# Incorporating rainfall uncertainty in a SWAT model: the river Zenne basin (Belgium) case study

Olkeba Tolessa Leta[1,*], Jiri Nossent[1], Ann van Griensven[1,2] and Willy Bauwens[1]
[1]Department of Hydrology and Hydraulic Engineering, Vrije Universiteit Brussel, Pleinlaan 2, 1050-Brussels, Belgium
[2]UNSECO-IHE Institute for Water Education, Core of Hydrology and Water Resources, The Netherlands
*Correspondence to: otolessa@vub.ac.be

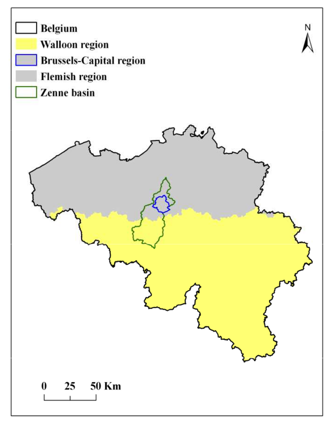
EGU General Assembly 2013

## Introduction

Distributed hydrologic models have been increasingly used as modelling tools for integrated river basin management and decision support . The assessment of the uncertainty of distributed models like the Soil and Water Assessment Tool (SWAT; Arnold et al., 1998) is an essential aspect of the decision making process, in order to design robust management strategies that take the predicted uncertainties into account. Model uncertainty stems from the uncertainties on the model parameters, the input data (e.g., rainfall), the calibration data (e.g., stream flow) and on the model structure itself. Hence, the objective of this study is to test the feasibility of incorporating rainfall uncertainty together with the other sources of uncertainty in a complex SWAT model of the river Zenne basin upstream of the Brussels-Capital region.

## The Zenne basin

- Location: Central part of Belgium.
- Basin area: 1162 $km^2$.
- Elevation: 1 to 171 mamsl.
- Predominant land uses: agriculture and urban.
- Predominant soils: loam and anthropogenic.
- Average annual rainfall: 852 mm.



## The SWAT model

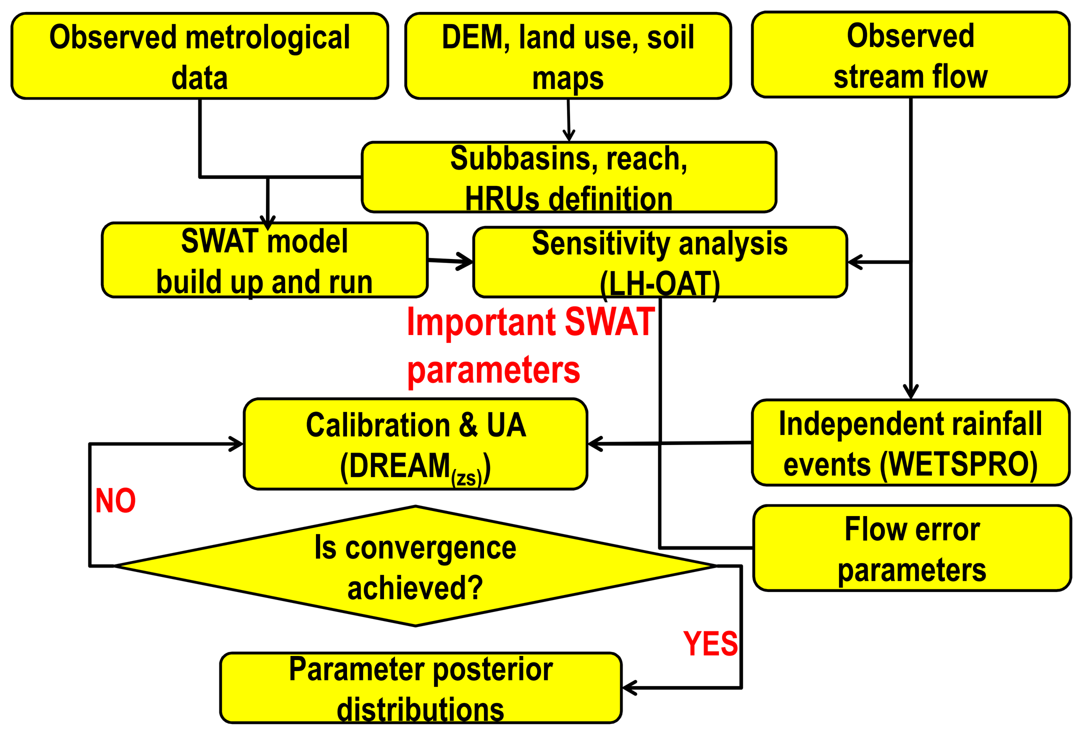
- A physically-based, semi-distributed, hydrologic model.
- Estimates runoff based on the SCS-CN method.
- Predicts watershed management impact on water, agricultural nutrients and chemical yields.

