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Assessing the role of uncertain precipitation estimates on the robustness of hydrological model parameters under highly variable climate conditions

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ABSTRACT

Study region: Four headwaters in Southern Africa.
Study focus: The streamflow regimes in Southern Africa are amongst the most variable in the world. The corresponding differences in streamflow bias and variability allowed us to analyze the behavior and robustness of the LISFLOOD hydrological model parameters. A differential split-sample test is used for calibration using seven satellite-based rainfall estimates, in order to assess the robustness of model parameters. Robust model parameters are of high importance when they have to be transferred both in time and space. For calibration, the modified Kling-Gupta statistic was used, which allowed us to differentiate the contribution of the correlation, bias and variability between the simulated and observed streamflow.
New hydrological insights: Results indicate large discrepancies in terms of the linear correlation (r), bias (β) and variability (γ) between the observed and simulated streamflows when using different precipitation estimates as model input. The best model performance was obtained with products which ingest gauge data for bias correction. However, catchment behavior was difficult to be captured using a single parameter set and to obtain a single robust parameter set for each catchment, which indicate that transposing model parameters should be carried out with caution. Model parameters depend on the precipitation characteristics of the calibration period and should therefore only be used in target periods with similar precipitation characteristics (wet/dry).

1. Introduction

Hydrological models are widely used for water resources modelling, both drought and flood forecasting, and climate change impact assessment studies, among others. Before applying these models their robustness needs to be tested vis-à-vis with the specific modelling objective to build model credibility and ensure model applicability (Klemeš, 1986). Operational models often need to be calibrated to obtain numerical values of model parameters. The aim of a calibration process is to obtain parameters which allow an acceptable representation of the hydrological behavior of the selected catchment, and moreover to obtain parameters which are robust and, therefore, be transposable towards other time periods as well. This

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assumption might only be valid if the uncertainty in the obtained model parameters is low and/or the conditions between the calibration and validation period are similar (stationary conditions). However, there are multiple reasons that might lead to changes in model parameters in time and, therefore, raise a lack of model robustness. The most obvious cause might be an inappropriate model structure (Butts et al., 2004; Bulygina and Gupta, 2009; Reusser and Zehe, 2011; Lin and Beck, 2012; Seiller et al., 2012). Recently, Coron et al. (2014) showed the inability of three models of increasing complexity in reproducing the water balance on different sub-periods. Another explanation for the lack of model robustness can be miscalibration (i.e. poor optimization algorithm) or overcalibration (i.e. insufficient calibration period, too many parameters, wrong objective function) of model parameters, as shown by Wagener et al. (2003), Hartmann and Bárdossy (2005), Son and Sivapalan (2007), Gupta et al. (2009), Ebtehaj et al. (2010), Efstratiadis and Koutsoyiannis (2010), Andréassian et al. (2012), Gharari et al. (2013) and Zhan et al. (2013). In addition, changes in time of some catchment features (e.g., land use change and management, operational rules of reservoirs, changes in groundwater level) are reflected in the model input data, and might also lead to lack of model robustness. For example, Fenicia et al. (2009) showed the major role of changes in land use management and forest age on the catchments' behavior.

To assess the model's robustness under highly variable climate conditions the standard split-sample test, used to calibrate the model in one period and test the model in another period, is not sufficient enough. Klemeš (1986) proposed a more powerful test, the so called *differential split-sample test*, where calibration and validation periods are chosen to represent markedly different hydro-meteorological conditions of the catchment. This differential split-sample test should be applied whenever a model is to be used to simulate flows in a basin under conditions different from those corresponding to the available flow record (Klemeš, 1986). A robust model should demonstrate its ability to perform equally well in the selected calibration and validation periods. Studies that performed a differential split-sample test are relatively scarce, because most models fail this test (Seibert, 2003). The studies of Refsgaard and Knudsen (1996), Donnelly-Makowecki and Moore (1999), Xu (1999), Seibert (2003), Wilby (2005) and Chiew et al. (2009) all applied a differential split-sample test. Most of these studies found a decrease in model performance due to the sensitivity of the model parameters in relation to different climate conditions. More recently, Merz et al. (2011) found in a test for 273 Austrian catchments that the parameters controlling snow and soil moisture were strongly influenced by climatic conditions. Vaze et al. (2010) and Coron et al. (2012) conducted studies with four and three hydrological models, respectively, on southeastern Australian catchments. They also found a strong climate influence in their models. According to Li et al. (2012) dry periods contain more information for model calibration compared to wet periods, when they investigated the transposability of model parameters for dry and wet conditions.

For successful streamflow predictions the model should be forced with accurate precipitation data (Beven, 2004). The impact of precipitation input on model performance is well documented in error analyses (Kavetski et al., 2003, 2006), as a function of catchment size (Moulin et al., 2009), raingauge density (Bárdossy and Das, 2008) or using various geostatistical methods (Sun et al., 2000). However, model robustness problems due to incorrect estimations of precipitation amounts are rarely reported in hydrological modelling, while it is well known that such errors might have a significant effect on the final values of model parameters (Oudin et al., 2006).

Considering the importance of the precipitation input on the reliability of model predictions, it is extremely challenging to perform reliable applications of hydrological models in ungauged or data-scarse areas. For Africa, "ground truth" precipitation is very sparse and, therefore remote sensing can be an ideal technique for obtaining time series of precipitation to be used as input data for hydrological modelling studies. Applications of satellite-based rainfall estimates (SRFE) for hydrological modeling are well documented (for e.g., Thiemig et al., 2013; Artan et al., 2007; Behrangi et al., 2011; Gourley et al., 2011; Stisen and Sandholt, 2010; Cohen Liechti et al., 2012), observing large differences in parameter values obtained from different rainfall inputs (Bitew and Gebremichael, 2011). However, most of these studies perform the standard split-sample test and do not discuss the robustness of the obtained model parameters and how the model structure compensate for the precipitation inaccuracy, and moreover if they are transposable to time periods other than the single validation period.

The aim of this study is to determine the robustness of the fully distributed LISFLOOD hydrological model by using different precipitation estimates as model input. To achieve this aim, this research focuses on five main research questions: (i) How accurate are the different precipitation data sets for streamflow simulations? (ii) What is the effect of uncertain input data (precipitation) on the estimates of model parameters? (iii) How will the model parameters obtained by calibration compensate for precipitation inaccuracy? (iv) Can a different source of precipitation overcome robustness problems? (v) Is a single calibration parameter set sufficient for hydrological forecasting or climate scenario modelling? These research questions are answered performing a differential split-sample test to calibrate the LISFLOOD hydrological model using different precipitation sources, to show differences in model parameters and to ensure a minimum standard for operational validation of this simulation model. Southern Africa is selected as a case study because of its highly inter and intra-annual hydrological variability, mainly due to rainfall patterns characterized by events of short duration and high intensities. Therefore, the precipitation estimates might present large differences with ground observations, i.e., they can be highly inaccurate. The corresponding differences in streamflow bias and variability will allow us to assess differences in model's behavior and robustness of model parameters.

The paper is organized as follows. Section 2 presents the precipitation estimates and other hydrological model data used in this research, providing a description of the sensitivity analysis, calibration procedure and climate characteristics during the hydrological simulations. Section 3 contains a description of the calibration and validation results of the differential split-