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Parameter optimization of distributed hydrological model with a modified dynamically dimensioned search algorithm

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ABSTRACT

A modified version of the dynamically dimensioned search (MDDS) is introduced for automatic calibration of watershed simulation models. The distinguishing feature of the MDDS is that the algorithm makes full use of sensitivity information in the optimization procedure. The Latin hypercube one-factor-at-a-time (LH-OAT) technique is used to calculate the sensitivity information of every parameter in the model. The performance of the MDDS is compared to that of the dynamically dimensioned search (DDS), the DDS identifying only the most sensitive parameters, and the shuffled complex evolution (SCE) method, respectively, for calibration of the easy distributed hydrological model (EasyDHM). The comparisons range from 500 to 5000 model evaluations per optimization trial. The results show the following: the MDDS algorithm outperforms the DDS algorithm, the DDS algorithm identifying the most sensitive parameters, and the SCE algorithm within a specified maximum number of function evaluations (fewer than 5000); the MDDS algorithm shows robustness compared with the DDS algorithm when the maximum number of model evaluations is less than 2500; the advantages of the MDDS algorithm are more obvious for a high-dimensional distributed hydrological model, such as the EasyDHM model; and the optimization results from the MDDS algorithm are not very sensitive to either the variance (between 0.3 and 1) for *randn*′ used in the MDDS algorithm or the number of strata used in the Latin hypercube (LH) sampling.

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1. Introduction

Hydrological models are an effective tool for hydrological cycle simulations of watershed runoff and flow routing processes to predict the magnitude of streamflows generated by a precipitation event. Conceptual hydrological models, traditionally based on a mathematical formulation of physical processes, often involve a large set of parameters (Saltelli et al., 2006). The accuracy of these predictions depends on how well the model structure is defined and how the model parameters are determined (Duan et al., 1994). More sophisticated and physically based distributed hydrological models (DHMs) with multiple parameters, such as EasyDHM (Lei et al., 2011), are designed to better represent realistic situations. Simulations with DHMs make better use of distributed driving forces and distributed basin parameters to display the different processes of the hydrological cycle, such as surface runoff, groundwater flow, sediment transport, solute transport, and other related processes.

As multiple physically based hydrological processes are considered in DHMs, these are characterized with high-dimensional parameter spaces. Estimation of all of the model parameters is very time-consuming even impossible (Hornberger and Spear, 1981). As many of these model parameters are not directly measurable, a model calibration is needed. Computer technology enables automatic calibration as a substitute for manual calibration, thus reducing the labor-intensive processing that is not only tedious but also strongly dependent on experience.

Many popular options, such as the DDS and SCE, have been introduced for hydrological model calibration. The SCE algorithm is a global optimization that was initially designed to solve the problems of conceptual watershed model calibration. In the past decade, numerous studies have shown that the SCE algorithm is effective and efficient (Duan et al., 1992, 1993, 1994). However, the SCE algorithm imposes high computational requirements,

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especially for DHMs. The DDS algorithm, which performs well with fewer iterations (less than 10,000), was introduced by Tolson and Shoemaker (2007) for calibration of watershed models. They reported that the DDS is more efficient and effective than SCE within the same computational budget in the context of automatic calibration of the Soil and Water Assessment Tool 2000 (SWAT2000). The DDS algorithm was then modified to produce a hybrid discrete dynamically dimensioned search (HD-DDS) (Tolson et al., 2009) to solve design problems for discrete single-objective constrained water distribution systems and for DDS approximation of uncertainty (Tolson and Shoemaker, 2008) (DDS-AU), which quantifies prediction uncertainty using prediction bounds rather than prediction limits in order to find behavioral parameter sets efficiently.

However, for most optimization algorithms, including those mentioned above, the model parameters are optimized directly without considering parameter sensitivity, which leads directly to the problem of dimensionality and over-parameterization when these algorithms are applied to models with many parameters.

In recent years, some attempts have been made to address the issue of over-parameterization. Van Griensven (2005) performed a sensitivity analysis to assess the relative importance of individual parameters prior to parameter optimization of SWAT. However, the low-sensitivity parameters (however meaningful in DHM) are fixed prior to the parameter estimation process and the calibration is carried out for the most influential parameters. This study focuses on how to make better use of parameter sensitivity in optimization for DHM calibration by introducing a modified dynamically dimensioned search algorithm, termed MDDS. The performance of the MDDS was compared to that of the DDS, the DDS identifying only the most sensitive parameters, and SCE, respectively, to verify the practicability of introducing parameter sensitivity information into the optimization algorithm.

