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An optimization based sampling approach for multiple metrics uncertainty analysis using generalized likelihood uncertainty estimation

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ABSTRACT

This paper investigates the use of an epsilon-dominance non-dominated sorted genetic algorithm II (ε-NSGAII) as a sampling approach with an aim to improving sampling efficiency for multiple metrics uncertainty analysis using Generalized Likelihood Uncertainty Estimation (GLUE). The effectiveness of ε-NSGAII based sampling is demonstrated compared with Latin hypercube sampling (LHS) through analyzing sampling efficiency, multiple metrics performance, parameter uncertainty and flood forecasting uncertainty with a case study of flood forecasting uncertainty evaluation based on Xinanjiang model (XAJ) for Qing River reservoir, China. Results obtained demonstrate the following advantages of the ε-NSGAII based sampling approach in comparison to LHS: (1) The former performs more effective and efficient than LHS, for example the simulation time required to generate 1000 behavioral parameter sets is shorter by 9 times; (2) The Pareto tradeoffs between metrics are demonstrated clearly with the solutions from ε-NSGAII based sampling, also their Pareto optimal values are better than those of LHS, which means better forecasting accuracy of ε-NSGAII parameter sets; (3) The parameter posterior distributions from ε-NSGAII based sampling are concentrated in the appropriate ranges rather than uniform, which accords with their physical significance, also parameter uncertainties are reduced significantly; (4) The forecasted floods are close to the observations as evaluated by three measures: the normalized total flow outside the uncertainty intervals (FOUI), average relative band-width (RB) and average deviation amplitude (D). The flood forecasting uncertainty is also reduced a lot with ε-NSGAII based sampling. This study provides a new sampling approach to improve multiple metrics uncertainty analysis under the framework of GLUE, and could be used to reveal the underlying mechanisms of parameter sets under multiple conflicting metrics in the uncertainty analysis process.

1. Introduction

Hydrological models have been widely used in water resources management. The performance of a hydrological model depends heavily on the selection of suitable model parameters (Tian et al., 2006; Deng et al., 2015). Traditional parameter calibration of a hydrological model aims to find a set of optimal parameter values which can best reflect the characteristics of the basin (Wang et al., 2011; Zhou et al., 2015). However, Beven and Binley (1992) reported the phenomenon of "equifinality" among parameter sets, which means different parameter sets may result in the same model performance. In order to deal with the "equifinality" phenomenon, Beven and Binley (1992) proposed the Generalized Likelihood Uncertainty Estimation (GLUE) method. In recent years, GLUE has been widely used to investigate the uncertainty of hydrological models. This helps us understand the parameters in hydrologic models (Montanari and Alberto, 2005; Mantovan and Todini, 2006; Liu et al., 2014), and also provides the uncertainty bounds of model predictions, which provides important information for informed decision making (Krzysztofowicz, 2002; Pappenberger et al., 2006; Zhang et al., 2014).

However, in GLUE, there is a computational burden to derive a sufficient number of behavioral parameter sets, imposed by the random sampling strategy typically used with GLUE approach (Beven and Binley, 2014). Here, a behavioral parameter set (i.e., a solution) means a solution whose likelihood function values meet a specific threshold for each function. For example, Latin hypercube sampling (LHS) is unable to control the sampling direction, thus a lot of non-behavioral parameter sets are produced. Therefore, there has been extensive research on sampling strategies in order to improve the efficiency of GLUE (Vachaud and Chen,

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2002). For example, GLUE and Bayesian approach are combined in order to utilize the posteriori distributions of parameters (Kuczera and Parent, 1998; Bates and Campbell, 2001). However, these strategies are unlikely to effectively sample the parameter space close to the global optimum from a statistical point of view (Gupta and Sorooshian, 1985). Considerable improvements in sampling can be made using an adaptive sampling method that uses information from past samples to update the search direction in the SCEM-UA algorithm, however, this algorithm can be applied to single criterion only (Vrugt et al., 2003; Blasone et al., 2008).

In the model calibration, it is important to use multiple metrics as a single metric cannot represent the characteristics of hydrological processes (Liu et al., 2009; Shafii et al., 2014). Within the traditional GLUE procedure, the performance of each parameter set is evaluated by a single likelihood function. The relevant literature mostly focused on selecting an appropriate objective function in rainfall–runoff modeling (Gupta and Sorooshian, 1985). However, a single objective function is often inadequate to fully represent all the important characteristics of the observed data (Zhang et al., 2013), and use of a different performance measure normally result in different sets of behavioral parameter values, causing inconsistency in uncertainty analysis results (Brazier et al., 2000; Gupta et al., 1999). Multiple objectives can be aggregated into a single criterion with different weights. However, this often increases uncertainty in practice due to the subjective nature of weighting. Multiple metrics approaches were proposed to consider multiple sets of observations and/or multiple evaluation metrics (Gupta et al., 1998; Legates and McCabe, 1999; Shafii et al., 2015; Van Griensven and Meixner, 2007), and they have already been applied to the GLUE methodology (Choi and Beven, 2007; Liu et al., 2009; Shafii et al., 2014, 2015). Handling multiple metrics, in particular, conflicting metrics, makes it more challenging to generate a large number of behavioral parameter sets in an efficient way.

