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A new approach to evaluate spatiotemporal dynamics of controlling parameters in distributed environmental models

Zhao Chen [a, *], Andreas Hartmann [b, c], Nico Goldscheider [a]

[a] Institute of Applied Geosciences, Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany
[b] Institute of Hydrology, Albert-Ludwigs-University of Freiburg, Freiburg, Germany
[c] Department of Civil Engineering, University of Bristol, UK

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ABSTRACT

Distributed environmental models are usually high-dimensional and non-linear. To comprehensively evaluate the spatiotemporal dynamics of model controls, we propose a novel multi-step approach based on Sobol's method to evaluate parameter sensitivity as well as interactions with respect to different model outlet points, using different objective functions to assess different hydrodynamic conditions; all varying through time. This complete sensitivity analysis can be performed for prior and posterior parameter ranges. The difference between them can be used to assess the influence of parameter constraints on the results of sensitivity analyses. We applied this holistic approach to an existing distributed karst watershed model. The results demonstrated that 1) a limited number of spatially-distributed parameters control the varying flow pattern, 2) the model is nonlinear and the influential parameters are highly correlated in the model domain and 3) the spatial patterns of identified parameter sensitivity and interactions are strongly influenced by the specified parameter bounds.

1. Introduction

Distributed modelling is widely applied to simulate broad classes of pathways for water movement through space, e.g., overland flow, unsaturated flow in the vadose zone, and saturated groundwater flow (Kampf and Burges, 2007). In recent years, these distributed hydrological models have become very popular in many applications, such as advancing scientific understanding of underlying hydrological processes at the surface (Lehning et al., 2006) and in the subsurface (Worthington, 2009); analyzing the potential impacts of land use (Andrew and Dymond, 2007) and climate change (Krysanova et al., 2007); and developing water quantity and quality management options for informed decision making (Ahrends et al., 2008; Peña-Haro et al., 2011).

Sensitivity analysis (SA) methods are often used for developing and evaluating complex distributed hydrological models (Christiaens and Feyen, 2002; Gamerith et al., 2013; Herman et al., 2013; Hill and Tiedeman, 2007; Nossent et al., 2011; Pappenberger et al., 2008; Sieber and Uhlenbrook, 2005; Tang et al., 2007a; van Werkhoven et al., 2008). Generally, SA is used to assess the contribution of individual inputs or groups of inputs on model outputs and to identify key inputs that control model outputs (Razavi and Gupta, 2015). Mostly, SA is assessed with respect to signatures or error metrics that are applied to model outputs. Performing a SA in model space domain may enhance understanding of the model response to not only variation in model inputs, but also their spatial distribution (Fisher et al., 1997; McIntyre et al., 2005; Moreau et al., 2013). Consequently, according to Wagener et al. (2009a), the SA results can be used to: 1) select input parameters to include in a calibration procedure or enable a more focused planning of future research and field measurement, 2) evaluate the realism of parameter values and boundary conditions, 3) prove that the model is sufficiently sensitive to represent the behavior of a natural system, and 4) reduce a model to its essential structures.

SA can be categorized into local and global methods (Saltelli et al., 2000). Compared to local methods, global methods vary all parameters simultaneously within predefined regions to quantify their importance and possible interactions (Saltelli, 2004). A global sensitivity analysis method that is very popular in many fields is the variance-based Sobol's method (Sobol', 1990). In general, variance-

* Corresponding author. Institute of Applied Geosciences, Karlsruhe Institute of Technology (KIT), Adenauerring 20b, Building 50.40, 76131 Karlsruhe, Germany.
E-mail address: zhao.chen@kit.edu (Z. Chen).

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based sensitivity analysis methods aim to quantify variance in model output based on variance in model inputs and their interactions with one another. For Sobol's method, these responses, caused either by a single parameter or by the interaction of two or more parameters, are expressed as sensitivity indices. These indices represent fractions of the unconditional model output variance. In recent years, this powerful SA technique has been increasingly applied to complex distributed models, because of its ability to incorporate parameter interactions and its relatively straightforward interpretation (Hall et al., 2005; Nossent et al., 2011; Pappenberger et al., 2008; Song et al., 2012; Tang et al., 2007a; van Werkhoven et al., 2008; Wagener et al., 2009b; Zhang et al., 2013). A powerful extension of the conventional application of Sobol's method is to evaluate event-scale spatial sensitivities (Tang et al., 2007a; van Werkhoven et al., 2008). Wagener et al. (2009b) demonstrated that the results strongly depend on the chosen objective function (i.e. considered system state) and suggested using a multi-objective approach to explore spatial parameter controls limited by event-scale. Focusing on the event-scale independence, dynamic controls of distributed models have been explored at a predefined time step throughout the model simulation by using the Method of Morris (Herman et al., 2013) and the Fourier amplitude sensitivity test (Reusser et al., 2011).

