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Using precipitation data ensemble and Bayesian Model Averaging for uncertainty analysis in hydrologic modeling.

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Introduction

Rapid population growth, urban sprawl, and intensification of agriculture impose severe pressure on Brasília's water resources. The project IWAS addresses the urgent needs of a sustainable water supply for the Federal District by means of IWRM approaches.

Integrated watershed modeling with SWAT (Arnold et al. 1998) plays a crucial role in this effort, but it is subject to huge uncertainty. One primary source of uncertainty is associated with the rainfall data that drive the hydrologic model, especially when sparse gauging networks are facing highly variable rainfall events (low correlation between gauges) as it is the case for Brasília, DF (Fig. 1).

In order to account for precipitation uncertainty, we run the SWAT model with multiple datasets on rainfall and apply ensemble based methods on the individual model results.

Material & Methods

The SWAT model was configured on the basis of (1) a DEM (CODEPLAN, 1991), (2) a land use classification (TNC, 2009), a soil map (EMBRAPA, 1978; 2004), (4) data on management practices (EMATER) and (5) water use (CAESB), as well as (6) meteorological inputs from one climate station (EMBRAPA) and three rain gauges (CAESB, ANA). However, only one rain gauge (TAQ) is situated directly within the basin (Fig. 2). Assuming uniform rainfall for the whole basin seems not sufficient in view of high variable rainfall. So we generated three further daily rain inputs for the period from 1998 to 2008 (see right side, Fig. 3 + 4).

Each rain input model was then calibrated against measured streamflow data (CAESB) using the identified most sensitive parameters (sensitivity analysis tool, van Griensven et al. 2006). As an objective auto-calibration method, we chose the Sequential Uncertainty Fitting procedure (SUFI-2, Abbaspour 2008).

Finally, the results of the individual models were combined by simple ensemble based methods (arithmetic ensemble mean) and more advanced Bayesian Model Averaging (BMA) schemes. BMA is a probabilistic multi-model averaging technique where individual predictions are weighted by the likelihood that a model is correct given the observations. In addition, the BMA variance is an uncertainty measure of the BMA prediction (Raftery et al. 2005).

Results

The most important results can be summarized as follows:

- for each rain input it is possible to achieve a good model performance by "goodness of fit" calibration (Fig.5, Tab.2)
- however, the ranges of best-fit parameter values indicate a remarkable parameter uncertainty (Fig. 6)
- the ensemble mean and the BMA prediction perform better than any individual prediction (Tab. 2)
- the BMA uncertainty interval covers most of the observations (Fig. 7) and might be used to account for rain input uncertainty in future scenario analysis

References

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van Griensven A , Meixner T, Grunwald S, et al. A global sensitivity analysis tool for the parameters of multi-variable catchment models. *J HYDROL* 2006; 324 (1-4):10-23.

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High spatial and temporal rainfall variability in Brasilia, DF vs. poor gauging networks in some parts, e.g. Pipiripau basin

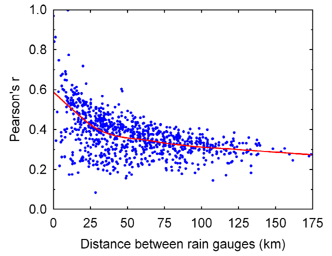


Fig. 1: Correlation of corresponding daily time series of 60 rain gauges in the DF and surrounding area. The solid line is a Lowess filter (40% strain).

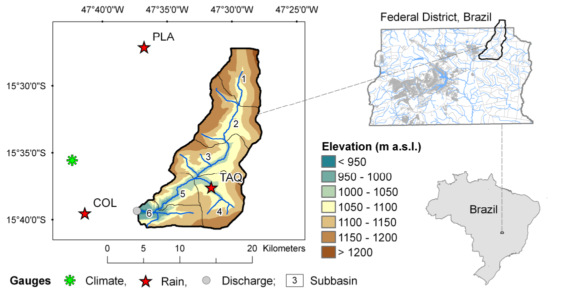


Fig. 2: Location map & rain gauges for the Pipiripau basin

Generation of multiple rainfall inputs (rainfall ensemble)

