



Using precipitation data ensemble for uncertainty analysis in SWAT streamflow simulation

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ARTICLE INFO

Article history:

Received 6 September 2011

Received in revised form 26 October 2011

Accepted 7 November 2011

Available online 15 November 2011

This manuscript was handled by Andras Bardossy, Editor-in-Chief, with the assistance of Uwe Haberlandt, Associate Editor

Keywords:

Precipitation variability

Uncertainty

SWAT model

Sequential Uncertainty Fitting

Bayesian Model Averaging

Brazil

SUMMARY

Precipitation patterns in the tropics are characterized by extremely high spatial and temporal variability that are difficult to adequately represent with rain gauge networks. Since precipitation is commonly the most important input data in hydrological models, model performance and uncertainty will be negatively impacted in areas with sparse rain gauge networks. To investigate the influence of precipitation uncertainty on both model parameters and predictive uncertainty in a data sparse region, the integrated river basin model SWAT was calibrated against measured streamflow of the Pipiripau River in Central Brazil. Calibration was conducted using an ensemble of different precipitation data sources, including: (1) point data from the only available rain gauge within the watershed, (2) a smoothed version of the gauge data derived using a moving average, (3) spatially distributed data using Thiessen polygons (which includes rain gauges from outside the watershed), and (4) Tropical Rainfall Measuring Mission radar data. For each precipitation input model, the best performing parameter set and their associated uncertainty ranges were determined using the Sequential Uncertainty Fitting Procedure. Although satisfactory streamflow simulations were generated with each precipitation input model, the results of our study indicate that parameter uncertainty varied significantly depending upon the method used for precipitation data-set generation. Additionally, improved deterministic streamflow predictions and more reliable probabilistic forecasts were generated using different ensemble-based methods, such as the arithmetic ensemble mean, and more advanced Bayesian Model Averaging schemes. This study shows that ensemble modeling with multiple precipitation inputs can considerably increase the level of confidence in simulation results, particularly in data-poor regions.

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1. Introduction

Hydrological models are useful tools for evaluating the hydrologic effects of factors such as climate change, landscape pattern or land use change resulting from policy decisions, economic incentives or changes in the economic framework (Beven, 2001; Falkenmark and Rockström, 2004). Rainfall data is typically the most important input for hydrological models, and therefore accurate data describing the spatial and temporal variability of precipitation patterns are crucial for sound hydrological modeling and river basin management. Among others, Dawdy and Bergmann (1969), Troutman (1983), Duncan et al. (1993), Faures et al.

(1995), Lopes (1996), Andréassian et al. (2001), and Bárdossy and Das (2008) have shown that neglecting spatial variability of rainfall can cause serious errors in model outputs. However, rain gauge networks are usually not able to fully represent the spatial pattern of rainfall, and thus watershed modelers are forced to cope with the uncertainties that arise from limited spatial sampling. This is especially true for the tropics, where rainfall is primarily of convective type and occurs mostly in small cells ranging from 10–20 km² to 200–300 km² (McGregor and Nieuwolt, 1998).

The Soil and Water Assessment Tool (SWAT) model (Arnold et al., 1998; Arnold and Fohrer, 2005) has been proven to be an effective tool for supporting water resources management for a wide range of scales and environmental conditions across the globe (Gassman et al., 2007). SWAT is a process-based hydrologic model that can simulate most of the key hydrologic processes at the basin scale (Arnold et al., 1998). Uncertainty in SWAT model output due to spatial rainfall variability has been analyzed in several applications. Hernandez et al. (2000) and Chaplot et al. (2005) found that increasing the number of rain gauges used for input

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data resulted in significantly improved streamflow estimates and sediment predictions. Cho et al. (2009) assessed the hydrologic impact of different methods for incorporating spatially variable precipitation input into SWAT. Because of its robustness to sub-watershed delineation, they recommend the Thiessen polygon approach in watersheds with high spatial variability of rainfall. Another potentially promising approach for improving precipitation data is by using remote sensing methods. Moon et al. (2004) as well as Kalin and Hantush (2006) reported that using Next-Generation Weather Radar (NEXRAD) precipitation resulted in as good or better streamflow estimates in SWAT as using rain gauge data.

An alternative to deterministic prediction methods is the use of probabilistic predictions, which are generated using a range of potential outcomes, and thus allows greater consideration of different sources of uncertainty (Franz et al., 2010). One approach to probabilistic forecasting is through the use of ensemble modeling techniques (Georgakakos et al., 2004; Gourley and Vieux, 2006; Duan et al., 2007; Breuer et al., 2009; Viney et al., 2009). The basis of ensemble modeling is that instead of relying on a single model prediction, it may be advantageous to combine the results of multiple individual models into an aggregate prediction. There are numerous different ensemble methods that can be used to merge the results from the contributing models. The most basic ensemble method is to use the arithmetic mean of the ensemble predictions (ensemble mean). Despite the simplicity of this approach, these ensembles have been shown to exhibit more predictive performance than single model predictions (e.g. Hsu et al., 2009; Viney et al., 2009; Zhang et al., 2009). Recently, more complex Bayesian Model Averaging (BMA) methods have been successfully applied to provide improved meteorological and hydrological predictions with corresponding uncertainty measures (Raftery et al., 2005; Duan et al., 2007; Huisman et al., 2009; Viney et al., 2009; Zhang et al., 2009; Franz et al., 2010;).

