forecasting for the river reaches upstream of the TGD. These previous studies employed various real-time correction methods to adjust hydraulic models by assimilating real-time hydrological observational data. The flood forecasting of each of the three studies is implemented for the same three real flood events used in this study by assimilating historical hourly observed stage data. Model flood-forecasting performances averaged over the three events are shown in Figure 16 for the three previous studies and this study, at lead times up to 12 h.

Overall, the flood-forecasting performance of this study is better than the models reported in previous studies. This performance improvement is mainly attributable to the consideration of not only updating the state variables (i.e., stages and discharges), but also correcting the parameters, (i.e., the Manning's roughness coefficients) in the probabilistic model developed here. In the previous studies, either only state variables were updated (Ge et al., 2005; Wu et al., 2013) or only parameters were corrected (Wu and Wang, 2008).

It is worth noting that the forecasting performance at a very short lead-time in the study of Ge et al. (2005) is better than what we achieved in this study. One explanation for this is that in their study, the optimal correction performance is

achieved only for individual stations; however, our study aims to achieve a balanced model performance at several hydrological stations simultaneously. To reach a global optimum, the accuracy at any individual cross-section may be sacrificed. For longer lead-times, the accuracy of stage predictions obtained in this study is higher than the study by Ge et al. (2005) mainly because of the dynamic updating of the model parameters. Furthermore, another advantage of this study is that, in addition to deterministic forecasting, our modeling approach can derive probabilistic flood forecasting with the PF assimilation method, thus enable incorporation of uncertainties in model forecasting into flood-control practices.

4 Conclusions

In this study, we developed and evaluated a real-time probabilistic channel flood-forecasting model for the reaches upstream of the TGD on the Yangtze River. This approach couples the hydraulic model with the PF and simultaneously updates/adjusts discharges, stages, and Manning's roughness coefficients. Real-time stage observations at multiple hydrological stations along the channel were assimilated into the modeling system to achieve ensemble probabilistic forecasting.

We tested the new modeling approach against synthetic and three real-world flood events. For both the synthetic and real-world flood events, we obtained similar patterns of model performance. The modeling approach developed here was shown to be capable of both effectively and simultaneously updating discharges, stages, and Manning's roughness coefficients, and progressively improving the prediction accuracy and probabilistic distribution approximation over the course of the flood events.

The performance of our modeling approach is in general better than that of previous models applied to the reaches upstream of the TGD on the Yangtze River, in terms of deterministic flood forecasting. In addition, our model's ability to reliably simulate probabilistic flooding is of important value for incorporating uncertainty into flood-control decision making. Overall, the modeling efforts undertaken in this study

hold the promise for improving flood forecasting for the Yangtze River, thereby enhancing societal resilience to flooding disasters in this highly populated region of China.

Despite the progress made in this study, we also recognize more efforts are still needed to further improve flood forecasting for the TGD on the Yangtze River. First, a more sophisticated 1D hydraulic model should be developed to enhance the flood flow simulation. Simplifications in the 1D hydraulic model used in this study, such as ignoring over-bank-flow and sediment transport, only allows limited physically based interpretation of the results and missed some processes relevant to flood forecasting. More physical processes deserve further integration into the model. Second, to improve model forecasting performance for longer lead times, further coupling the hydraulic model with hydrological and meteorological models awaits future research. With precipitation predicted by meteorological models and runoff simulated by hydrological models, the longer lead time in flood forecasting capacity is going to benefit the operation of the TGD to control flood and generate hydropower. Finally, the uncertainty of the probabilistic forecasting could be better estimated by incorporating more sources of uncertainty in the PF assimilation, such as forcing uncertainty, model structure uncertainty, and parameter uncertainty. Future efforts addressing the above concerns hold the promise to further improve the proposed modeling approach.

