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Evaluating uncertainty estimates in distributed hydrological modeling for the Wenjing River watershed in China by GLUE, SUFI-2, and ParaSol methods

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ABSTRACT

Hydrological models always suffer from different sources of uncertainties. As the distributed hydrological models play a very important role in water resource management, reliable quantification of uncertainty in hydrological modeling results is quite necessary. The purpose of this study is to apply three uncertainty analysis methods to a distributed hydrological modeling system, quantify the impact of parameter uncertainties, and examine their performance and capability. Due to the important location and typical hilly features, the upper reaches of the Wenjing River watershed in Western China were selected as the study area. The soil and water assessment tool (SWAT) model was applied to simulate the surface runoff during 1998–2002 and validated by the observed data. After global sensitivity analysis and modeling calibration, the Nash–Sutcliffe coefficient (NSE) and coefficient of determination (R^2) values of surface runoff for calibration are 0.75 and 0.80, and for verification periods were up to 0.74 and 0.87, respectively. Three uncertainty analysis methods were further conducted and compared within the same modeling framework: (1) the sequential uncertainty fitting algorithm (SUFI-2), (2) the generalized likelihood uncertainty estimation (GLUE) method, and (3) the parameter solution (ParaSol) method. Through the comparison of a set of proposed evaluation criteria for uncertainty analysis methods in this study, including *R*-factor, *P*-factor, the ratio of *P*-factor and *P*-factor, computation efficiency, and performance of best estimates (NSE and R^2), the SUFI-2 method was able to provide more reasonable and balanced predictive results than the other two methods.

1. Introduction

Hydrological models are simplified, conceptual, mathematical representatives of hydrologic processes to simulate water balance and cycle (Moradkhani and Sorooshian, 2009). A large number of hydrological models have been developed and applied in variety of areas such as flood control, water resources management, water quality control, land planning, and climate change studies. The hydrological models can be classified into lumped and distributed models. Unlike the lumped models, which treat the study basin as a single unit and only require a small number of parameters and inputs, distributed models are able to account for the spatial variability of the watershed (Refsgaard, 1997; Carpenter and Georgakakos, 2006). The high demands of distributed variables and inputs make the applications of distributed models constrained previously until accelerating development of computer technology in recent years.

Due to the complexity of the hydrological system and the lack of information, uncertainty inherently exists and challenges the implementation of distributed hydrological models. The potential improvement in hydrological prediction for distributed models requires a great number of high resolution inputs and parameters, leading to more uncertainties involved in modeling processes. Generally, uncertainties arise from measurement errors associated with system input, from model structural problems due to assumptions and simplification, and from approximation in determining parameters (Blasone et al., 2008; Yang et al., 2008). Among these three sources, parameter uncertainty is inevitable but relatively easy to control through an appropriate calibration especially for some conceptual or empirical parameters. The direct measurement of parameters is usually labor-intensive, time-consuming and costly, leading to quantitative or qualitative limitations in

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observed data and introducing uncertainties into the modeling system. In addition, some conceptual parameters usually estimated by empirical equations and literature references also lead some uncertainties to the system (Gong et al., 2011; Shen et al., 2012; Xue et al., 2013). Furthermore, the interactions and correlations between parameters can also cause uncertainties. For example, different parameter sets might result in similar prediction results. This non-uniqueness (known as the phenomenon of equifinality) is an inherent property of inverse modeling (Beven and Binley, 1992; Abbaspour et al., 2007; Abbaspour, 2011). Any inappropriate modification or adjustment of key parameters may further increase the level of uncertainty and cause unwanted consequences. In some cases, underestimation of uncertainty may cause unexpected losses and overestimation of uncertainty may lead to waste of resources (Shen et al., 2012). Therefore, uncertainty analysis is necessary and critical to ensure the success of hydrological modeling (Beven and Binley, 1992; Vrugt et al., 2003; Yang et al., 2007a,b).

There are growing interests in investigating uncertainties associated with hydrological studies and their effects on model performance nowadays (Yang et al., 2007a; Shen et al., 2008; Yang et al., 2008; Jin et al., 2010; Shen et al., 2010). A variety of methods have been developed to characterize, quantify and control the parameter and modeling uncertainties, such as Bayesian techniques (Kuczera and Parent, 1998; Thiemann et al., 2001; Vrugt et al., 2003; Kavetski et al., 2003), sequential uncertainty fitting (SUFI-2) (Abbaspour et al., 2007), generalized likelihood uncertainty estimation (GLUE) (Freer et al., 1996), Markov chain Monte Carlo (MCMC) (Vrugt et al., 2003; Marshall et al., 2004), automatic calibration and response surfaces (Mugunthan and Shoemaker, 2006), and parameter solution (ParaSol) (van Griensven and Meixner, 2004). Among these methods, SUFI-2, GLUE and ParaSol are three widely used methods for parameter uncertainty analysis in environmental modeling. The SUFI-2 method has been extensively applied to analyze parameter sensitivity and identify critical sources of uncertainty in modeling watersheds (Abbaspour et al., 2007; Yang et al., 2008; Tang et al., 2012). The GLUE method has been applied to assess uncertainty in various modeling endeavors such as rainfall-runoff modeling (Beven and Binley, 1992), soil erosion calculation (Brazier et al., 2001), groundwater simulation and well capture zone delineation (Feyen et al., 2001), and flood inundation (Aronica et al., 2002). Particularly in hydrological studies, the GLUE method has become one of the most popular tools in the past two decades to analyze parameter uncertainties (Freer et al., 1996; Shrestha et al., 2009). The ParaSol method is used to perform optimization and uncertainty analysis for complex models based on a modified shuffled complex evolution algorithm (SCE-UA) (Duan et al., 1992). Due to its high efficiency in handling multi-objective problems, this method has been demonstrated as a robust, flexible and suitable tool for model calibration in complicated hydrological studies (Duan et al., 1994; Duan, 2003; van Griensven and Meixner, 2004, 2007; Abbaspour, 2011).

