Atmospheric Research 161–162 (2015) 93–101

Contents lists available at ScienceDirect

Atmospheric Research

journal homepage: www.elsevier.com/locate/atmos

Impact of complexity of radar rainfall uncertainty model on flow simulation

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ARTICLE INFO

Article history:
Received 17 September 2014
Received in revised form 13 February 2015
Accepted 9 April 2015
Available online 15 April 2015

Keywords:
Ensemble generator
MDEG
Copula
Flow simulation
Model uncertainty

ABSTRACT

A large number of radar rainfall uncertainty (RRU) models have been proposed due to many error sources in weather radar measurements. It is recognized that these models should be integrated into overall uncertainty analysis schemes with other kinds of model uncertainties such as model parameter uncertainty when the radar rainfall is applied in hydrological modeling. We expect that the RRU model can be expressed in a mathematically extensible and simple format. However, the complexity of the RRU has been growing as more and more factors are considered such as spatio-temporal dependence and non-Gaussian distribution. This study analyzes how the RRU propagates through a hydrological model (the Xinanjiang model) and investigates which features of the RRU model have significant impacts on flow simulation. A RRU model named Multivariate Distributed Ensemble Generator (MDEG) is implemented in the Brue catchment in England under different model complexities. The generated ensemble rainfall values by MDEG are then input into the Xinanjiang model to produce uncertainty bands of ensemble flows. Comparison of five important indicators that describe the characteristics of uncertainty bands shows that the ensemble flows generated by MDEG with non-Gaussian marginal and joint distributions are close to the ones with Gaussian distributions. In addition, the dispersion of the uncertainty bands increases dramatically with the growth of the MDEG model complexity. It is concluded that the Gaussian marginal distribution and spatio-temporal dependence using Gaussian copula is considered to be the preferred configuration of the MDEG model for hydrological model uncertainty analysis. Further studies should be carried out in a variety of catchments under different climate conditions and geographical locations to check if the conclusion is valid beyond the Brue catchment under the British climate.

1. Introduction

Uncertainty can result from either an intrinsic part of all natural systems (natural variability) or lack of knowledge to obtain perfect models (knowledge uncertainty). In hydrological modeling, knowledge uncertainty mainly stems from a lack of understanding and knowledge about the real hydrological process, which is represented in model parameter uncertainty, input data uncertainty, model output uncertainty, model state uncertainty (e.g., moisture conditions and snow cover of catchment), data sampling uncertainty and model structure uncertainty. Many studies focus on the model parameter uncertainty and attribute the model output uncertainty to the uncertain parameter (Kuczera, 1983; Beven and Binley, 1992; Freer et al., 1996; Kuczera and Parent, 1998; Thiemann et al., 2001; Kanso et al., 2003; Vrugt et al., 2003; Todini, 2004; McCarthy et al., 2008; Zhang et al., 2008; Schoups and Vrugt, 2010). However, it is acknowledged that input data uncertainty such as rainfall uncertainty is of upmost importance to the hydrological model (Kavetski et al., 2006a,b; Götzinger and Bárdossy, 2008; Reichert and Mieleitner, 2009). Weather radar, with its advantages of providing three-dimensional observation of the atmosphere with high spatial and temporal resolutions and large areal coverage, has gradually been accepted as an important data source for hydrological applications during the past half century (Collier, 1986; Wood et al., 2000; He et al., 2011). Since radar measures rainfall remotely and indirectly, it is challenging to quantify radar data uncertainty and many methods have been proposed to describe the uncertainty of radar rainfall (Harrold et al., 1974; Kitchen et al., 1994; Villarini and Krajewski, 2010). To completely demonstrate the hydrological model uncertainty, we need to study the combined effects of the radar rainfall uncertainty (RRU) and other kinds of uncertainties (such as parameter uncertainty) on model output. However, we find that this goal is extremely hard to achieve through the conventional Bayesian theory as strict assumptions are required. For example, Kavetski et al. (2006a,b) assumed that the input rainfall uncertainty is independent of the input data itself. Götzinger and Bárdossy (2008) expressed the

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http://dx.doi.org/10.1016/j.atmosres.2015.04.002
0169-8095/

parameter uncertainty in terms of its sensitivity with the assumption that parameters are unrelated. Although both studies have presented two possible schemes to tackle the combined effects of input data and model parameter uncertainties on model output, they cannot be implemented for all RRU models. In fact, it is a great challenge to integrate a complicated RRU model with the existing analysis methods of model parameter uncertainty or/and model structure uncertainty. From this point of view, we expect that the RRU model should meet the aforementioned assumptions, and more importantly, it can be expressed in a mathematically extensible and simple format.

The RRU is commonly modeled with the help of reference ground measurement such as rain gauge. The bias between radar and gauge rainfall is considered in almost all the published RRU models (Harrold et al., 1974; Collier, 1986; Smith and Krajewski, 1991; Anagnostou et al., 1998; Seo et al., 1999; Borga and Tonelli, 2000; Ciach et al., 2000; Habib et al., 2008). The error variance of radar rainfall is recognized and calculated in the early 1990s (Barnston, 1991; Ciach and Krajewski, 1999; Ciach, 2003; Habib et al., 2004). Considering the fact that RRU increases with the growth of rainfall intensity, the rainfall intensity is regarded as an important term in some RRU models (Ciach et al., 2007; Villarini et al., 2009, 2010; Habib and Qin, 2013). Later, the spatial dependence of uncertainty between different radar grids is integrated to the models (Villarini et al., 2009; AghaKouchak et al., 2010a,b), and temporal correlation is also considered recently (Germann et al., 2009; He et al., 2011; Dai et al., 2013, 2014a,b). In the current study, the influence of synoptic regime such as seasons and wind on RRU is analyzed (Ciach et al., 2007; Habib and Qin, 2013; Dai et al., 2014a,b). The general assumption of the Gaussian distribution of rainfall residual errors is questioned and the scheme to tackle non-Gaussian uncertainty is proposed (Dai et al., 2013).

