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Research papers

Assimilation of soil moisture and streamflow observations to improve flood forecasting with considering runoff routing lags

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ABSTRACT

Assimilation of either soil moisture or streamflow has been well demonstrated to improve flood forecasting. However, it is difficult to assimilate two different types of observations into a rainfall–runoff model simultaneously because there is a time lag between soil moisture and streamflow owing to the runoff routing process. In this study, we developed an effective data assimilation scheme based on the ensemble Kalman filter and smoother (named as EnKF-S) to exploit the benefits of the two observation types while accounting for the runoff routing lag. To prove the importance of accounting for the time lag, a scheme named Dual-EnKF was used to compare. To demonstrate the schemes, we designed synthetic cases regarding two typical flood patterns, i.e., flash flood and gradual flood. The results show that EnKF-S can effectively improve flood forecasting compared with Dual-EnKF, particularly when the runoff routing has distinct time lags. For the synthetic cases, EnKF-S reduced root–mean–square error (RMSE) by more than 70% relative to the data assimilation scheme without considering runoff routing lags. Therefore, this effective data assimilation scheme holds great potential for short-term flood forecasting by merging observations from ground measurement and remote sensing retrievals.

1. Introduction

In early July 2016, widespread flooding in central and southern China killed more than 200 people and destroyed more than 100,000 houses. Nearly 2,000,000 people were forced to leave their hometowns. Although flood forecasting has been a long-term concern in the hydrology community (Adams and Pagano, 2016), this event reignited public concern on the importance of flood forecasting. Producing a reliable forecasting method with a sufficient lead time is valuable for reducing the losses from floods, particularly flash floods (Li et al., 2013a; Shih et al., 2014). However, the reliability of flood forecasting is generally hampered by various uncertainties in flood forecasting from the initial conditions, model input forcing, parameters, and model structures (Xie et al., 2014; Xie and Zhang, 2010, 2013).

To reduce these uncertainties, many technologies (eg., multi-objective evolutionary algorithms, data assimilation methods like variational techniques, Kalman filter and its variants) have been developed (Evensen, 2009; Reed et al., 2013); of these, data assimilation shows promise and has been increasingly used in hydrology in the past decade. In particular, assimilating multiple observation types into rainfall–runoff models was effective and encouraged for flood forecasting (López López et al., 2016; Li et al., 2013a; Liang et al., 2013; Wanders et al., 2014; Xie et al., 2014). The most popular observations types arguably include soil moisture, streamflow and snow data.

Exact estimation of soil moisture conditions will significantly improve streamflow prediction, particularly in short-term flood forecasting (Berthet et al., 2009; Brocca et al., 2012; Crow et al., 2005; Weissling et al., 2007), because it dominates the process of rainfall transform into infiltration and runoff (Chen et al., 2014; Massari et al., 2014). Assimilating soil moisture from ground measurement or remote-sensing retrievals can compensate for the deficiency of the antecedent conditions. Therefore, soil moisture is a favorable observation variable in data assimilation. Several successful cases of soil moisture assimilation to update model states, parameters, and output variables have been reported (Alvarez-Garreton et al., 2014, 2015; Chen et al., 2011; Crow and Ryu, 2009; Wanders et al., 2014). For example, Brocca et al., 2009 carried out assimilation of near-surface soil moisture to improve storm rainfall-runoff modeling in a small experimental plot. Moreover, remote sensing soil moisture retrievals can be used not only to adjust pre-storm soil moisture conditions but also for

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storm-scale rainfall accumulations (Alvarez-Garreton et al., 2016; Chen et al., 2014; Crow and Ryu, 2009; Massari et al., 2014).

In addition to soil moisture, streamflow and snow water equivalent are preferable in data assimilation (Sun et al., 2015; Wanders et al., 2014; Bergeron et al., 2016). Streamflow is a response to rainfall and temperature that has strong correlations with model state variables defined in related rainfall–runoff models, and streamflow measurement is more convenient than soil moisture retrieval from remote sensing for basin-scale applications. Thus, assimilating streamflow observations in hydrological modeling has received special recognition in the past decade (Li et al., 2013a). For example, Abaza et al., (2014) assimilated streamflow observations sequentially within an ensemble prediction system to enhance short-term hydrological forecasting. Chen et al., 2013 applied the Ensemble Square-Root-Filter method for real-time flash flood forecasting. Moreover, snow water equivalent observations were also widely used in snow-dominated regions. Bergeron et al. (2016) found that combined assimilation of streamflow and snow water equivalent is favorable during the snowmelt period. We focus on assimilation of soil moisture and streamflow observations in this study.

