IWAS International Water Research Alliance Saxony

Using precipitation data ensemble and Bayesian Model Averaging for uncertainty analysis in SWAT streamflow simulation

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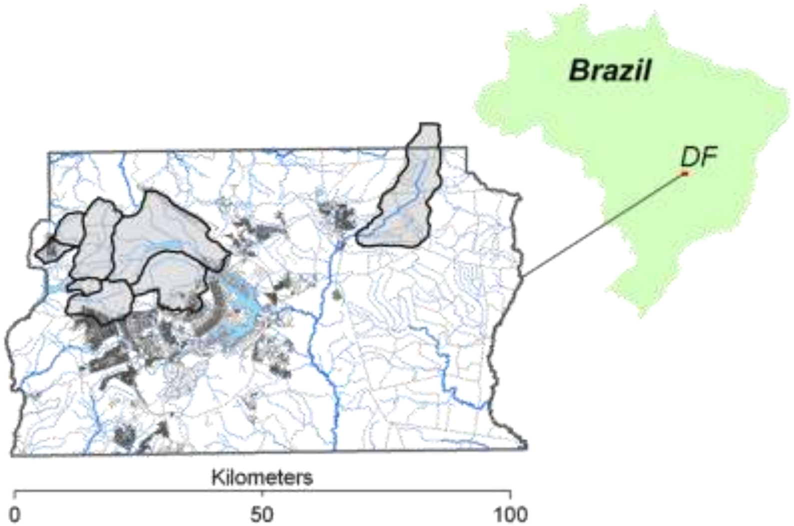
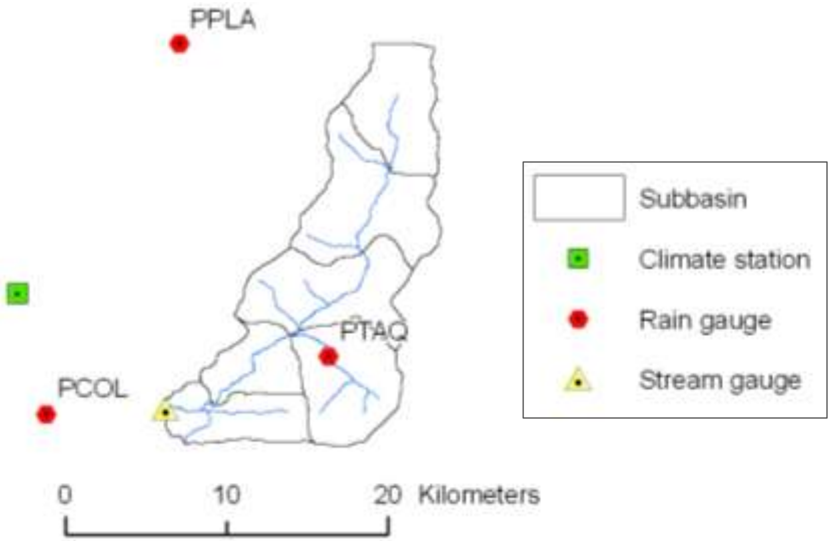
Study area & rain input uncertainty



Study area
Pipiripau
215 km²

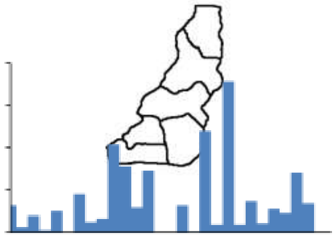


Only one rain gauge within the watershed!

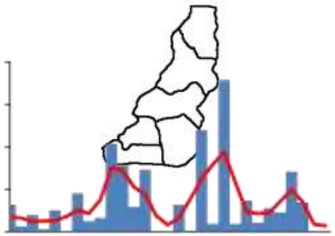
Representative???

