Journal of Hydrology 529 (2015) 1095–1115

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Significant uncertainty in global scale hydrological modeling from precipitation data errors

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ARTICLE INFO

Article history:
Received 8 March 2015
Received in revised form 31 July 2015
Accepted 28 August 2015
Available online 4 September 2015
This manuscript was handled by Konstantine P. Georgakakos, Editor-in-Chief, with the assistance of Matthew McCabe, Associate Editor

Keywords:
Global hydrological modeling
Forcing uncertainty
Model calibration
Parameter uncertainty

SUMMARY

In the past decades significant progress has been made in the fitting of hydrologic models to data. Most of this work has focused on simple, CPU-efficient, lumped hydrologic models using discharge, water table depth, soil moisture, or tracer data from relatively small river basins. In this paper, we focus on large-scale hydrologic modeling and analyze the effect of parameter and rainfall data uncertainty on simulated discharge dynamics with the global hydrologic model PCR-GLOBWB. We use three rainfall data products; the CFSR reanalysis, the ERA-Interim reanalysis, and a combined ERA-40 reanalysis and CRU dataset. Parameter uncertainty is derived from Latin Hypercube Sampling (LHS) using monthly discharge data from five of the largest river systems in the world. Our results demonstrate that the default parameterization of PCR-GLOBWB, derived from global datasets, can be improved by calibrating the model against monthly discharge observations. Yet, it is difficult to find a single parameterization of PCR-GLOBWB that works well for all of the five river basins considered herein and shows consistent performance during both the calibration and evaluation period. Still there may be possibilities for regionalization based on catchment similarities. Our simulations illustrate that parameter uncertainty constitutes only a minor part of predictive uncertainty. Thus, the apparent dichotomy between simulations of global-scale hydrologic behavior and actual data cannot be resolved by simply increasing the model complexity of PCR-GLOBWB and resolving sub-grid processes. Instead, it would be more productive to improve the characterization of global rainfall amounts at spatial resolutions of 0.5° and smaller.

1. Introduction

Hydrological models synthesize our knowledge of the rainfall–storage–runoff transformation. These models are used widely for flood forecasting, and investigation of water resources systems and climate change, and use relatively simple mathematical equations to conceptualize and aggregate the complex myriad of spatially distributed and highly interrelated water, energy and vegetation processes in a watershed. As a result, most of the model parameters in hydrologic models do not represent direct measurable quantities but can only be derived indirectly by calibration against a historical record of input–output data (Beven and Binley, 1992; Vrugt et al., 2005; Gosling and Arnell, 2011). In this process the parameters are adjusted in such a way that the difference between the simulated model output and observations is minimized (Gupta et al., 1998; Vrugt et al., 2003).

In the past decades much progress has been made toward the development of efficient calibration strategies for hydrological models and the treatment and quantification of uncertainty. Most of this work has used relatively simple lumped and semi-distributed hydrological models that represent watersheds with area ranging between 100 and 10,000 km^2 (Sorooshian and Dracup, 1980; Gupta et al., 1998; Andréassian et al., 2001; Vrugt et al., 2003; Muleta and Nicklow, 2005; Balin et al., 2010; McMillan et al., 2010; Vaze et al., 2010, amongst many others). Less attention has been paid to calibration of global hydrological

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http://dx.doi.org/10.1016/j.jhydrol.2015.08.061
0022-1694/

models (GHMs) that attempt to simulate (predict) terrestrial-scale soil moisture, recharge, surface runoff, groundwater table, and discharge dynamics. Some notable exceptions include the recent work of Troy et al. (2008), Gosling and Arnell (2011), Nasonova et al. (2011) and Pappenberger et al. (2011). Not only do GHMs pose significant computational challenges, they also require a wealth of input data to accurately characterize global scale variations in land-use, soil type, elevation, climate conditions, and groundwater table depths (amongst others). Yet, all these data exhibit a large spatial variability and high degree of uncertainty which compromises, sometimes severely, the predictive capability of GHMs (Beven and Cloke, 2012; Duan et al., 2006; Teuling et al., 2009).

The lack of high-quality and high-resolution input and forcing data, and considerable CPU-requirements of GHMs, necessitates the use of a very coarse grid resolution to resolve global scale hydrologic fluxes and state variables (Haddeland et al., 2011). This introduces a very high level of process aggregation, which unavoidably introduces significant structural errors and requires appropriate sub-grid parameterization (Beven and Cloke, 2012). Moreover, the (discharge) datasets available for model evaluation are limited and their accuracy and reliability varies considerably over the world (Renard et al., 2010). Consequently appropriate parameterizations will not be spatially uniform and can only be tested and optimized locally (Beven and Cloke, 2012; McMillan et al., 2010).

