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Global sensitivity analysis of a three-dimensional nutrients-algae dynamic model for a large shallow lake

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ABSTRACT

Sensitivity analysis is a primary approach used in mathematical modeling to identify important factors that control the response dynamics in a model. In this paper, we applied the Morris sensitivity analysis method to identify the important factors governing the dynamics in a complex 3-dimensional water quality model. The water quality model was developed using the Environmental fluid dynamics code (EFDC) to simulate the fate and transport of nutrients and algal dynamics in Lake Dianchi, one of the most polluted large lakes in China. The analysis focused on the response of four water quality constituents, including chlorophyll-a, dissolved oxygen, total nitrogen, and total phosphorus, to 47 parameters and 7 external driving forces. We used Morris sensitivity analysis with different sample sizes and factor perturbation ranges to study the sensitivity with regard to different output metrics of the water quality model, and we analyzed the consistency between different sensitivity scenarios. In addition to the analysis with aggregate outputs, a spatiotemporal variability analysis was performed to understand the spatial heterogeneity and temporal distribution of sensitivities. Our results indicated that it is important to consider multiple characteristics in a sensitivity analysis, and we have identified a robust set of sensitive factors in the water quality model that will be useful for systematic model parameter identification and uncertainty analysis.

1. Introduction

Water quality models (WQMs) have been developed and applied as valuable tools for quantitative analysis of the cause-and-effect relation between management scenarios and water quality responses, and WQMs have been used widely to support decision-making about management of water quality (Vieira and Lijklema, 1989; Zou et al., 2006, 2007; Liu et al., 2014). The recent advances in computing power and data collection have accelerated the development of sophisticated water quality modeling, which can reproduce accurately the hydrodynamic and biochemical conditions of a water body (Castelletti et al., 2010). During the past decades, many complex dynamic WQMs have been developed, such as WASP, QUAL2K, CAEDYM, CE-QUAL-W2, Delft3D-ECO, PCLake (Mooij et al., 2010), and EFDC (Hamrick, 1992; Park et al., 1995). In general, a complicated water quality model represents the dynamics of water quality processes using a large number of parameters, and the majority of these parameters cannot be measured accurately. Therefore, the only way to develop a model that approximates reality is through model calibration processes that identify proper parameter values (Chapra, 1997; Zou and Lung, 2004). In practice, the complexity in model due to an increased number of parameters would cause a leap in computational requirements and increase the difficulty of calibration because of the highly interactive parameter spaces and the nonlinear, non-monotonous objective spaces (Gupta et al., 1998; Herman et al., 2013a). Therefore, it is desirable to reduce the difficulty of calibration by focusing on a subset of parameters, because in many cases, a small number of model parameters are often responsible for most of the variability in the model's outputs (Morris et al., 2014).

Sensitivity analysis has long been used to identify the subset of important input factors that control model outputs (Saltelli et al.,

Abbreviations: EFDC, environmental fluid dynamics code; WQMs, water quality models; OAT, one-factor-at-a-time; Chla, chlorophyll-a; TN, total nitrogen; TP, total phosphorus; DO, dissolved oxygen; SOD, sediment oxygen demand.

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2004; Janse et al., 2010; Makler-Pick et al., 2011; Nossent et al., 2011; Ciric et al., 2012; Neumann, 2012; Sun et al., 2012). There are two main branches of methods for sensitivity analysis: local and global methods. Local sensitivity analysis involves the one-factor-at-a-time (OAT) experiment, where a single factor is perturbed while all other factors are fixed to assess the variation in output. This method can generate sensitivity information that is generally local to the parameter values that are taken, except for models that are linear or weakly nonlinear (i.e., can be adequately represented by a first-order polynomial approximation) (Ahmadi et al., 2014). On the contrary, global sensitivity analysis explores the influence of a factor throughout the full multi-dimensional space by varying all factors simultaneously, therefore it is well suited for factor interactions and non-linear relationships between factors and model outputs (Saltelli et al., 2008). However, global sensitivity analysis is often computationally expensive (Campolongo et al., 2007) and has relatively fewer applications in complex modeling of water quality.

Modern WQMs are usually large-scaled, sophisticated (non-linear and factors interaction), and computationally expensive. Thus, various criteria should be considered in selecting an appropriate sensitivity analysis method. Makler-Pick et al. (2011) suggested that a method selection process should include the following key criteria: (i) the computational cost, (ii) the ability to account for the interactions between factors, (iii) the ability to account for the nonlinearities and non-monotonicity in models, (iv) the input data required for the analysis, and (v) the ability to use the output of sensitivity analysis. Considering these criteria, only a small number of approaches are suitable for complex modeling of water quality.