Precipitation data ensemble & model calibration

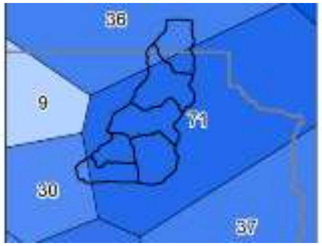
TAQ
gauge Taquara
uniform rainfall



TAQM
Weighted sliding mean of TAQ
uniform rainfall



THIE
Thiessen polygons
spatial distributed rainfall



TRMM
TRMM radar data
spatial distributed rainfall

Sensitivity Analysis (van Griensven et al., 2006)

Latin-Hypercube- & One-factor-At-a-Time-Sampling, 280 runs, 9 parameters out of 27

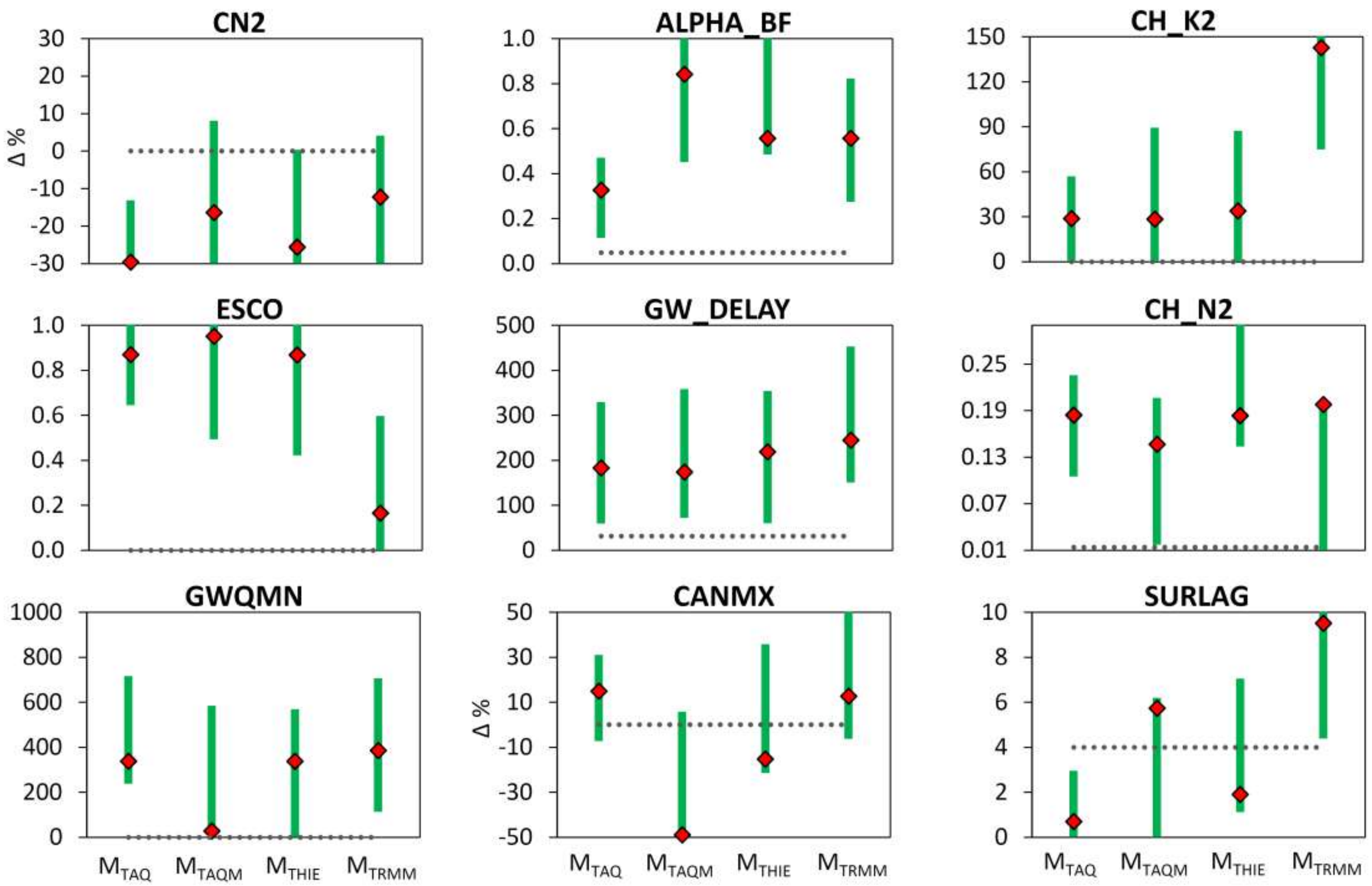
Sequential Uncertainty Fitting (SUFI-2, Abbaspour et al., 2004)

Iterative process: OF → P_{min}-P_{max} → LH-sampling (1000) → Assessment → Update P_{min}-P_{max}