However, in past studies (e.g. Nossent et al., 2011; Sieber and Uhlenbrook, 2005; Song et al., 2012; Zhang et al., 2013), the distributed parameter field was mostly assumed to be spatially-homogenous. Only a few studies (Herman et al., 2013; Tang et al., 2007a; van Werkhoven et al., 2008) have investigated the sensitivity of model behavior to heterogeneous spatially-distributed parameters. Furthermore, the effects of spatially-distributed parameters are only assessed by analyzing the variance of non-spatially-distributed model output. To fill this knowledge gap, the present work will focus on characterizing uncertainty for spatially-heterogeneous distributed parameters, and their apportionment on spatially-distributed model outputs. Additionally, the issue of parameter constraints and their influence on the results of sensitivity analyses is generally not considered in any detail. The final aim of the present work is to develop a balanced approach based on Sobol's method for 1) spatial and temporal sensitivity analysis which is suitable for non-stationary, spatially-distributed models with high complexity, high parameter interactions, and high non-linearity, 2) identifying the spatiotemporal processes controlling model behavior, 3) comprehensive evaluation of parameter realism across model time and space domains and 4) assessing the impact of parameter constraints on previous sensitivity analysis results.

We applied our method to the existing distributed karst watershed model by Chen and Goldscheider (2014). In general, karst aquifers are highly sensitive to environmental changes and more vulnerable to contamination than other aquifer types due to their specific hydraulic properties (Goldscheider and Drew, 2007). The model case study focused on a complex karstified alpine carbonate aquifer system in the Schwarzwasser Valley (Austria/Germany), where the aquifer drainage dynamics are characterized by extreme hydraulic spatial heterogeneity (Goldscheider, 2005). Our new method is used to evaluate the spatiotemporal dynamics of model controls in the watershed model.

2. Study area

The Hochifen-Gottesacker karst system is located in the Northern Alps on the Germany/Austria border (Fig. 1a). It has an area of about 35 km^2, and an altitude varying between 1000 m asl (the lowest part of the Schwarzwasser valley) and 2230 m asl (the summit of Mt. Hochifen). It should be noted that in this study, we consider summer periods when snow processes are not important. A hydrogeological conceptual model was developed through geological mapping and several quantitative multi-tracer tests (Goldscheider, 2005; Göppert and Goldscheider, 2008). In the study area, the Schrattenkalk limestone with a thickness of about 100 m acts as the main karst aquifer, and is underlain by marl formations. Flow paths in the karst aquifer are controlled by geologic structures and generally follow plunging synclines. Hydrologically, the karst aquifer is directly recharged (autogenically) from precipitation and indirectly (allogenically) from surface streams, which drain the part of the catchment area that consists of low permeability Flysch rocks. The tracer tests confirmed that two parallel drainage systems exist in this valley: a surface stream and a continuous underground karst drainage system along the valley axis (Goldscheider, 2005). The karst aquifer is mainly drained by three outlets: 1) an estavelle (QE) at 1120 m asl associated with a cave forms a reversible hydraulic connection between the two drainage systems and discharges up to about 4 m^3/s, 2) a large but intermittent and intermediate overflow spring (QA) at 1080 m asl discharges up to about 8 m^3/s but is inactive in extended dry periods and in winter and 3) a permanent spring (QS) at 1035 m asl in the valley that discharges between 0.16 and about 3.5 m^3/s.

3. Methodology

Three basic research questions guided us to design this holistic approach to evaluating spatiotemporal dynamics of controlling parameters in distributed environmental models:

1. What are the sensitive model parameters in space and time across the model domain? We evaluated parameter sensitivity using Sobol's method with respect to different model outlet points, using different objective functions to assess different hydrodynamic conditions as a function of time.
2. How do parameter interactions influence the model behavior? We quantified interactions between model parameters using Sobol's method in model space and time domains, in order to better understand model complexity and model internal process dynamics.
3. How are our results influenced by the choice of parameter ranges? We used the DREAM algorithm to constrain the model and to explore posterior parameter bounds derived from the posterior distributions. The complete sensitivity analysis was performed for both initial (prior) and posterior parameter ranges. So we could assess differences between the parameter sensitivity based on prior and posterior information, and assess the influence of parameter constraints on previous sensitivity analysis results.

3.1. Model setup

For the present work, we used a slightly modified version of the existing distributed watershed model by Chen and Goldscheider (2014), which is mainly based on the distributed hydrology-hydraulic water quality simulation model – Storm Water Management Model (SWMM, version 5.0) developed by the EPA (Rossman, 2010). In our model, recharge, storage and drainage of water in the karst catchment are represented by a concept-based reservoir module, which is directly coupled to a downstream conduit drainage module simulating highly variable flow in the underground karst drainage system along the valley axis (Fig. 1b and c). The karst catchment is divided into four sub-catchments (I – IV) corresponding to local tectonic structures. The recharge for individual sub-catchments is calculated separately using interpolated meteorological input data over the study area, while allogenic