TAQ	• Rainfall data of gauge Taquara
TAQM	• Smoothed version of TAQ obtained by sliding mean
THIE	• Thiessen method including neighbor gauges
TRMM	• Tropical Rain Measuring Mission (TRMM) radar data

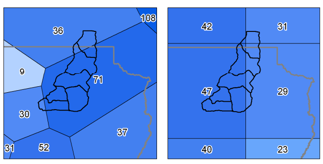


Fig. 3: Rainfall in mm on Feb. 20th 2004 following THIE (left) and TRMM (right)

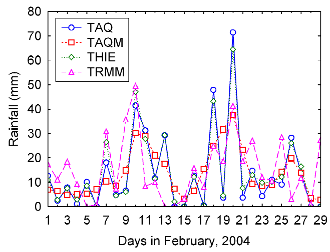


Fig. 4: Daily catchment rainfall in February 2004 according to the rainfall inputs TAQ, TAQM, THIE, and TRMM

SWAT streamflow calibration & validation using the rainfall ensemble

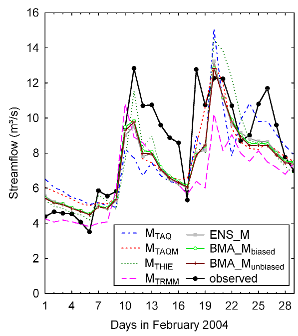
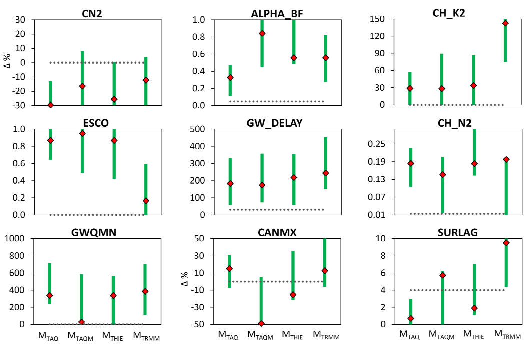


Fig. 5: Simulated stream flow by different rain input models, ensemble mean (ENS_M), and BMA means (biased and unbiased)

Fig. 6: Calibrated "best" parameter values (red rhombuses) and final parameter ranges (green bars) for the four rain input models within the initial parameter range (y-axis domain); the initial parameter values are shown by the dotted line



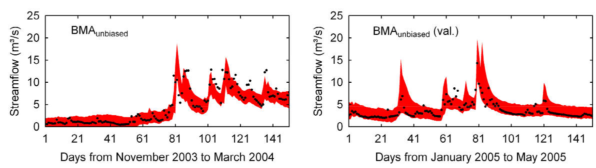
Calibration parameters
CH_K2 = Eff. hydraulic conductivity in main channel alluvium (mm/h)
CH_N2 = Manning's "n" for main channel
GW_DELAY = Groundwater delay time (days)
GWQMN = Water depth in shallow aquifer for return flow (mm H2O)
CN2 = SCS runoff curve number
ALPHA_BF = Baseflow recession constant
ESCO = Soil evaporation compensation factor
CANMX = Max. canopy storage (mm H2O)
SURLAG = Surface runoff lag coefficient

Tab. 2: Evaluation coefficients for the rain input models, the ensemble mean, and BMA means

	Calibration (2001 - 2004)			Validation (2005 - 2008)		
	NSE	R^2	PBIAS	NSE	R^2	PBIAS
M_{TAQ}	0.79	0.80	+7.7	0.73	0.79	-11.8
M_{TAQM}	0.83	0.83	+3.0	0.76	0.82	-14.0
M_{THIE}	0.81	0.81	+6.4	0.69	0.79	-15.2
M_{TRMM}	0.74	0.74	-1.6	0.43	0.58	-9.5
ENS_M	0.84	0.84	+3.9	0.80	0.84	-12.6
BMA_M_{biased}	0.85	0.85	0.0	0.78	0.84	-15.3
$BMA\_M_{unbiased}$	0.84	0.85	+3.0	0.81	0.85	-12.8

Bayesian Model Averaging (BMA) to derive uncertainty intervals

Fig. 7: 90% uncertainty interval obtained by BMA



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