The objective of this study is to account for precipitation uncertainty in streamflow simulations by using an ensemble of precipitation data-sets as input for the SWAT model. By means of the Sequential Uncertainty Fitting (SUFI-2) procedure (Abbaspour et al., 2007) we aim to estimate parameter uncertainty and predictive uncertainty for each of the rain input models. Finally, we try to improve the SWAT streamflow predictions and provide more reliable uncertainty estimates by merging the individual model outputs using simple ensemble combination methods and more advanced Bayesian Model Averaging (BMA) schemes.

The study is part of the IWAS project (International Water Research Alliance Saxony, <http://www.iwas-sachsen.ufz.de/>) which aims to contribute to an Integrated Water Resources Management in hydrologically sensitive regions by creating system specific solutions. For the Federal District of Brazil (DF), IWAS is addressing the urgent needs for sustainable water supplies in face of rapid population growth, urban sprawl, and intensification of agriculture (Lorz et al., 2011). Within this context, the current study provides a framework for further model-based scenario analyses in this region.

2. Materials and methods

2.1. Study area

This study was conducted on the Pipiripau River basin, located in the north-eastern part of the DF (Fig. 1). The 215 km² basin is mainly covered by well drained Ferralsols which are low in nutrients (EMBRAPA, 1978). The Pipiripau River basin is situated within the Brazilian Central Plateau, with an altitude ranging from 920 to 1230 m a.s.l. and primarily moderate slopes ranging from 0.5° and 4°. Approximately 70% of the basin is intensively used for large-scale agriculture producing soybeans, corn and pasture, and to a smaller extent by irrigated horticulture. The remaining 30% is mainly covered by gallery forests and different types of Cerrado vegetation, which varies from very open to closed savannas (Oliveira-Filho and Ratter, 2002). The basin is mostly rural, with only a few small settlements.

The study region is categorized as a semi-humid tropical climate. Most of the precipitation (on average 1300 mm year⁻¹) occurs during the summer from November to March. Analysis of time series from 60 rain gauges in the DF region shows a rapidly decreasing correlation with distance between precipitation measurements (Fig. 2). This illustrates the high spatial variability of rainfall in this region, which presents a significant challenge for developing accurate precipitation input data.

The Pipiripau River is a perennial river with a long-term average flow rate of 2.9 m³ s⁻¹ for the period 1971–2008 (stream gauge FRINOCAP, Fig. 1). Water withdrawal for drinking water supply of nearby cities and for agricultural irrigation demands has increased over this time period, which has exacerbated low-flow conditions during the dry season (May–October). This effect can be observed by comparing the 5th percentile flow rates over two separate time

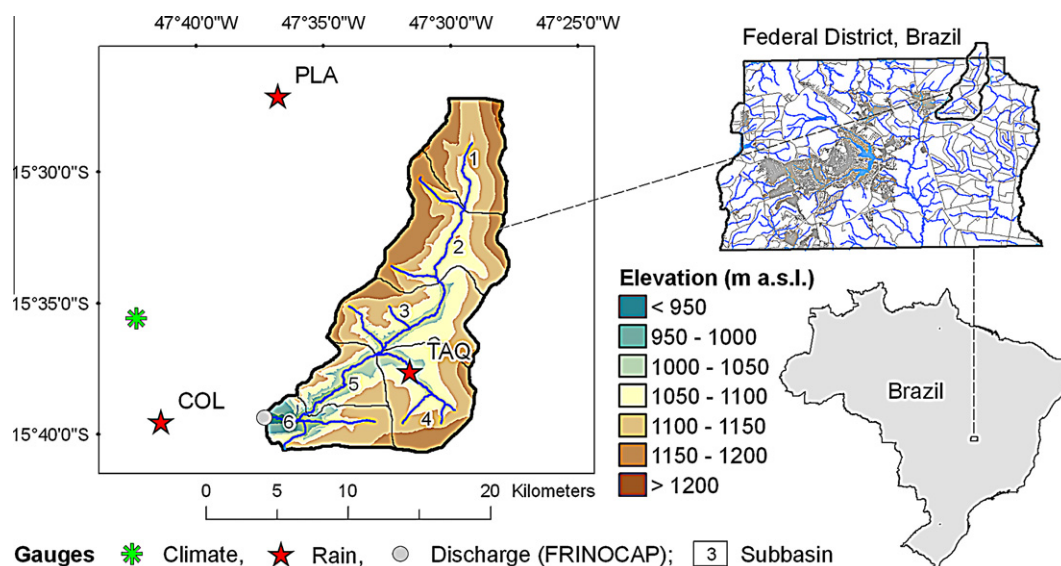


Fig. 1. Location map, Pipiripau basin.

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