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Review papers

Bayesian flood forecasting methods: A review

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ABSTRACT

Over the past few decades, floods have been seen as one of the most common and largely distributed natural disasters in the world. If floods could be accurately forecasted in advance, then their negative impacts could be greatly minimized. It is widely recognized that quantification and reduction of uncertainty associated with the hydrologic forecast is of great importance for flood estimation and rational decision making. Bayesian forecasting system (BFS) offers an ideal theoretic framework for uncertainty quantification that can be developed for probabilistic flood forecasting via any deterministic hydrologic model. It provides suitable theoretical structure, empirically validated models and reasonable analytic-numerical computation method, and can be developed into various Bayesian forecasting approaches. This paper presents a comprehensive review on Bayesian forecasting approaches applied in flood forecasting from 1999 till now. The review starts with an overview of fundamentals of BFS and recent advances in BFS, followed with BFS application in river stage forecasting and real-time flood forecasting, then move to a critical analysis by evaluating advantages and limitations of Bayesian forecasting methods and other predictive uncertainty assessment approaches in flood forecasting, and finally discusses the future research direction in Bayesian flood forecasting.

Results show that the Bayesian flood forecasting approach is an effective and advanced way for flood estimation, it considers all sources of uncertainties and produces a predictive distribution of the river stage, river discharge or runoff, thus gives more accurate and reliable flood forecasts. Some emerging Bayesian forecasting methods (e.g. ensemble Bayesian forecasting system, Bayesian multi-model combination) were shown to overcome limitations of single model or fixed model weight and effectively reduce predictive uncertainty. In recent years, various Bayesian flood forecasting approaches have been developed and widely applied, but there is still room for improvements. Future research in the context of Bayesian flood forecasting should be on assimilation of various sources of newly available information and improvement of predictive performance assessment methods.

Contents

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1. Introduction

According to the fifth IPCC (Intergovernmental Panel on Climate Change) climate assessment report, extreme weather events were increased during the 21st century due to climate change (Pachauri et al., 2014). Accelerated hydrological cycle leads to increased frequency of intense precipitation events and enhanced fluctuation in streamflow to some extent, which in turn results in more frequent floods and droughts (Reggiani and Weerts, 2008a). Floods were seen as one of the most common and largely distributed natural disasters in the world, and caused significant damage to life and property over the past few decades (Balica et al., 2013). So there is an increasing need for flood control measures, both structural and non-structural. Among them, flood forecasting and estimation is an effective method that allows time for mitigating action. If floods could be predicted accurately in advance, then their negative impacts could be minimized.

Hydrologic models used for forecasting river stage, river discharge or runoff volumes are usually deterministic, and forecast results are normally exhibited as time series of estimates. However, their estimates are not free of error and contain limited amount of information though operationally simple. From the viewpoint of a decision maker who must make a rational flood mitigation decision based on the information provided by a hydrologic forecaster, a point estimate of the predictand may be insufficient (Krzysztofowicz, 1999, 2001). In order to provide more valuable information, the uncertainty associated with the predictand needs to be quantified in terms of probability distribution and degree of certitude, decisions should be made according to this probability distribution instead of just a single value of estimate (Krzysztofowicz, 1983). The growing demand for forecast products and the increasing capability to quantify predictive uncertainty give an impetus for research into probabilistic forecasting of hydrologic variates.

It is widely recognized that proper uncertainty quantification associated with a hydrologic forecast is of great importance for both operational application and scientific research (Biondi et al., 2010). In recent years many approaches have been developed for uncertainty quantification and reduction, but there are still challenges as uncertainties could arise from a variety of sources (Biondi and De Luca, 2012). Among the methodologies well suited for flood forecasting process, Bayesian forecasting system (BFS) provides an ideal theoretic framework that can be developed for different purposes using probabilistic forecast of inputs via any deterministic hydrologic model. It considers and quantifies all sources of uncertainties which gives more reliable estimation (Krzysztofowicz, 1999).