In this study, the method of Morris (1991) was selected and applied to a complex water quality model of a shallow lake. This method is a global sensitivity analysis that requires less computational demand than other global methods, such as the variance-based sensitivity analysis (e.g., Sobol's (Saltelli, 2002), EFAST (Saltelli et al., 1999), etc.). The method of Morris is a screening method proposed by Morris (1991) and modified by Campolongo et al. (2007). Unlike the variance-based or regression-based methods, which can be prohibitive computationally for water quality models with large number of parameters and long simulation times (Saltelli et al., 2008) or require assumptions regarding the types of functions underlying the model, screening methods are more appropriate for complex WQMs due to their ability to capture general sensitivity structures with a significantly lower computational requirement. Although the method of Morris does not implement individual computation of sensitivity indices for interactions, this is not a critical limitation preventing us from achieving the goal of this study. This can be justified by many previous studies using the method of Morris to successfully identify the influential and non-influential factors in models and derive information regarding parameter interactions and model non-linearity (Morris, 1991; Gamerith et al., 2013; King and Perera, 2013). A few studies (Campolongo and Saltelli, 1997; Saltelli et al., 2006) have proven the robustness of this method, and Herman et al. (2013a) demonstrated that this method performs well in comparison to Sobol's analysis in identifying influential parameters at a greatly reduced computational expense. Campolongo and Saltelli (1997) and DeJonge et al. (2012) also found a strong correlation between the total sensitivity indices of Morris and FAST/Sobol's methods, and they suggested that the Morris sensitivity indices could be used quantitatively.

Previous applications of global sensitivity analysis focused generally on watershed models (Sun et al., 2012; Ahmadi et al., 2014) and spatially aggregated aquatic ecosystem models (Makler-Pick et al., 2011; Ciric et al., 2012; Zheng et al., 2012; Morris et al., 2014), but only a few studies involved complex water quality models of multi-dimensional lakes/reservoirs because of the computational limitation. A relevant study (Salacinska et al., 2010) applied Morris to a two-dimensional ecological model (GCM) to find sensitivity parameters for algae blooms, but it only identified sensitive parameters for a single state variable.

Practically, to implement a sensitivity analysis, the model output at a specific time (Morris et al., 2014; Li et al., 2015) or in an aggregate form (Salacinska et al., 2010) is used to measure the response of the simulated state variables. Water quality in lakes and reservoirs has inherent temporal and spatial variability due to climate, hydrodynamics, inputs of pollutants, and bathymetry (Missaghi et al., 2013). In a model with a multi-dimensional representation of physical, chemical, and biological processes, sensitive factors that control the model's behavior might also vary across the spatial domain. Furthermore, time-dependent sensitivity should be considered also in a dynamic model, because time-varying sensitivity may occur (Wang et al., 2013; Herman et al., 2013b, 2013c).

The objective of this study was to identify the influential and non-influential factors (including parameters and external drivers) for a three-dimensional water quality model for Lake Dianchi, China. The result of this study will be used to facilitate the future enhancement of the existing Lake Dianchi model into an uncertainty based watershed management decision support platform for Lake Dianchi. In order to understand the robustness of the sensitivity analysis result, we designed a variety of analysis to explore the variability in sensitivity results with regard to different settings in the Morris sensitivity analysis, including the perturbation range, sample size, constituents, and aggregation metrics. In addition, we also analyzed the spatial and temporal variability of the sensitivity distribution to gain further insights regarding the system behavior.

The paper is organized as follows: The theoretical background of the EFDC model and the sensitivity analysis method, and the computational experiments are introduced briefly in Section 2. The results are described in detail and discussed in Section 3. Finally, we present a summary and a discussion of future work.

2. Materials and methods

2.1. Study area

Lake Dianchi, the sixth largest lake in China, is located on the Yunnan-Guizhou Plateau of southwestern China (Fig. 1), at an altitude of 1887 m. The surface area of the lake is approximately 300 km^2 and the watershed area is approximately 2920 km^2 (latitude 24°28′–25°28′N, longitude 102°30′–103°00′E). The lake has a total storage capacity of 1.5×10^9 m^3, and an average depth of 5.2 m. There are 29 rivers flow into the lake and 1 outlet drains the lake. The climate in this area is subtropical, moist monsoon with an annual precipitation of 932 mm (Zhou et al., 2014).

Lake Dianchi was historically a clean lake. However, rapid urbanization and industrial development that began in the 1980s produced tremendous nutrient loads in the lake, causing deterioration of the lake's water quality (Wang et al., 2014). Among all the inflows, those from the north of the basin contribute most of the nutrient loading. During the past decades, Lake Dianchi has lost its function as a source of drinking and irrigation water, and it has become one of the three most polluted large lakes in China. Monthly water quality data were collected from eight regular monitoring sites (Fig. 1), and these data have been used to calibrate and validate the modeling of water quality of Lake Dianchi (Wang et al., 2014).

2.2. Lake Dianchi water quality model

The water quality model of Lake Dianchi was developed based on a sophisticated computational platform titled