The aforementioned models may indeed contribute to elaborate and rigorous description on the uncertainty of radar rainfall. However, with the growth of model complexity, it becomes more and more difficult to integrate the RRU models to overall uncertainty analysis schemes for other uncertainties. Therefore, it is important that the RRU model should only reflect its most important features. Analysis of the uncertainty propagation of radar rainfall through hydrological models can demonstrate which RRU characteristics have practical impacts on flow simulation. Some studies attempted to illustrate how the RRU affected the calibration of hydrological model (Carpenter and Georgakakos, 2004; Fu et al., 2011; He et al., 2011; Schröter et al., 2011). Cunha et al. (2012) investigated the impacts of the deterministic bias, random error and spatial correlation of the RRU model on flow simulation. It is accomplished by applying various artificial coefficients of a proposed uncertainty model on a hydrological model. In our study, we have designed a comprehensive experiment to investigate the impact of important features of RRU on flow simulation. The primary goal of this study is to tackle the following three key issues. Firstly, is it essential to apply the RRU model in the flow simulation? In other words, does RRU incur significant influence on the flow simulation? Secondly, Gaussian distribution of rainfall residual error is a key assumption in the conventional Bayesian-based hydrological model uncertainty analysis (Beven et al., 2008). It is useful to know the degree of difference between the Gaussian and non-Gaussian RRU distributions. As a result, we can have a general understanding on whether a realistic RRU with the non-Gaussian distribution could be replaced with the Gaussian distribution. Finally, it is acknowledged that the spatial and temporal dependences of RRU are significant features that should be considered in the RRU models (Ciach et al., 2007; Germann et al., 2009). But it is unclear if they have remarkably impact on the simulated flow. To answer these questions, we have implemented a RRU model named Multivariate Distributed Ensemble Generator (MDEG) with different model complexities and generated ensemble rainfall values under different designed situations. The generated rainfall ensemble members are then fed into a hydrological model to investigate the uncertainty of simulated flow.

This paper is organized as follows. Section 2 describes the data and models used in this study. Section 3 details the designed scenarios and evaluated methods, and Section 4 discusses the results of simulated flow under different scenarios. Conclusions and future work are summarized in Section 5.

2. Materials and models

2.1. Study area and datasets

The Brue catchment in Somerset, south-west England (51.08°N and 2.58°W), is chosen as the experimental catchment for this study. The elevation of the catchment ranges between 35 m to 190 m above sea level (see Fig. 1). Radar and rain gauge datasets are collected from the Hydrology Radar Experiment (HYREX) project. The radar data with 0.5° of oblique angle are from the Wardon Hill radar, located at a range around 40 km from the center of the catchment. The radar completes one cycle every 5 min. The basic parameters of the radar, including the location, beam width and Z–R relationship are listed in Table 1. The gauge rainfall is collected from a dense network of 49 tipping bucket gauges (TBRs) with 0.2 mm resolution. There are 28 radar pixels which have at least one rain gauge in each pixel (see Fig. 1). A river gauging station located at Lovington provides the flow data. There is an automatic weather station within the catchment which records solar and net radiation, wet and dry bulb temperature, wind speed and direction and atmospheric pressure every 15 min. The evapotranspiration of the catchment is estimated using these datasets. We have also collected land cover data from the Global Land Cover 2000 project (GLC 2000) in order to improve the accuracy of the simulated flow. All the data used in this study are described in Table 2.

The radar rainfall, gauge rainfall, flow and other weather data from October 1993 to October 1998 are used as the calibration data, while the datasets covering the period from 5 November 1998 to 7 February 1999 are used to evaluate the proposed scheme. They are accumulated to 1 h for the following calculation.

2.2. The multivariate distributed ensemble generator (MDEG)

The multivariate distributed ensemble generator (MDEG) is a radar rainfall uncertainty model proposed by Dai et al. (2014a,b). It is designed to model the radar rainfall uncertainty and expressed in the form of ensemble rainfall values. The core part of MDEG is an empirical-based model with the assumption that the true pixel-scale rainfall is composed of a deterministic component and a random component. The radar rainfall estimate is regarded as a major term. The strictly statistical representation of the model is:

$$\psi = h(R) + \varepsilon(R) \tag{1}$$

where Ψ is the true rainfall, which is concurrent and collocated with the radar measurement R. h and ε are the deterministic component and random error respectively. The ensemble generator is to produce a number of Ψ values by adding a series of random fields that satisfy the given distribution to the deterministic part, so Eq. (1) changes to:

$$\psi_{t,i} = h_t(R_t) + \varepsilon_{t,i}(R_t) \tag{2}$$

where Ψ, h and ε are expressed for ensemble member i and time step t. For the ensemble generator, the key issue is about the distribution of random error. With gauge measurement as the reference rainfall, MDEG derives the distribution of random error from the available radar–gauge data pairs. The Ψ–R relationship is described by the distribution of gauge rainfall (GR) conditioned on the radar rainfall (RR) estimates (see Fig. 2). The size of sub-sample of gauge rainfall given an exact RR value is usually insufficient in modeling a reliable GR|RR distribution. For this reason, we generate the gauge sub-sample