This paper provides a comprehensive review on Bayesian flood forecasting approaches and discusses the research direction within this field. BFS can be developed for diversified probabilistic forecasting systems suitable for various purposes. Here the paper only focuses on the review of BFS approaches used for flood forecasting from the year of 1999 until now. The work is outlined as follows. Section 2 is an overview of fundamentals of BFS and recent advances in BFS. Section 3 presents a comprehensive literature review on BFS application and comparison between all the predictive uncertainty assessment methods in flood forecasting. Section 4 summarizes the limitations and discusses the future research direction in Bayesian flood forecasting. A list of abbreviations is provided in Table 4 for clarity.

2. Overview of advances in Bayesian forecasting system (BFS)

2.1. Fundamentals of BFS

Bayesian forecasting system is a robust theoretical framework that can be used for probabilistic forecast through deterministic hydrologic model of any complexity (Krzysztofowicz, 1999). In the domain of flood forecasting, BFS could be developed to produce probabilistic river stage forecast (PRSF), probabilistic river discharge forecast (PRDF) or probabilistic runoff volume forecast (PRVF) at any time step.

In the BFS, the total uncertainty associated with the hydrologic forecast is broken down into two sources: precipitation uncertainty and hydrologic uncertainty. Precipitation uncertainty is related to the future average precipitation amount. Hydrologic uncertainty is the aggregate of all other uncertainties. These sources include: imperfections of the hydrologic model (e.g. model structure, model parameters), measurement errors of physical variables (e.g. temperature, streamflow, and precipitation), incorrect temporal and spatial downscaling of the total precipitation (e.g. deterministic forecast of spatial disaggregation of total precipitation amount into subbasins, deterministic forecast of subperiods' precipitation amount from temporal disaggregation of total amount) and so on. In the first place, precipitation uncertainty and hydrologic uncertainty are quantified respectively, and then integrated together to produce a probabilistic forecast (Krzysztofowicz, 1999, 2002a; Krzysztofowicz and Kelly, 2000; Krzysztofowicz and Herr, 2001). It is technically impractical and perhaps unnecessary to specifically quantify every source of uncertainty. Usually only a few sources dominate the contribution to the total uncertainty, therefore a compromise between the exactness and practicality can be reached by limiting the decomposition into the dominant uncertainties and all other uncertainties in the aggregate (Krzysztofowicz, 1999; Krzysztofowicz and Kelly, 2000).

The decomposition method of uncertainties leads to the fundamental structure of BFS shown in Fig. 1. There are two processors attach to the hydrologic model. One processor propagates the precipitation uncertainty into the output uncertainty under the assumption of nonexistence of hydrologic uncertainty. Another processor maps the hydrologic uncertainty into the output uncertainty based on the assumption that no precipitation uncertainty exists within this process. The two uncertainties are then incorporated together to generate a probabilistic forecast and this incorporation is nonmonotonic and nonadditive. Therefore, the BFS consists of three interrelated structural components: (1) Input uncertainty processor (IUP), the dominant source of input uncertainty is future precipitation, thus this processor is also called precipitation uncertainty processor (PUP), (2) Hydrologic uncertainty processor (HUP), (3) Integrator (INT). If the hydrologic predictand is river stage, then for PUP, the distribution of precipitation amount and response function induces the distribution of model river stage. For HUP, given the marginal prior distribution of actual river stage, prior dependence parameters, likelihood dependence parameters and marginal initial distribution of model river stage, the posterior distribution and posterior density can be derived by Bayesian revision process. Based on the output of PUP and HUP, the task of INT is to produce the predictive distribution and predictive density (Krzysztofowicz, 1999, 2002a).

2.2. Developments in BFS from 1999 to 2015

Since Krzysztofowicz introduced BFS in 1999, it has been gaining in popularity worldwide. Then two types of BFS were formed, one is to obtain a probabilistic river stage forecast (PRSF) on the basis of probabilistic quantitative precipitation forecast (PQPF), another one is to generate probabilistic stage transition forecast (PSTF) in accordance with PQPF. These two types of BFS rest on the same theoretic structure, but the second BFS provide more information such as river stage process evolution besides each river stage. There are two kinds of HUP within the BFS: precipitation-independent hydrologic uncertainty processor (PI-HUP) and precipitation-dependent hydrologic uncertainty