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References

- Anderson, J.L., 2010. A non-Gaussian ensemble filter update for data assimilation. *Monthly Weather Review* 138(11) 4186-4198.
- Andreadis, K.M., Clark, E.A., Lettenmaier, D.P., Alsdorf, D.E., 2007. Prospects for river discharge and depth estimation through assimilation of swath - altimetry into a raster - based hydrodynamics model. *Geophysical Research Letters* 34(10).
- Balica, S., Popescu, I., Beevers, L., Wright, N., 2013. Parametric and physically based modelling techniques for flood risk and vulnerability assessment: a comparison. *Environmental Modelling & Software* 41 84-92.
- Bi, H., Ma, J., Wang, F., 2015. An Improved Particle Filter Algorithm Based on Ensemble Kalman Filter and Markov Chain Monte Carlo Method. *Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of* 8(2) 447-459.
- Borup, M., Grum, M., Madsen, H., Mikkelsen, P.S., 2015. A partial ensemble Kalman filtering approach to enable use of range limited observations. *Stochastic environmental research and risk assessment* 29(1) 119-129.
- Castellarin, A., Di Baldassarre, G., Bates, P., Brath, A., 2009. Optimal cross-sectional spacing in Preissmann scheme 1D hydrodynamic models. *Journal of hydraulic engineering* 135(2) 96-105.
- Chaudhry, M.H., 2007. *Open-channel flow*. Springer Science & Business Media.
- Chow, V.T., Maidment, D.R., Mays, L.W., 1988. *Applied hydrology*.
- Costabile, P., Macchione, F., 2012. Analysis of one-dimensional modelling for flood routing in compound channels. *Water Resources Management* 26(5) 1065-1087.
- Costabile, P., Macchione, F., 2015. Enhancing river model set-up for 2-D dynamic flood modelling. *Environmental Modelling & Software* 67 89-107.
- Costabile, P., Macchione, F., Natale, L., Petaccia, G., 2015. Flood mapping using LIDAR DEM. Limitations of the 1-D modeling highlighted by the 2-D approach. *Natural Hazards* 77(1) 181-204.
- Fang, H.-W., Rodi, W., 2003. Three-dimensional calculations of flow and suspended sediment transport in the neighborhood of the dam for the Three Gorges Project (TGP) reservoir in the Yangtze River. *Journal of Hydraulic Research* 41(4) 379-394.
- Fang, H.-W., Wang, G.-Q., 2000. Three-dimensional mathematical model of suspended-sediment transport. *Journal of Hydraulic Engineering* 126(8) 578-592.
- Fang, H., Han, D., He, G., Chen, M., 2012. Flood management selections for the Yangtze River midstream after the Three Gorges Project operation. *Journal of Hydrology* 432 1-11.

882 Ge, S., Chen, H., Li, Y., 2005. Real time updating of hydrodynamic model by using Kalman filter. *Journal*
883 *of hydraulic engineering* 36(6) 687-693.

884 Giustarini, L., Matgen, P., Hostache, R., Montanari, M., Plaza, D., Pauwels, V.R.N., De Lannoy, G.J.M., De
885 Keyser, R., Pfister, L., Hoffmann, L., Savenije, H.H.G., 2011. Assimilating SAR-derived water level data
886 into a hydraulic model: a case study. *Hydrology and Earth System Sciences* 15(7) 2349-2365.

887 Gordon, N.J., Salmond, D.J., Smith, A.F., 1993. Novel approach to nonlinear/non-Gaussian Bayesian
888 state estimation, *IEE Proceedings F (Radar and Signal Processing)*. IET, pp. 107-113.

889 Han, D., Fang, H., Bai, J., He, G., 2011. A coupled 1-D and 2-D channel network mathematical model
890 used for flow calculations in the middle reaches of the Yangtze River. *Journal of Hydrodynamics, Ser. B*
891 23(4) 521-526.

892 Hsu, M., Fu, J., Liu, W., 2006. Dynamic routing model with real-time roughness updating for flood
893 forecasting. *Journal of hydraulic engineering* 132(6) 605-619.

894 Kim, Y., Tachikawa, Y., Shiiba, M., Kim, S., Yorozu, K., Noh, S.J., 2013. Simultaneous estimation of inflow
895 and channel roughness using 2D hydraulic model and particle filters. *Journal of Flood Risk*
896 *Management* 6(2) 112-123.

897 Lai, R., Fang, H., He, G., Yu, X., Yang, M., Wang, M., 2013. Dual state-parameter optimal estimation of
898 one-dimensional open channel model using ensemble Kalman filter. *Journal of Hydrodynamics, Ser. B*
899 25(4) 564-571.

