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An evaluation of impacts of DEM resolution and parameter correlation on TOPMODEL modeling uncertainty

Kairong Lin, Qiang Zhang *, Xiaohong Chen

Department of Water Resources and Environment, Sun Yat-sen University, Guangzhou 510275, China
Key Laboratory of Water Cycle and Water Security in Southern China of Guangdong High Education Institute, Sun Yat-sen University, Guangzhou 510275, China

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SUMMARY

Hydrological modeling uncertainties are the results of many factors such as input error, calibration accuracy, parameter uncertainty, model structure, and so on. Wherein, input errors and parameter uncertainties are the two of the major factors influencing the uncertainties of hydrological modeling. TOPMODEL is a rainfall–runoff model that bases its distributed predictions on analysis of watershed topography, which is widely used in hydrological modeling practices. In this study, the effects of DEM resolution and parameter correlation on TOPMODEL modeling uncertainties are evaluated by using GLUE technique. The uncertainty evaluation is performed by modeling the rainfall–runoff processes of three tributaries in the Hanjiang River, one of the major tributaries of the Yangtze River, China. The results show no evident effects of the DEM resolution on the uncertainty intervals of the TOPMODEL simulation. This can be attributed to the fact that the modeling uncertainty is due solely to changes of DEM resolution by fixing the parameter values to avoid the artifacts resulted from interactions between $\ln(a/\tan(B))$ and the parameters. In addition, the copula functions are used to produce more behavioral parameter sets for the same sample time intervals when the model parameters are in good correlation, and which can benefit thorough evaluation of effects of parameter correlation on the hydrological modeling uncertainty. With the same number of the behavioral parameter sets, after putting the parameter correlation under consideration, the simulated runoff series by the TOPMODEL with the behavioral parameter sets can fit reasonably better the observed runoff series. Thus, the uncertainty due to parameter correlation of the TOPMODEL modeling can be considerably removed. This study is of great theoretical and practical merits in sound understanding of the modeling behaviors of the TOPMODEL under the influences of inputs and parameter correlation.

1. Introduction

Hydrological models have been widely used to investigate many practical and pressing issues that arise during planning, design, operation, and management of water resources systems (Benke et al., 2007; Lin et al., 2007). The crucial step for hydrological modeling is to identify values of model parameters and this procedure is also referred to as calibration procedure (Sorooshian and Gupta, 1995). Estimation and specification of parameters are the two important procedures for calibration of hydrological model. However, the parameter redundancy and correlations between parameters result in universal equifinality in modeling behaviors of the hydrological models (Beven and Binley, 1992). Accordingly the generalized likelihood uncertainty estimation (GLUE) method proposed by Beven and Binley (1992) is devoted to the investigation of the hydrological modeling uncertainty by generating the prediction limits for the modeled streamflow series and a set of behavioral parameter sets (Freer et al., 1996; Blazkova and Beven, 2002; McMichael et al., 2006; Montanari, 2005, 2007; Yang et al., 2007, 2008; Xiong and O'Connor, 2008; Jin et al., 2010).

The hydrological system is complicated, being affected by the climate changes such as atmospheric circulation, precipitation, air temperature, the underlying surface properties such as the geological conditions, vegetation and soil conditions, and also human activities such as water reservoirs and land use changes (Zhang et al., 2009, 2010). Generally, a hydrological model consists of a large number of mathematical equations describing changing properties of hydrological processes, e.g. streamflow series, and estimating the streamflow variations of the future. Additional inputs represent the spatial mosaic of climate, soil type, topography and land use (Benke et al., 2007). Topography was taken as an important factor in the evaluation of the hydrological responses of the upland and forested watersheds to precipitation changes (e.g. Beven and Wood, 1983; Wolock and Price, 1994) due to the effects of gravity on the movement of water in a watershed. Many

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* Corresponding author. Tel./fax: +86 20 84113730.
E-mail address: zhangq68@mail.sysu.edu.cn (Q. Zhang).

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researches found that topography can influence many aspects of the hydrological system (Wolock and Price, 1994; Zhang and Montgomery, 1994; Wolock and McCabe, 1995; Sørensen and Seibert, 2007). TOPMODEL (Beven and Kirkby, 1979) is a rainfall–runoff model that bases its distributed predictions on an analysis of watershed topography in a semi-distributed way. Thus, the spatial distribution of topographical properties extracted by digital elevation model (DEM) should be firstly identified for the sake of hydrological modeling with TOPMODEL. Previous studies have shown that DEM resolution has the potential to influence the spatial patterns of the topographic index $\ln(a/\tan B)$ and thus the TOPMODEL simulation results. Quinn et al. (1995) indicated that different DEM resolutions can cause different spatial patterns of the $\ln(a/\tan B)$. Zhang and Montgomery (1994) showed that the mean of the $\ln(a/\tan B)$ distribution increased as data resolution became coarser. Wolock and Price (1994) showed that model predictions of the depth to the water table, the ratio of overland flow to total flow, peak flow, and variance and skew of predicted streamflow were affected by both the DEM map scale and data resolution. Further analyses showed that the effects of DEM map scale and data resolution on model predictions should be attributed to the sensitivity of the predictions to the mean of the $\ln(a/\tan B)$ distribution, which was affected by both DEM map scale and data resolution. Thus, DEM resolution has the potential to affect the TOPMODEL simulations. In this case, one objective of this study is to clarify whether or not hydrological modeling uncertainty could be affected by the DEM resolutions.