Several contributions can be found in the hydrological literature that have investigated the role of parameter and forcing data uncertainty in GHMs. For instance, Fekete et al. (2004) analyzed the influence of precipitation data uncertainty on simulated global runoff with the UHN global water balance model. The uncertainty in simulated runoff was of similar size as the uncertainty in the precipitation and especially large in semi-arid regions. A similar study by Biemans et al. (2009) used the global vegetation and hydrology model LPJmL to evaluate seven precipitation datasets for discharge simulation of 294 basins. The uncertainty in simulated discharge was found to be about three times higher than the uncertainty in basin average precipitation. These findings make a strong case for hydrological model calibration using the meteorological dataset selected for the final model application. Pappenberger et al. (2011) concluded that the quality of meteorological data has improved considerably in the past decade, which hence should improve our ability to simulate the hydrology of large river basins.

Recent studies by Gosling and coworkers have investigated the sensitivity of the Mac-PDM.09 GHM to parameter and forcing (precipitation) data. The study of Gosling et al. (2010) used fourteen different model simulations to determine the sensitivity of the model output to variations in the field capacity and variability of the soil moisture capacity. The second study, published in Gosling and Arnell (2011) used an ensemble of 9 different scenarios from 21 different GCMs to analyze the impact of forcing data uncertainty. More recently, Nasonova et al. (2011) investigated the effect of different forcing datasets on the SWAT simulated water balance. Results demonstrate that the simulated surface runoff strongly depends on the precipitation dataset being used. This finding is perhaps not surprising, but highlights the need for accurate forcing data and information on river regulation in global hydrologic modeling.

Several other recent studies have focused attention on the effect of model selection in global hydrologic modeling. For instance, Haddeland et al. (2011) combined several Land Surface Models (LSMs) and GHMs in the WATCH project to generate a multi-model ensemble of the global water cycle. The ensemble of simulations exhibited a large spread, even though the constituent models resolved similar processes, but with differing parameter values. Gudmundsson et al. (2011) also conducted a multi-model comparison in the context of the WATCH project and demonstrated that the ensemble spread was particularly large during low flow events, but the ensemble mean reliably estimated mean and extreme flows.

Thus far, we have focused our attention on contributions whose main goal was to illustrate the effect of parameter, model, or forcing data uncertainty in global hydrologic modeling, without recourse to parameter estimation. Several authors have focused on global scale parameter estimation. For instance, Fekete et al. (2002) used a correction factor in the WBMplus model to match discharge data from neighboring stations. Troy et al. (2008) calibrated their global scale hydrological model at only 2% of the grid cells, and used the remaining cells to explore the potential for regionalization of the parameters and to assess sub-basin variability. Another study by Döll et al. (2003) considered the calibration of the GHM WaterGAP model. This work demonstrated that careful tuning of the runoff coefficient significantly improved the agreement between the observed and simulated discharge data. Widén-Nilson et al. (2007) calibrated the global water balance model WASMOD-M using measurements of average areal discharge, thereby avoiding problems of flow regulation. Basin specific values of the WASMOD-M model parameters were selected from a sample of 1680 different parameter combinations. Wood et al. (1992) calibrated the global VIC model using the well-known Shuffled Complex Evolution (SCE) algorithm (Duan et al., 1992; Nijssen et al., 2001). Calibration reduced the annual average bias and the relative Root Mean Square Error (RMSE) of the monthly discharge values from 62 to 37% and 29 to 10%, respectively.

Altogether, published studies demonstrate that calibration of GHMs is difficult, and hampered by (1) a lack of quality and high-resolution input data to accurately characterize surface and subsurface properties, (2) significant uncertainty in the forcing data, (3) high computational demands, and (4) limited availability of reliable discharge observations. The present study will show that rainfall uncertainty constitutes the largest source of error in global scale hydrologic modeling, while parameter uncertainty explains only a minor source of streamflow simulation uncertainty. Our analysis is based on a single model, and unlike previous studies jointly considers the effect of parameter and rainfall data uncertainty in modeling discharge dynamics of some of the largest rivers in the world. We also investigate the merits of calibration of PCR-GLOBWB for each meteorological forcing dataset individually.

This paper is organized as follows. Section 2 presents an overview of the different meteorological datasets and river basins used herein. This is followed by a short description of PCR-GLOBWB and its most important calibration parameters, and a brief explanation of Latin Hypercube Sampling (LHS) used to quantify parameter uncertainty. In Section 3 we report some of the main findings of our study and present the simulated hydrograph uncertainty ranges for each different river basin and forcing dataset. Here, we are especially concerned with a comparison of the simulated discharge dynamics with their observed counterparts, and investigate whether the simulation (prediction) uncertainty of PCR-GLOBWB decreases by down sampling of the original behavioral parameter sets. Section 4 summarizes our main conclusions and provides an outlook for future work.

2. Data and methods

2.1. Meteorological forcing

Three different meteorological forcing datasets are used in this paper. This includes: (1) a combination of the dataset of the Climate Research Unit of the University of East Anglia