## The differential evolution adaptive metropolis (DREAM) algorithm

- A Markov chain Monte Carlo sampler (Vrugt et al., 2008).
- Designed for parameter optimization and uncertainty analysis (UA).
- Searches parameter values by maximizing the likelihood function of residuals sum of squares.

## Uncertainty treatment and parameter optimization

- SWAT model: built-up for 1997-2001; 1997-1999 (warming-up) & 2000-2001 (calibration).
- 3 sources of uncertainty are treated:
  - **The rainfall uncertainty**: multiplicative error corruption for independent rainfall events, identified by the WETSPRO (Willems, 2009).
  - **The parameter uncertainty**: the most sensitive SWAT parameters, screened by the Latin Hypercube One-factor-At-a-Time (LH-OAT).
  - **The flow uncertainty:** the standard deviation of the error is assumed to be a linear function of the flow (Schoups & Vrugt, 2010).




| Parameters | Description | units | minimum | maximum |
|---|---|---|---|---|
| Alpha-bf | Groundwater recession constant | days | 0 | 1 |
| Ch-K2 | Channel transmission losses | mm/h | 0 | 150 |
| Ch-N2 | Channel roughness coefficient | - | 0 | 0.1 |
| CN2 | SCS curve number at moisture condition II | - | 45 | 95 |
| ESCO | Soil evaporation compensation factor | - | 0 | 1 |
| Gw-Delay | Groundwater delay | days | 0 | 40 |
| Gw-Revap | Groundwater revap coefficient | - | 0.02 | 0.2 |
| Gwqmn | Groundwater flow occurrence threshold | mm | 0 | 2000 |
| Revapmn | Groundwater revap occurrence threshold | mm | 1 | 500 |
| Sol-Awc | Soil water availability | - | 0.05 | 0.3 |
| Surlag | Surface runoff lag coefficient | days | 0 | 10 |
| a | Output error intercept | $m^3/s$ | 0 | 1 |
| b | Output error slope | - | 0 | 1 |
| Φ | Rainfall multipliers | - | 0.5 | 2 |

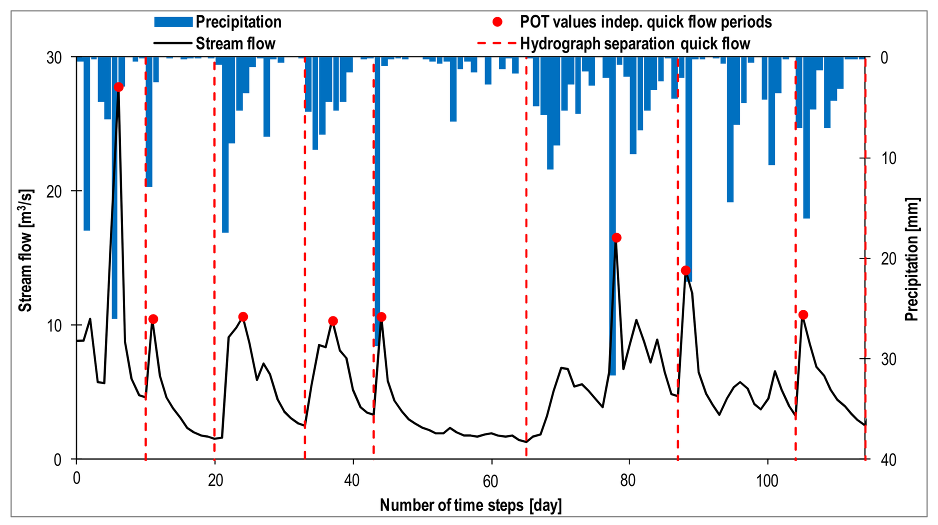
The considered parameters

### The flow uncertainty model:

$\sigma_e = a + b*Y$, where; $\sigma_e$ is measurement error standard deviation; a , b are parameters & Y is the flow.

### The rainfall multipliers identification:

Equivalent to independent rainfall periods & used for rainfall error corruption: $r_j = \phi_j * \tilde{r}_j$, where $r_j$ is the corrected rainfall depth for event j; $\phi_j$ is the rainfall multiplier & $\tilde{r}_j$ is the observed rainfall.