Precipitation data ensemble & model calibration

Results: Parameter uncertainty

Model calibration 2001-2004

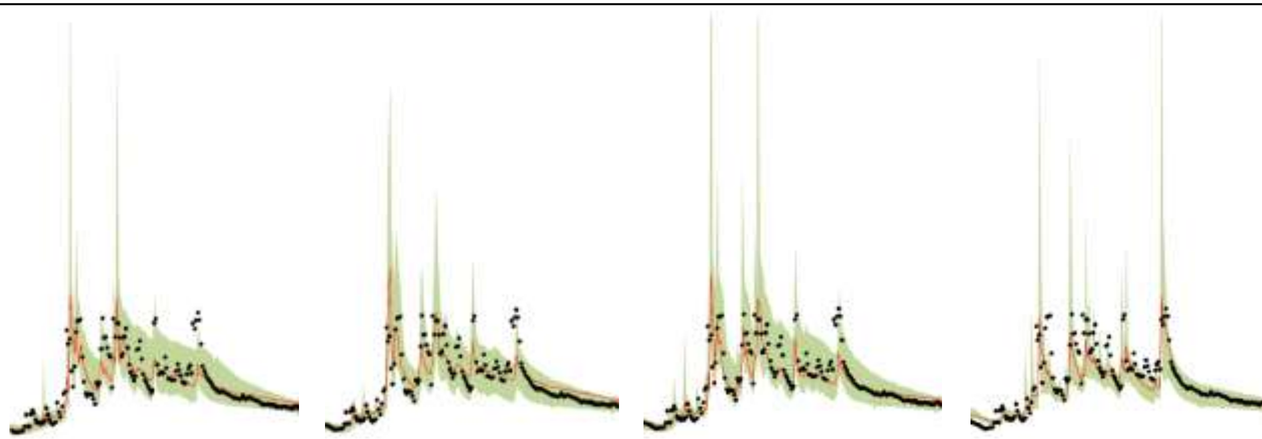


Precipitation data ensemble & model calibration

Results: Model performance in calibration period 2001-04 (validation period 2005-08), simulated vs. measured streamflow at gauge Frinocap

		M_{TAQ}	M_{TAQM}	M_{THIE}	M_{TRMM}
Best simulation					
	NSE	0.79 (0.73)	0.83 (0.76)	0.81 (0.69)	0.74 (0.43)
	PBIAS	+7.7 (-11.8)	+3.0 (-14.0)	+6.4 (-15.2)	-1.6 (-9.5)
95PPU					
	POC	88.0 (80.4)	78.7 (84.8)	86.9 (86.9)	83.6 (47.3)

Example graphs:
Rain season 2003/2004



POC:
Percentage Of Coverage (of Observations)

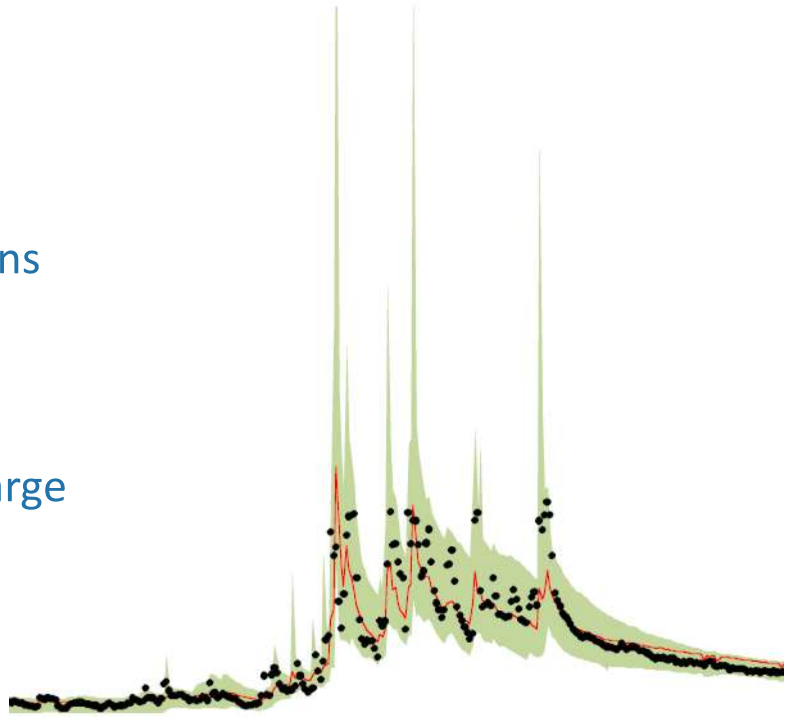
Ensemble combination: Simple methods

Ensemble mean

- Arithmetic mean of ensemble member predictions
- Improved model performance:
  NSE = 0.84 (0.80), PBIAS = +3.9 (-12.6)

