Journal of Hydrology 519 (2014) 2049–2066

Contents lists available at ScienceDirect

Journal of Hydrology

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

# Combined uncertainty of hydrological model complexity and satellite-based forcing data evaluated in two data-scarce semi-arid catchments in Ethiopia

Malte Knoche [a,*], Christian Fischer [b], Eric Pohl [c], Peter Krause [d], Ralf Merz [a]

[a] Department of Catchment Hydrology, Helmholtz Centre for Environmental Research – UFZ, Theodor-Lieser-Str. 4, D-06120 Halle, Germany
[b] Department of Geoinformatics, Hydrology and Modelling, Friedrich Schiller University of Jena, Löbdergraben 32, D-07743 Jena, Germany
[c] Remote Sensing Group, Geology Institute, Bergakademie Freiberg University of Mining and Technology, Bernhard-v-Cotta Str. 2, D-09599 Freiberg, Germany
[d] Thüringen State Institute for Environment and Geology, Göschwitzer Str. 41, D-07745 Jena, Germany

ARTICLE INFO

*Article history:*
Received 20 December 2013
Received in revised form 26 September 2014
Accepted 3 October 2014
Available online 13 October 2014
This manuscript was handled by Konstantine P. Georgakakos, Editor-in-Chief, with the assistance of Alon Rimmer, Associate Editor

*Keywords:*
Hydrological modeling
Data scarcity
Uncertainty
Remote sensing precipitation
Model complexity
East Africa

SUMMARY

In water resources modeling, meteorological data scarcity can be compensated by various global data sets, but those data sets can differ tremendously. In the literature, hydrological models of differing complexity are proposed for estimating the water resources of semi-arid catchments, and also to evaluate rainfall data sets. The goal of this paper is to provide a joint analysis of modeling uncertainty due to different input data and increasing model complexity. Impacts of mutually concealed uncertainties on model performance and model outputs are exemplified in two data sparse semi-arid catchments in Ethiopia. We applied a semi-distributed and a fully distributed hydrological model, having different levels of complexity. Three different satellite-based rainfall data sets and two temperature products were used as model inputs. The semi-distributed model demonstrated good validation performances, while the fully distributed model was more sensitive to data uncertainties. The application of TRMM version 6 completely failed and the high-resolution CMORPH precipitation estimate outperformed TRMM version 7. In contrast, the use of high-resolution temperature data did not improve the model results. The large differences in remotely sensed input data were buffered inside the hydrological models. Therefore, data set evaluations regarding only the simulated hydrographs were less meaningful. In contrast, the investigation of parameter evolution and distributed outputs' variability appeared to be a valuable tool to uncover the interdependencies of data and model uncertainties. We suggest this procedure to be applied by default in water resources estimations that are affected by data scarcity, but especially when data sets are evaluated using hydrological models. Our case study demonstrates that estimations of groundwater recharge and actual evapotranspiration vary largely, depending on the applied data sets and models. The joint analysis reveals large interdependencies between data and model evaluations. It shows that traditional studies focusing only on one part of uncertainty, either the input uncertainty or the uncertainty arising from the choice of model structure are limited in their explanatory power of the modeling performance, particularly in poorly gauged regions.



## 1. Introduction

East Africa is often threatened by severe water scarcity. Millions rely on unsecure availability of fresh-water. This problem is further enhanced over the last decade by an eminent economic growth (Shiklomanov, 2000; AfDB et al., 2013). The resulting water demand and the ongoing growth of population ask for reliable estimations of water resources. However, the hydro-meteorological infrastructure is old and sparsely distributed across the country with its complex topography and subsurface. Hydrological models are a common tool for water resources management in data sparse regions such as East Africa. Modelers are challenged by the following questions: (i) which climate data should be used to drive the model, (ii) what model should be used and (iii) how to verify that data and model are sufficient to be used for water resources management. The first two questions have individually been discussed in numerous publications, illustrating a high complexity of the depicted problem:

* Corresponding author. Tel.: +49 345 558 5490.
*E-mail addresses:* malte.knoche@ufz.de (M. Knoche), christian.fischer.2@uni-jena.de (C. Fischer), eric.pohl@geo.tu-freiberg.de (E. Pohl), peter.krause@tlug.thueringen.de (P. Krause), ralf.merz@ufz.de (R. Merz).

http://dx.doi.org/10.1016/j.jhydrol.2014.10.003
0022-1694/

### 1.1. Which climate data should be used?

When ground-based rainfall data are missing or rare, satellite based rainfall estimates (e.g. TRMM, CMORPH) are frequently applied to drive hydrological models (e.g. Velpuri et al., 2012). However, those data sets are affected by high uncertainties resulting from physical sensor limitations, limited space–time coverage and spatial resolution (Prigent, 2010; Yong et al., 2014). The known uncertainties raise the question of the extent of their impact on water resource estimations. Therefore, data sets are sometimes indirectly tested with hydrological models by comparing the model performances (e.g. Xue et al., 2013). This partly leads to critical judgments on the applicability of satellite based precipitation estimates (e.g. Meng et al., 2014).