900 Laio, F., Tamea, S., 2007. Verification tools for probabilistic forecasts of continuous hydrological
901 variables. *Hydrology and Earth System Sciences Discussions* 11(4) 1267-1277.

902 Lamberti, P., Pilati, S., 1996. Flood propagation models for real-time forecasting. *Journal of Hydrology*
903 175(1) 239-265.

904 Liu, K., Li, Z., Yao, C., Chen, J., Zhang, K., Saifullah, M., 2016. Coupling the k-nearest neighbor
905 procedure with the Kalman filter for real-time updating of the hydraulic model in flood forecasting.
906 *International Journal of Sediment Research*.

907 Liu, S., Shao, Y., Yang, C., Lin, Z., Li, M., 2012a. Improved regional hydrologic modelling by assimilation
908 of streamflow data into a regional hydrologic model. *Environmental Modelling & Software* 31 141-149.

909 Liu, Y., Gupta, H.V., 2007. Uncertainty in hydrologic modeling: Toward an integrated data assimilation
910 framework. *Water resources research* 43(7).

911 Liu, Y., Weerts, A., Clark, M., Hendricks Franssen, H., Kumar, S., Moradkhani, H., Seo, D., Schwanenberg,
912 D., Smith, P., Van Dijk, A., 2012b. Advancing data assimilation in operational hydrologic forecasting:
913 progresses, challenges, and emerging opportunities. *Hydrology and Earth System Sciences*, 16 (10),
914 2012.

915 Madsen, H., Skotner, C., 2005. Adaptive state updating in real-time river flow forecasting—A combined
 916 filtering and error forecasting procedure. *Journal of Hydrology* 308(1) 302-312.

917 Matgen, P., Montanari, M., Hostache, R., Pfister, L., Hoffmann, L., Plaza, D., Pauwels, V.R.N., De Lannoy,
 918 G.J.M., De Keyser, R., Savenije, H.H.G., 2010. Towards the sequential assimilation of SAR-derived water
 919 stages into hydraulic models using the Particle Filter: proof of concept. *Hydrology and Earth System*
 920 *Sciences* 14(9) 1773-1785.

921 Merkurjeva, G., Merkurjev, Y., Sokolov, B.V., Potryasaev, S., Zelentsov, V.A., Lektuers, A., 2014.
 922 Advanced river flood monitoring, modelling and forecasting. *Journal of Computational Science*.

923 Minglei, R., Bende, W., Liang, Q., Guangtao, F., 2010. Classified real-time flood forecasting by coupling
 924 fuzzy clustering and neural network. *International Journal of Sediment Research* 25(2) 134-148.

925 Moradkhani, H., 2008. Hydrologic remote sensing and land surface data assimilation. *Sensors* 8(5)
 926 2986-3004.

927 Moradkhani, H., DeChant, C.M., Sorooshian, S., 2012. Evolution of ensemble data assimilation for
 928 uncertainty quantification using the particle filter - Markov chain Monte Carlo method. *Water*
 929 *resources research* 48(12).

930 Moradkhani, H., Hsu, K., Gupta, H., Sorooshian, S., 2005a. Uncertainty assessment of hydrologic model
 931 states and parameters: Sequential data assimilation using the particle filter. *Water resources research*
 932 41(5).

933 Moradkhani, H., Hsu, K.L., Gupta, H., Sorooshian, S., 2005b. Uncertainty assessment of hydrologic
 934 model states and parameters: Sequential data assimilation using the particle filter. *Water Resources*
 935 *Research* 41(5).

936 Neal, J.C., Atkinson, P.M., Hutton, C.W., 2007. Flood inundation model updating using an ensemble
 937 Kalman filter and spatially distributed measurements. *Journal of Hydrology* 336(3) 401-415.

938 Neal, J.C., Atkinson, P.M., Hutton, C.W., 2009. Evaluating the utility of the ensemble transform Kalman
 939 filter for adaptive sampling when updating a hydrodynamic model. *Journal of Hydrology* 375(3)
 940 589-600.

941 Nguyen, Q.K., Kawano, H., 1995. Simultaneous solution for flood routing in channel networks. *Journal*
 942 *of hydraulic engineering* 121(10) 744-750.