Because assimilating either soil moisture or streamflow can achieve acceptable estimations, we hypothesize that the simultaneous assimilation of the two observation types can substantially improve flood forecasting which has been proved by several studies (Aubert et al., 2003; Barrett and Renzullo, 2009; López López et al., 2016; Lee et al., 2011; Sun et al., 2016; Wanders et al., 2014; Yan and Moradkhani, 2016). For instance, López López et al. (2016) compared an individual assimilation of soil moisture or streamflow observations with a joint assimilation of both observations. The result indicated that the joint assimilation leads to a further improvement for streamflow simulation. Although this concept is encouraging, it is difficult to exploit the advantages of simultaneous assimilation of multiple observation types. One reason is that each type characterizes a specific hydrological process, and the observation correlates with other variables across different spatial and temporal scales. Specifically, soil moisture responds to a rainfall event immediately, whereas streamflow has a late response.

The assimilation of multiple observation types has an improvement on the simulation of discharge as shown by other studies. However, most of these studies ignored the uncertainties from the routing process which is especially influential in short-term flood forecasting. Runoff travels over hillslope and river network and then becomes streamflow (generally referred as routing), So in the short-term flood event, streamflow at a basin outlet is the cumulative result of generated runoff for a period of hours to several days, which is known as time delay in the routing process. Consequently, the uncertainties from state variables will accumulated in the streamflow; thus, assimilation of streamflow observations to update current state variables directly may still have room for improvement (McMillan et al., 2012; Pauwels and De Lannoy, 2009).

To mitigate this issue, previous studies have suggested several useful solutions (Pauwels and De Lannoy, 2009). McMillan et al., 2013 found that the retrospective ensemble Kalman filter (REnKF) can overcome instabilities in the standard ensemble Kalman filter (EnKF), solving the time lag between upstream catchment wetness and flow at the gauging locations. This filter using an iterative approach to update preceding model states needs large storage space and computational complexity. An alternative approach is the ensemble Kalman smoother (EnKS), which was successfully used by Li et al. (2013a) to improved states and streamflow prediction by considering time delay in the routing process. Although acceptable results have been achieved, most of these studies only assimilated one type of observation, such as streamflow.

In this study, we attempt to establish an effective data assimilation scheme (named as EnKF-S) based on the EnKF and the EnKS for short-term flood forecasting. The novelty of the EnKF-S scheme is not a simple application of the EnKF or the EnKS, but it is capable of assimilating multi-source of observations (e.g., soil moisture, streamflow) with a consideration of the runoff routing lags. In this scheme, soil moisture observations are used to update current soil moisture storage and runoff state variables. Considering the importance of these states in the routing process, the EnKS method is employed to update current soil moisture, discharge, and runoffs within a time window when streamflow observations are available. In order to highlight the advantages of the scheme, another scheme based the dual EnKF method (named as Dual-EnKF) is compared.

In the following section, a rainfall–runoff model and the proposed data assimilation scheme are presented with a description of the synthetic experiments. Section 3 provides the results of the data assimilation with respect to two typical flood patterns: flash food and gradual flood. Section 4 discusses the factors that can impact the data assimilation, and Section 5 presents the conclusions.

2. Methodology

2.1. Rainfall–runoff model

The Xin'anjiang (XAJ) model is a conceptual hydrological model widely used for flood forecasting (Li et al., 2013b; Si et al., 2015; Zhao, 1992). XAJ was developed on the basis of conceptual runoff generation under saturated condition, which means all rainfall is stored in the soil until the soil moisture content reaches field capacity; thereafter, the net rainfall drains out in the form of runoff without further loss (Zhao, 1995). As shown in Fig. 1, the structure of the model is divided into four components: evapotranspiration (ET), runoff generation, runoff separation, and runoff concentration (Li et al., 2013b).

In the ET simulation, the precipitation input (*Prec*) and potential evaporation (*PET*) are used to drive a three-layer model to calculate the actual evapotranspiration (*ET*). The basic principle of this process is that evapotranspiration occurs in the upper soil layer until the water storage in that layer is exhausted; then, the water in the lower layers will commence to evaporate. The runoff generation (R_o) is calculated as the following equation:

$$R_o = PE + W - WM, \tag{1}$$

where W is the initial soil moisture, PE is the net rainfall calculated with *Prec* and *PET*, and WM is the sum of WUM, WLM, and WDM. Owing to the spatial variability of the tension water capacity and free water storage capacity over a basin, the runoff generation shows diversity at different locations or different times, which can be described by a storage capacity curve. This curve is demonstrated as

$$\alpha = 1 - \left(1 - \frac{WM'}{WMM}\right)^{B}, \tag{2}$$

where B is a parameter associated with the features of the basin, and WM' and WMM are the point water-storage capacity and the maximum water-storage capacity, respectively. Then in the runoff separation, the runoff is further divided into three parts: surface flow (RS), interflow (RI) and ground water (RG). In the runoff routing process, the convergence speed of runoff in the soil is slower than that at the surface; therefore, the interflow flow and ground water will be routed by a linear reservoir before arriving to the outlet of the catchment. These three runoff components are transferred into QS, QI, and QG. Finally, a unit hydrograph (UH) is used to simulate