There are numerous studies in the literature analyzing the impacts of different remotely sensed rainfall products in hydrological modeling, including some studies focusing on poorly gauged African river basins. E.g. Khan et al. (2011) reported underestimations of simulated runoff using TRMM3B42 V6 when modeling the Nzoia Basin, Lake Victoria, Kenya. Gebregiorgis et al. (2012) compared three satellite rainfall estimates by modeling the Mississippi River Basin. They found a high correlation (0.85) between runoff error and the hit bias of the precipitation data and furthermore a correlation of 0.75 between missed precipitation and soil moisture error. Bitew and Gebremichael (2011) discovered CMORPH and the TRMM real-time product perform better than post-processed TRMM6 and infrared-based rainfall estimates in an Ethiopian highland's catchment. Milzow et al. (2011) used the SWAT model to find out major differences between TRMM, FEWS (Famine early warning system) and ERA-Interim rainfall data in the Okavango basin. Stisen and Sandholt (2010) compared different rainfall data sets inside the MIKE SHE model in the Senegal River Basin. Their study reveals that satellite data used in pre-calibrated models (forced by rain gauges) leads to weak performances. In contrast, models calibrated and forced by satellite inputs have Nash–Sutcliffe efficiencies (NSE) between 0.63 and 0.87. Therefore, the judgment of input data sets which is based solely on the assessment of simulated runoff after calibration might be insufficient because other water balance components might be affected negatively. However, water balance components other than runoff remain mostly disregarded when data sets are tested directly in hydrological models. An exception is represented by Stisen et al. (2008) who perform a comparison of infrared-based rainfall estimates with rain gauge data within the MIKE-SHE model. They discovered that actual evapotranspiration is highly sensitive to different rainfall inputs in the Senegal Basin.

Temperature estimates are also required to drive hydrological models. The use of remote sensing products and reanalysis data are an appealing approach in data scarce regions, but large uncertainties may accompany these data sets. For example, Becker et al. (2010) applied ECMWF temperatures with a spatial resolution of 0.75° (ca. 6800 $km^2$ per pixel) in modeling the East African Rift System's hydrology. In contrast, Deus et al. (2013) applied MODIS land surface temperatures (LST) in 5.6 $km^2$ resolution in the data-scarce Lake Manyara Basin, Rift Valley, Tanzania. The first application cannot cover the spatial heterogeneity of air temperature (AT), especially over complex terrain, while the latter application raises the question whether LST is an adequate replacement for AT in water resource estimations. The impact of largely differing spatial resolutions and temperature magnitudes remains unclear. Alternatively, air temperatures can be modeled from LST, but with a significantly higher effort (e.g. Cristóbal et al., 2008) since the derivation of AT from LST "is far from straight forward" as Vancutsem et al. (2010) figured out in East Africa.

In contrast to precipitation data, evaluations of temperature data sets by using hydrological models are unusual. E.g. Wang et al. (2009) and Wang et al. (2011) evaluated MODIS LST and GLDAS AT by using the WEB-DHM distributed model in a semi-arid basin. The influence of other uncertainties (model, precipitation) has not been discussed.

### 1.2. What model should be used?

In addition to the need for meteorological data, finding an adequate model structure for data-sparse semi-arid catchments reveals the agony of choice. Subsurface complexity and consequently the model complexity correspond with scarcity of soil and catchment information. There are diverging approaches to setup models for such an environment. Collick et al. (2009) developed a simple semi-distributed model for semi-arid regions under monsoonal influence (Ethiopian highlands). Güntner and Bronstert (2004) highlight the importance of taking into account the re-infiltration processes in large scale modeling of semi-arid catchments (Brazilian Caatinga). They suggest the application of fully distributed models to account for lateral redistribution processes. Love et al. (2011) confirm these findings and show their semi-distributed model is not able to reproduce hydrology of more ephemeral and drier catchments. They could not extend a Nash–Sutcliffe efficiency of 0.3 when applying the HBVx model in 15 semi-arid catchments in Zimbabwe. In contrast, Reed et al. (2004) found distributed models not to perform better than lumped models in the data-rich central USA.

However, detailed studies on what is an appropriate model structure and model complexity for data-sparse semi-arid regions are rare and focus on hydrograph simulation only (e.g. Jothityangkoon et al., 2001; Ghavidelfar et al., 2011). Model choice is often affected by other factors. For example, Van Griensven et al. (2012) carried out an extensive review of 20 applications of the Soil and Water Assessment Tool (SWAT) in East Africa and concluded that the main reason for the application of SWAT by numerous scientists was much more due to its handy applicability inside GIS software than its physical representation of the depicted catchments.

### 1.3. How to verify data and model, both?

Although the limitations of hydrological models in data-sparse semi-arid catchments are clearly mentioned by many authors (e.g. Love et al., 2011), strict calibration and validation procedures (e.g. Klemes, 1986) are often missing or weakly documented in model applications in East African catchments (Van Griensven et al., 2012).

To our knowledge, what is missing in the literature, are analyses of the combined effect of input data and model structure on the performance and outputs of hydrological models in data sparse semi-arid catchments. Some studies focus exclusively on data set evaluations, others on model evaluation. However, the compensation of data set uncertainty by hydrological models and the concealment of model uncertainty by data uncertainties remain underexposed in the meantime. The objective of this paper is to fill this gap and to combine data set evaluation and model evaluation. Uncertainties resulting from data of land cover or subsurface properties are ignored in this study (see Branger et al., 2013).

On the example of two data-sparse catchments in Ethiopia, we specifically address two scientific questions: (A) What is the impact of different input data-model-combinations on the efficiency of reproducing runoff? (B) What is the impact of different input data-model-combinations on the evolution of model parameters and the spatial patterns of groundwater recharge and evapotranspiration?

The paper is organized as follows. First, we present an overview on the catchment characteristics and different remote sensing