95PPU of ensemble SUFI-2 distribution

- Cumulative distribution of SUFI-2 simulations considering all ensemble members
- Improved POC: 95.3 (93.4)
- Width for peakflow conditions extremely large



Ensemble combination: Bayesian Model Averaging

Bayesian Model Averaging (BMA)

- Standard method for combining predictive distributions from different sources
- Widely applied in the social and health sciences

BMA mean (Raftery et al. 2005)

- Weighted average (of linear functions) of ensemble member predictions:

$$E(y|f_1, f_2, \ldots, f_K) = \sum_{k=1}^{K} w_k (a_k + b_k f_k)$$

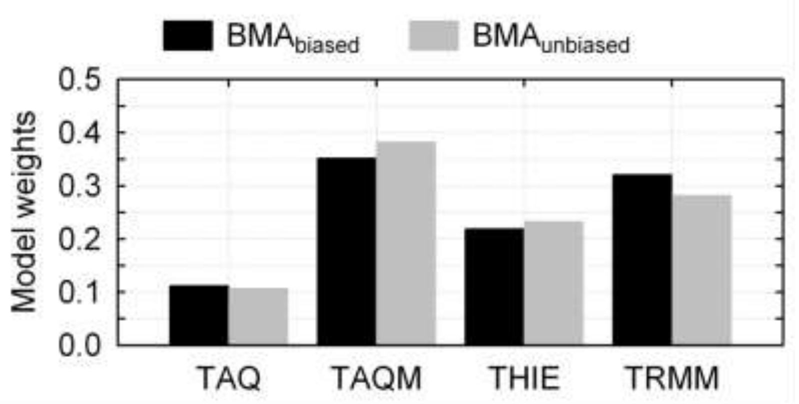
- Weights are calculated by maximizing a log-likelihood function

Probabilistic ensemble predictions and uncertainty intervals (e.g. 95PPU) deriveable!

Ensemble combination: Bayesian Model Averaging

Results BMA

- Model weights ~ Model performance
- BMA mean outperformed ensemble member predictions and ensemble mean
- Bias correction not necessarily advisable
- 95PPU with accurate POC
- 95PPU closer for peakflow conditions but wider for low flow in dry season (in comparison to SUFI-2)