943 Noh, S., Tachikawa, Y., Shiiba, M., Kim, S., 2011. Applying sequential Monte Carlo methods into a
 944 distributed hydrologic model: lagged particle filtering approach with regularization. *Hydrology and*
 945 *Earth System Sciences* 15(10) 3237-3251.

946 Noh, S.J., Rakovec, O., Weerts, A.H., Tachikawa, Y., 2014. On noise specification in data assimilation
 947 schemes for improved flood forecasting using distributed hydrological models. *Journal of Hydrology*
 948 519 2707-2721.

949 Noh, S.J., Tachikawa, Y., Shiiba, M., Kim, S., 2012. Ensemble Kalman filtering and particle filtering in a
 950 lag-time window for short-term streamflow forecasting with a distributed hydrologic model. *Journal of*
 951 *Hydrologic Engineering* 18(12) 1684-1696.

Paiva, R., Collischonn, W., Bonnet, M., De Goncalves, L., Calmant, S., Getirana, A., Da Silva, J.S., 2013. Assimilating in situ and radar altimetry data into a large-scale hydrologic-hydrodynamic model for streamflow forecast in the Amazon. *Hydrology and Earth System Sciences* 17(7) 2929-2946.

Pasetto, D., Camporese, M., Putti, M., 2012. Ensemble Kalman filter versus particle filter for a physically-based coupled surface–subsurface model. *Advances in Water Resources* 47 1-13.

Saavedra, I., Lopez, J., Garc í a-Mart í nez, R., 2003. Dynamic wave study of flow in tidal channel system of San Juan River. *Journal of hydraulic engineering* 129(7) 519-526.

Schumann, G., Bates, P.D., Horritt, M.S., Matgen, P., Pappenberger, F., 2009. Progress in integration of remote sensing–derived flood extent and stage data and hydraulic models. *Reviews of Geophysics* 47(4).

Seo, D.-J., Liu, Y., Moradkhani, H., Weerts, A., 2014. Ensemble prediction and data assimilation for operational hydrology.

Snyder, C., Bengtsson, T., Bickel, P., Anderson, J., 2008. Obstacles to high-dimensional particle filtering. *Monthly Weather Review* 136(12) 4629-4640.

Thirel, G., Salamon, P., Burek, P., Kalas, M., 2013. Assimilation of MODIS snow cover area data in a distributed hydrological model using the particle filter. *Remote Sensing* 5(11) 5825-5850.

Vrugt, J.A., ter Braak, C.J., Diks, C.G., Schoups, G., 2013. Hydrologic data assimilation using particle Markov chain Monte Carlo simulation: Theory, concepts and applications. *Advances in Water Resources* 51 457-478.

Wang, Z.-y., Chunhong, H., 2009. Strategies for managing reservoir sedimentation. *International Journal of Sediment Research* 24(4) 369-384.

Weerts, A.H., El Serafy, G.Y., 2006. Particle filtering and ensemble Kalman filtering for state updating with hydrological conceptual rainfall - runoff models. *Water resources research* 42(9).

Werner, M., Schellekens, J., Gijsbers, P., Van Dijk, M., Van den Akker, O., Heynert, K., 2013. The Delft-FEWS flow forecasting system. *Environmental Modelling & Software* 40 65-77.

Wu, X., Wang, C., 2008. Application of Real-time Roughness Updating Based on Hydrodynamic Model in Flood Forecasting. *Water Resources and Power* 26(5).

Wu, X., Wang, C., Chen, X., Xiang, X., Zhou, Q., 2008. Kalman filtering correction in real-time forecasting with hydrodynamic model. *Journal of Hydrodynamics, Ser. B* 20(3) 391-397.

Wu, X., Xiang, X., Wang, C., Chen, X., Xu, C., Yu, Z., 2013. Coupled Hydraulic and Kalman Filter Model for Real-Time Correction of Flood Forecast in the Three Gorges Interzone of Yangtze River, China. *Journal of Hydrologic Engineering* 18(11) 1416-1425.

Yang, Y., Liu, B., 1991. Estimation model of roughness changing and its application in Three Gorges of Yangtze River. *Yangtze River* 22(12) 9-15.

Zong, Y., Chen, X., 2000. The 1998 flood on the Yangtze, China. *Natural Hazards* 22(2) 165-184.