However, limited studies have been reported on comparing the capability of these three uncertainty analysis methods (i.e., SUFI-2, GLUE and ParaSol) in capturing the impact of parameter uncertainty within the same modeling framework (Vrugt et al., 2003; Mantovan and Todini, 2006). In order to fill the knowledge gap, this study is to apply these three methods to a distributed hydrological modeling system, quantify the impact of parameter uncertainties, and examine their performance and capability. A case study was conducted in the Wenjing River watershed, China, by using the solid and water assessment tool (SWAT). The results can provide a scientific reference for understanding the strength and shortcomings of three uncertainty analysis methods. The uncertainty analysis method with best performance can be selected to evaluate the impacts of uncertainties and improve the prediction accuracy of hydrological modeling for future studies.

2. Methodology

The general framework of three uncertainty analysis methods (SUFI-2, GLUE and ParaSol) is shown in Fig. 1. The detailed introduction of three uncertainty analysis methods and the SWAT model is provided in the following sections.

2.1. SUFI-2

Based on a Bayesian framework, the SUFI-2 method determines uncertainties through the sequential and fitting process. In SUFI-2, the several iterations for updating the estimates of unknown parameters are required to achieve the final estimates. In this method, parameter uncertainties account for different possible sources, including model input, model structure, parameters, and observed data for calibration and validation purposes. An objective function needs to be defined before uncertainty analysis and assigned with a required stopping rule.

The degree to which all uncertainties considered is quantified by a measure referred to the *P*-factor. The *P*-factor is the percentage of observed data bracketed by the 95% prediction uncertainty (95PPU) (which is calculated at the 2.5% and 97.5% levels of the cumulative distribution of the output variables). Another measure quantifying the strength of uncertainty analysis is called the *R*-factor, which is equal to the average thickness of 95PPU band divided by the standard deviation of the observed data. A *P*-factor of 1 and *R*-factor of 0 is a simulation that exactly matches the observed data, which is the ideal case of simulation and cannot be achieved for real cases due to uncertainties from different sources and measurement errors. Certainly, a large *P*-factor can be achieved at the expense of a larger *R*-factor. If the *R*-factor is large, the ranges of parameters are larger than the optimal parameter ranges and more parameter uncertainties will remain. Usually, a value of less than 1 is a desirable result for the *R*-factor. Hence, a balance between these two factors has to be monitored while decreasing parameter uncertainty, and the ratio of *P*-factor and *R*-factor can be used to evaluate the strength and goodness of fit of uncertainty analysis. When acceptable *P*-factor and *R*-factor are obtained, the reduced parameter uncertainty ranges are the preferred ones (Abbaspour, 2011).

The SUFI-2 method assumes a large parameter uncertainty (or physically meaningful range) to ensure the observed data fall into the 95PPU for the first iteration, and decrease the uncertainty in steps while monitoring the *P*-factor and *R*-factor for next several iterations. The goal of the SUFI-2 method is to search for bracketing most of the observed data with the smallest possible uncertainty band, which means the good results should have a relatively large *P*-factor with relatively small *R*-factor. These two measures can also be used to evaluate the performance of other uncertainty analysis methods. The initial parameter ranges are updated by calculating the sensitivity matrix and equivalent of Hessian matrix, followed by calculating the covariance matrix, 95% confidence intervals of the parameters, and correlation matrix. Parameters are then updated with new ranges which are always centered around the values of the optimal parameter set that leads to the best simulation (using Eqs. (4) and (5) shown below). The major procedures of SUFI-2 are shown as follows (Abbaspour et al., 2007; Yang et al., 2008; Abbaspour, 2011; Xue et al., 2013):

Step 1. An objective function and reasonable parameter ranges $[b_{j,min}, b_{j,max}]$ are pre-defined. There are a number of ways to formulate an objective function, and the Nash–Sutcliffe coefficient (NSE) and coefficient of determination (R^2) are two of the most popular