	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

Conclusions

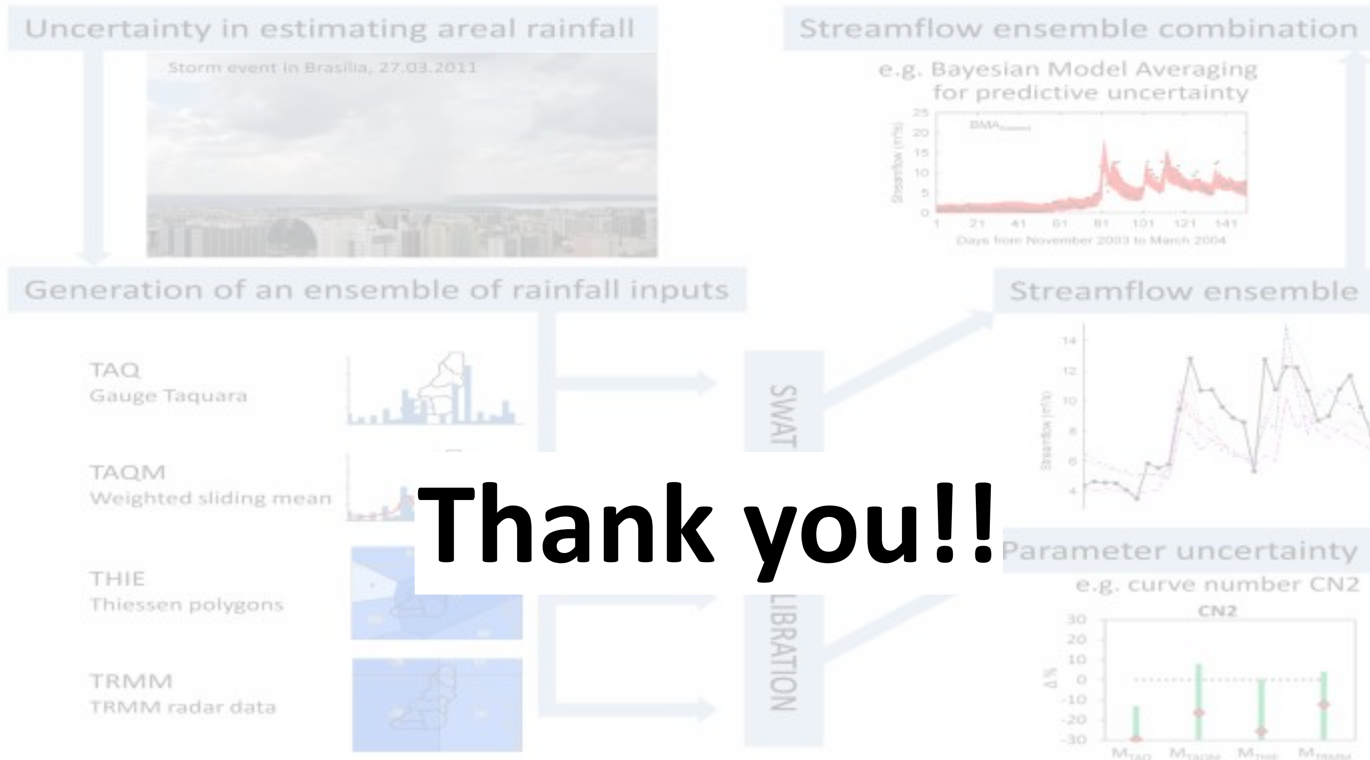
- Rain input uncertainty -> when taken into account: increasing parameter uncertainty

- Good streamflow simulations for all considered rain inputs
  => question of parameterization

- Improved deterministic predictions when ensemble predictions were combined
  (BMA mean > Ensemble mean >> predictions of ensemble members)

- Improved predictive uncertainty intervals when considering the whole ensemble, but none of the generated 95PPUs was completely satisfactory for all hydrologic conditions

Using ensembles is worth the effort!



Thank you!!

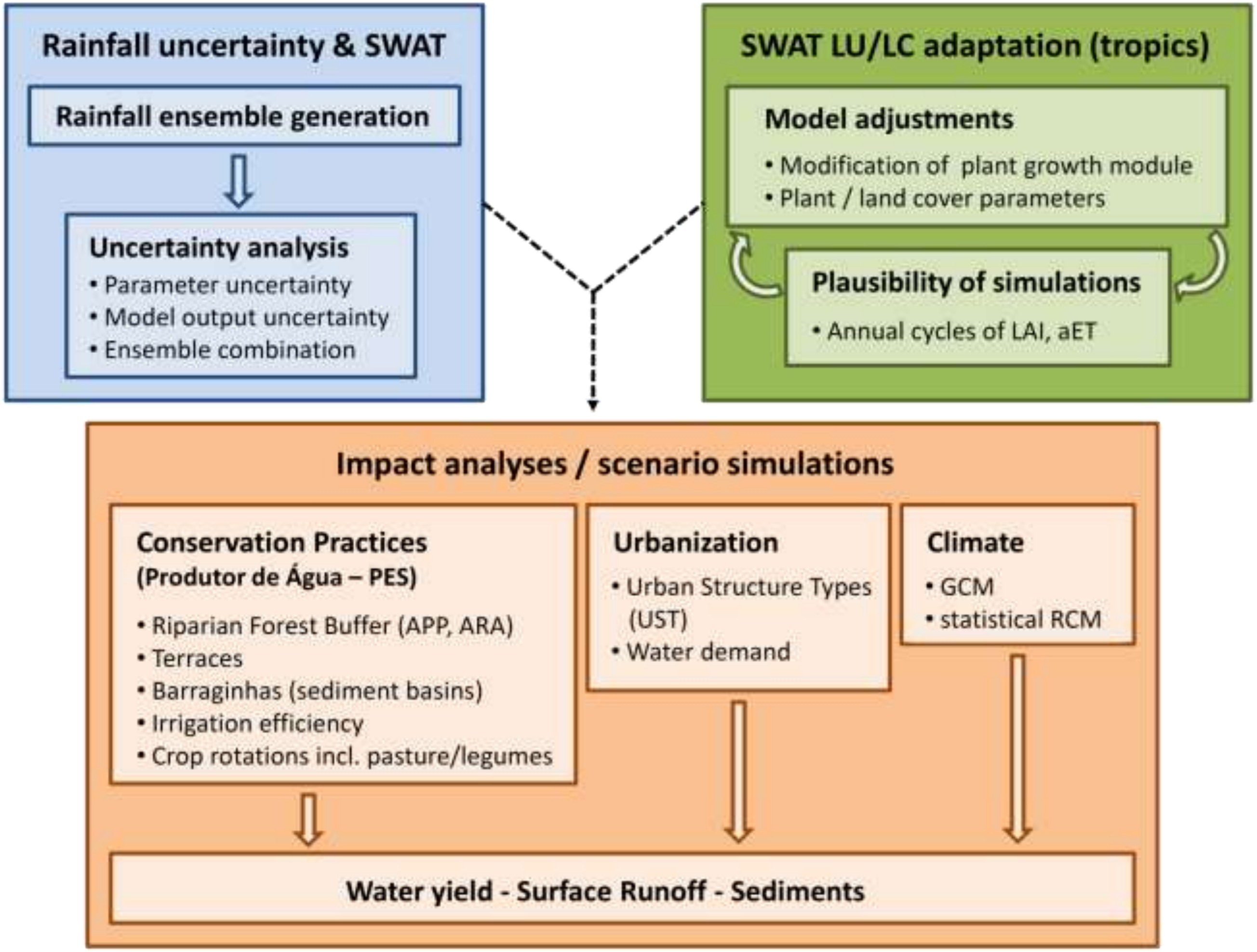
Abbaspour, K.C., Johnson, C., van Genuchten, M.T., 2004. Estimating Uncertain Flow and Transport Parameters Using a Sequential Uncertainty Fitting Procedure. Vadose Zone Journal, 3: 1340-1352.