This study proposes a multi-objective optimization based sampling approach for multiple metrics uncertainty analysis within the framework of GLUE. One of the novelty of the research work is that optimization algorithms are applied for sampling. Multi-objective optimization algorithms that can be used include ε-NSGAII, NSGA-II, SPEA, BORG MOEA and so on (Zitzler and Thiele, 1999; Deb et al., 2000; Kollat and Reed, 2006; Hadka and Reed, 2013; Fu et al., 2013). Epsilon-dominance non-dominated sorted genetic algorithm II (ε-NSGAII) is selected to demonstrate the validity as it makes use of a fast non-dominating sorting approach and ε-dominance archiving to distinguish behavioral solutions during the search process and its effectiveness and reliability has been demonstrated with various optimization problems (Deb et al., 2000; Kollat and Reed, 2006; Fu et al., 2012, 2013; Chu et al., 2015). The ε-NSGAII can store the 'best' solutions found and the search operator exploits this information to steer the search to promising regions. The effectiveness of ε-NSGAII based sampling is demonstrated by comparing with Latin hypercube sampling (LHS) with a case study of flood forecasting uncertainty evaluation in Qing River basin, northeastern China. The validity of ε-NSGAII based sampling is demonstrated through comparison with LHS. LHS is one of the most popular sampling methods used in GLUE. Although other sampling approaches could be used as well, LHS is an efficient approach to generate a large number of samples, as sampling efficiency is a key problem when we try to solve a multiple criteria GLUE.

The paper is organized as follows. Section 2 introduces the methodology including multiple metrics GLUE, ε-NSGAII based sampling, Xinanjiang hydrological model and uncertainty evaluation metrics. Section 3 introduces the study region and data. Results and discussion are given in Section 4. Conclusions are drawn in Section 5.

2. Methodology

In this study, Latin hypercube sampling (LHS) and ε-NSGAII based sampling within multiple metrics GLUE are compared to demonstrate the performance of ε-NSGAII based sampling. The flow chart of the methodology is shown in Fig. 1.

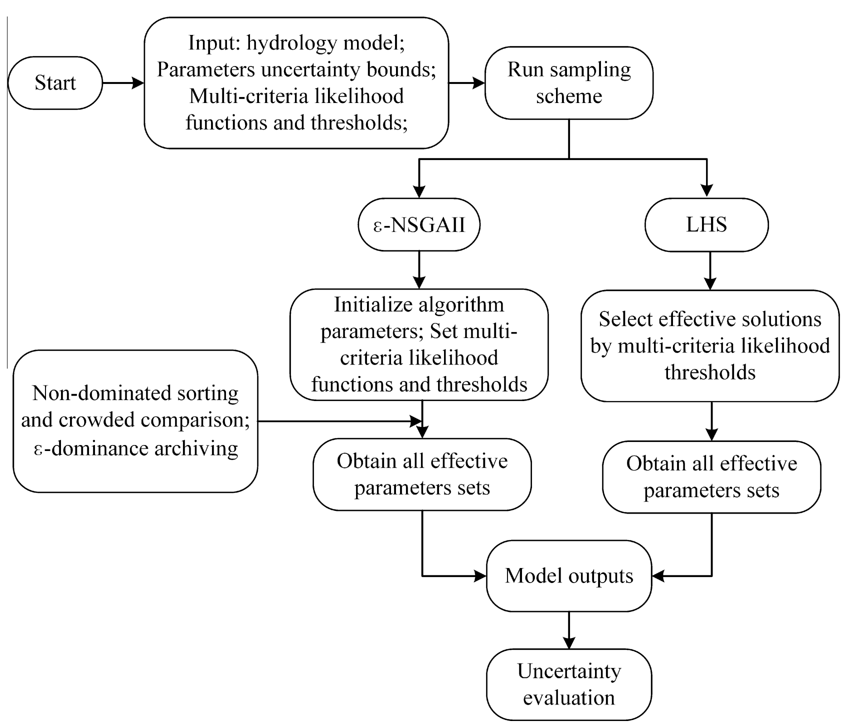

Fig. 1. Flow chart of the methodology.