Prediction uncertainty is the result of various factors such as input error, calibration accuracy, parameter correlation, model structure, and so on. Beven and Freer (2001a) attempted to address the effects of some factors on the modeling uncertainty, such as model nonlinearity, covariation of parameter values and errors in model structure, input data or observed variables, using the GLUE procedure. Blasone and Vrugt (2008) and Yang et al. (2008) found that parameter correlation can result in the hydrological modeling uncertainty. Recent years have witnessed an explosion of methods devoted to derive meaningful uncertainty bounds for hydrological model predictions. Methods aiming to represent model parameter, state and prediction uncertainty include classical Bayesian (Kuczera and Parent, 1998; Thiemann et al., 2001; Vrugt et al., 2003), pseudo-Bayesian (Beven and Binley, 1992; Freer et al., 1996), set-theoretic (Keesman, 1990), multiple criteria (Gupta et al., 1998; Madsen, 2003), sequential data assimilation (Vrugt et al., 2005; Moradkhani et al., 2005), and multi-model averaging methods (Ajami et al., 2007; Vrugt and Robinson, 2007). Generally, it is assumed that the parameters of the model were independent mutually. In fact, complexity and correlation within the parameter space are the two important factors having the potential to cause hydrological modeling uncertainty. With this in mind, another objective of this study is to address the effects of parameter correlation on the hydrological modeling uncertainty.

With the help of GLUE technique, this study attempts to discuss the influences of parameter correlation and DEM resolution on the hydrological modeling uncertainty by taking TOPMODEL as the case model. Undoubtedly, this study will be of theoretical and practical merits in obtaining deep insight into the causes behind the hydrological modeling uncertainty, one of the crucial but tough problems in the hydrological modeling practices. This paper is organized as the follows: Section 2 briefly describes the basic equation and parameters of TOPMODEL; In Section 3, we introduce three catchments and related hydrological data analyzed in this study; Section 4 is devoted to analyze the effects of grid DEM on uncertainty of TOPMODEL; and Section 5 discusses the effect of parameter correlation on uncertainty of TOPMODEL. Finally, the last section contains the major conclusions.

2. Methodology

2.1. Basic equations and parameters of TOPMODEL

Since Beven and Kirkby firstly proposed TOPMODEL in 1979, many changes, some minor and some substantial, have been made over the past 20 years (e.g. Beven and Wood, 1983; Beven et al., 1995; Duan and Miller, 1997; Scanlon et al., 2000; Beven and Freer, 2001b; Walter et al., 2002; Xiong and Guo, 2004). The 1995 version (Beven et al., 1995) is subjected to the most frequent application and assessment (Beven, 1997) and is recognized widely. Therefore, the 1995 version of TOPMODEL is referred to as the original version in this study.

The structure of the original version of TOPMODEL is shown in Fig. 1, which shows that the total runoff is generally the sum of two major flow components: saturated excess overland flow from variable contributing areas and subsurface flow from the saturated zone. The infiltration excess overland flow component can also be included based on the properties of soil and rainfall of the river basin (Beven et al., 1995). Basic equations of this version are listed as the follows.

The actual evaporation rate, E, is calculated by:

$$E_a = E_p\left(1 - \frac{S_{rz}}{SR_{\max}}\right) \tag{1}$$

where S_{rz} and $SR_{\max}$ are the root zone storage deficit and maximum allowable root storage deficit, respectively; E_p is the reference or potential evaporation rate.

The precipitation that falls over the root zone in saturation state forms the unsaturated store, and is transferred (unsaturated flow or recharger) to the saturated store at a rate proportional to the depth of the unsaturated store (S_{uz}) and inversely proportional to both the local saturated deficit (SD) and the recharger delay parameter (T_d). It can be expressed as:

$$q_v = \frac{S_{uz}}{SD \cdot T_d} \tag{2}$$

where SD is the local saturated deficit due to gravity drainage and depends on the depth of the local water table (z).

Another fundamental equation shows the relation of local transmissivity $T(Z_i)$ to the groundwater table depth Z_i, that is,

$$T(Z_i) = T_0 \exp\left(\frac{-Z_i}{S_{zm}}\right) \tag{3}$$

where T_0 is the transmissivity of the soil in the saturated state and S_{zm} is the maximum moisture deficit.

The original TOPMODEL has four parameters, i.e. the maximum allowable root storage deficit ($SR_{\max}$), the transmissivity of the soil in saturated state (T_0), the maximum moisture max deficit (S_{zm}), and the recharger delay parameter (T_d). All of these parameters must be optimized. Ranges of parameters in TOPMODEL for Monte Carlo simulations are listed in Table 1. Ranges for T_0 are shown in log in relation to the graph scales (Beven and Freer, 2001a).

2.2. The indices selected for uncertainty evaluation

Uncertainty interval at each time step is the major result by the GLUE technique in terms of evaluations of the hydrological modeling uncertainty. In this study, three indices, i.e. containing ratio (CR), interval width (IW), and the Nash–Sutcliffe efficiency index (R^2), are adopted aiming to evaluate the uncertainty interval. The definitions of these three indices are introduced as the follows:

Containing ratio (CR) is devoted to estimate the capability of the uncertainty intervals to capture the observed values, which is defined as the ratio of the number of the observations falling within