Arnold, J.G., Srinivasan, R., Muttiah, R., Williams, J., 1998. Large area hydrologic modeling and assessment part I: Model development. Journal of the American Water Resources Association, 34: 73-89.

Raftery, A.E., Gneiting, T., Balabdaoui, F., Polakowski, M., 2005. Using Bayesian Model Averaging to Calibrate Forecast Ensembles. Monthly Weather Review, 133: 1155-1175.

van Griensven, A., Meixner, T., Grunwald, S., Bishop, T., Diluzio, M., Srinivasan, R., 2006. A global sensitivity analysis tool for the parameters of multi-variable catchment models. Journal of Hydrology, 324: 10-23.

Overview SWAT within IWAS-Brazil project



Sensitivity analysis

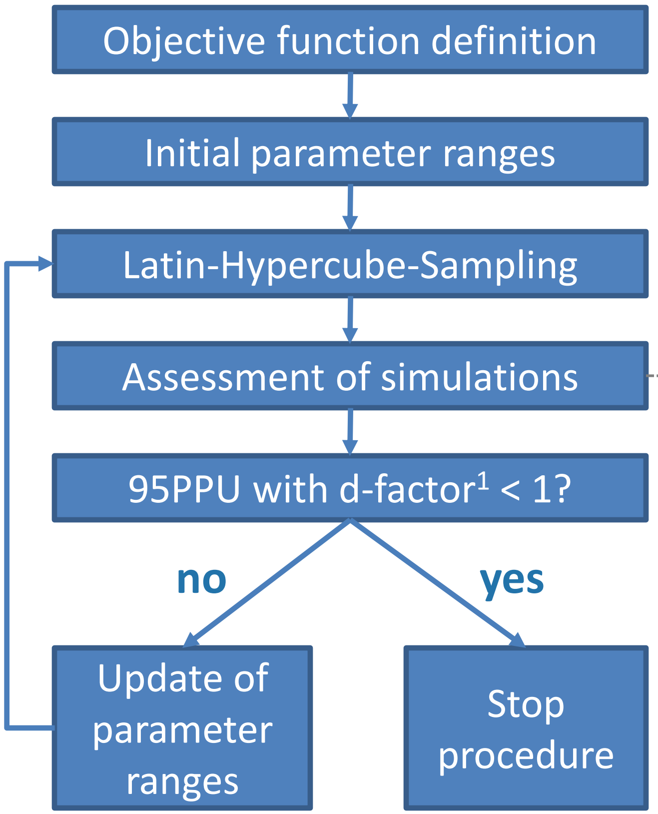
Sensitivity Analysis Tool (van Griensven et al. 2006)