An initial sensitivity analysis should be conducted to determine the parameters to which the hydrological model is most sensitive. Numerous different sensitivity analysis techniques (local or global) have been developed and applied (Saltelli et al., 2004; Makler-Pick et al., 2011; Ratto et al., 2012; Plischke, 2012; Castaings et al., 2012), such as the one-step-at-a-time method (OAT method) (Sun et al., 2012), LH-OAT method (van Griensven et al., 2006), the Sobol method (Sobol, 1993; Rosolem et al., 2012), and Monte Carlo simulation method (MC method) (Cea et al., 2011). The LH-OAT method is a first-order second-moment (FOSM) method that estimates the mean (first moment) and variance (second moment) of model output, through computation of the derivatives of model output, in order to model input at a single point (Yen, 1993; van Griensven et al., 2006). Its Taylor expansion form can be expressed as follows:

$$M(\theta) = \mathrm{M}\left(\overline{\theta}\right) + \sum_{i=1}^{k} \frac{\partial M}{\partial \theta_i}\left(\theta_i - \overline{\theta_i}\right) \tag{1}$$

where $\theta = \{\theta_1, \ldots, \theta_k\}$ denotes the input random variables of $\overline{\theta} = \{\overline{\theta_1}, \ldots, \overline{\theta_k}\}$ and$\partial M/\partial\theta$ are derivatives evaluated at the mean values $\overline{\theta}$.

Sobol analysis is another widely used variance-based method. The Taylor expansion can be expressed as follows:

$$f(\theta_1, \theta_2, \ldots, \theta_k) = \mathrm{f}_0 + \sum_{i=1}^{k} f_i(\theta_i) + \sum_{1 \le i \le j \le k} f_{ij}(\theta_i, \theta_j) + \ldots + f_{1,2,\ldots k}(\theta_1, \theta_2, \ldots, \theta_k) \tag{2}$$

where $\theta = \{\theta_1, \theta_2, \ldots, \theta_k\}$ is the vector of k model factors. The Sobol approach decomposes the function $f(\theta_1, \theta_2, \ldots, \theta_k)$ into terms of increasing dimensionality so that each successive dimension represent and increasing degree of interaction among the parameters. Moreover, Rosolem et al. (2012) introduced a multi-criteria implementation of the Sobol method based on the notion of multiple-criteria ranking. Compared with the LH-OAT method, the Sobol method considers parametric interactions reflecting the sensitivity of complex nonlinear models (Yang, 2011; Nossent et al., 2011). MC method consists of a random selection of input scenarios according to their probabilities of occurrence (Carpani et al., 2012). The major disadvantage of the Sobol method and Monte Carlo simulation method, especially in this study, is the high computational demand. The goal of this study is to make good use of parameter sensitivity during the calibration period without much increase in computational burden. Another advantage of combining sensitivity analysis with automatic optimization methods is that there are relatively mature theories for both sensitivity analysis and automatic optimization algorithms, which have been accepted as reliable and are seldom questioned. In this study, the LH-OAT method was introduced for its ability to handle the nonlinear, nonadditive, and nonmonotonic problems of complex hydrological models (Saltelli et al., 2009).

The rest of this paper is organized as follows: Section 2.1 gives a brief introduction to the SCE algorithm. Section 2.2 describes the original DDS algorithm. Section 2.3 describes the sensitivity analysis technique, LH-OAT. Section 2.4 gives a detailed explanation of the modified parts of the algorithm. Section 2.5 introduces a distributed hydrological model, EasyDHM, used as the optimization problem. Sections 2.6 and 2.7 are on the objective function and the study area, respectively. Section 3 presents the results and discussion. Section 4 provides the conclusions and discusses future research directions.

2. Methodology

This paper aims to take advantage of combining sensitivity analysis with the DDS algorithm and to obtain improved solutions. The performance of the DDS algorithm modified by introducing sensitivity information was compared to that of the original DDS algorithm. Moreover, another benchmark optimization algorithm, the SCE algorithm, was utilized. The method of fixing the insensitive parameters and only calibrating the most sensitive parameters has been widely used by hydrological modelers. A performance comparison was made between the MDDS and the DDS identifying only the 15 most sensitive parameters. The techniques used are given in the following sections.

2.1. The shuffled complex evolution method

The SCE method is based on a synthesis of four concepts that have proved successful for global optimization: a) combination of probabilistic and deterministic approaches, b) clustering, c) systematic evolution of a complex of points spanning the space in the direction of global improvement, and d) competitive evolution. A detailed description of the SCE algorithm can be found in Duan et al., (1993).

The SCE algorithm used was coded in Fortran and some necessary modifications were made. The random number generation methods differed between the SCE and DDS algorithms. The random numbers used in the SCE algorithm were generated by the built-in function of Intel Fortran so as to use the same generation method with both the DDS and MDDS algorithms and purely compare the evaluation strategies of these algorithms. The random seed used in the three algorithms was the same. In addition, a parameter convergence judgment is not used in the SCE algorithm,

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