- 280 simulations for each rain input model
- combined Latin-Hypercube & One-Factor-At-A-Time sampling
- Selection of 9 parameters for calibration (out of 27)

Parameter	Sensitivity Rank					
	M_{TAQ}	M_{TAQM}	M_{THIE}	M_{TRMM}	Sum	
CN2	2	2	1	1	6	SCS runoff curve number
ALPHA_BF	1	1	2	3	7	Baseflow recession constant
CH_K2	3	3	3	2	11	Eff. hydraulic conductivity in main channel alluvium (mm/h)
ESCO	4	5	4	4	17	Soil evaporation compensation factor
GW_DELAY	5	4	5	7	21	Groundwater delay time (days)
CH_N2	8	6	9	5	28	Manning's "n" value for the main channel
GWQMN	7	9	6	6	28	Water depth in shallow aquifer for return flow (mm H2O)
CANMX	9	7	8	8	32	Maximum canopy storage (mm H2O)
SURLAG	6	11	7	9	33	Surface runoff lag coefficient

Model calibration / uncertainty analysis using SUFI-2

Sequential Uncertainty Fitting (SUFI-2) (Abbaspour et al. 2004)



- Jacobian matrix: $J_{ij} = \frac{\Delta g_i}{\Delta b_j} \quad i = 1, \ldots, C_2^n \quad j = 1, \ldots, m$
- Hessian $H = J^T J$ and covariance $C = s_g^2 (J^T J)^{-1}$
- Standard deviation of parameter b_j: $s_j = \sqrt{C_{jj}}$
- 95% confidence interval of parameter b_j:

$$b_{j,\text{lower}} = b_j^* - t_{\nu,0.025} s_j \quad \text{and} \quad b_{j,\text{upper}} = b_j^* + t_{\nu,0.025} s_j$$

- Parameter sensitivity $S_j = \bar{b}_j \frac{1}{C_2^n} \sum_{i=1}^{C_2^n} \left| \frac{\Delta g_i}{\Delta b_j} \right|$
- Parameter correlation $A_{ij} = \frac{C_{ij}}{\sqrt{C_{ii}} \sqrt{C_{jj}}}$
- Updated parameter uncertainties (assumed here to have uniform distributions) are calculated from:

$$b'_{j,\text{max}} = b_{j,\text{upper}} + \text{Max}\left(\frac{(b_{j,\text{lower}} - b_{j,\text{min}})}{2}, \frac{(b_{j,\text{max}} - b_{j,\text{upper}})}{2} \right)$$

$$b'_{j,\text{min}} = b_{j,\text{lower}} - \text{Max}\left(\frac{(b_{j,\text{lower}} - b_{j,\text{min}})}{2}, \frac{(b_{j,\text{max}} - b_{j,\text{upper}})}{2} \right)$$

[1]d-factor = avg. width of 95PPU / std. dev. of measurements

Ensemble combination: Bayesian Model Averaging

BMA mean (Raftery et al. 2005)

- Weighted average (of linear functions) of ensemble member predictions:

$$E(y|f_1, f_2, \dots, f_K) = \sum_{k=1}^{K} w_k (a_k + b_k f_k)$$

- Calculation of weights by maximizing the likelihood function:

$$\ell(w_1, w_2, \dots, w_k, \sigma^2) = \log\left(\sum_{k=1}^{K} w_k \cdot \sum_{t=1}^{T} g(y_t | f_{k,t}) \right)$$

conditional PDF

$\approx N(a_k + b_k f_k, \sigma^2)$

$\Rightarrow$ solved using the expectation-maximization (EM) algorithm where weights and variance are iteratively updated until convergence of log-likelihood

BMA probabilistic ensemble predictions (Raftery et al. 2005)

(i) generate a value of *k* from the numbers {1,…,K} with the probabilities $\{w_1, \dots, w_k\}$

(ii) draw a replication of *y* from the PDF $g(y|f_k)$

(iii) repeat steps (i) and (ii) to obtain 1000 values of *y* for each time step $\Rightarrow$ **95PPU derivable!**