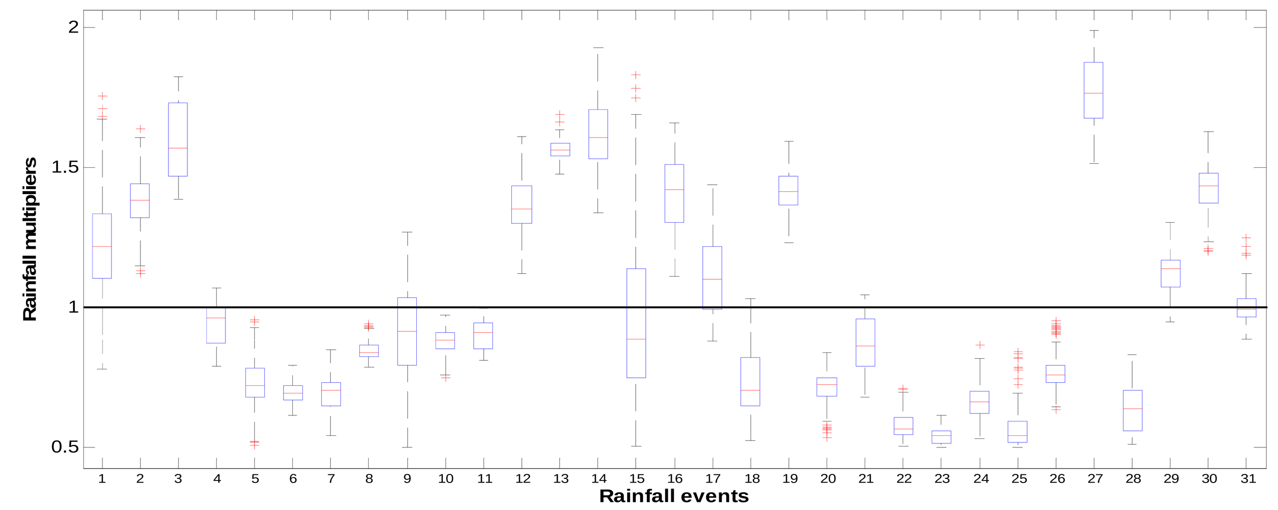



The rainfall events

We assumed a uniform prior distribution over the prior range of parameter values.

## The input uncertainty

The marginal posterior distributions of the 31 rainfall multipliers vary widely between individual events, as a consequence of rainfall measurement errors and the spatial variability on rainfall.

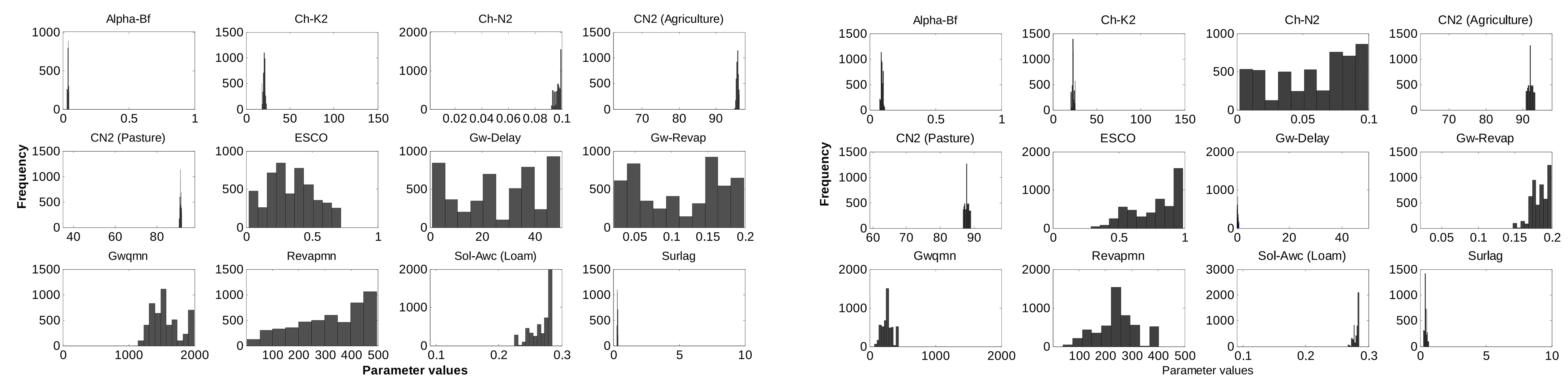



- Some rainfall events are underestimated (multipliers > 1).
- Some rainfall events are overestimated (multipliers < 1).

Marginal posterior distributions of the rainfall multipliers for the last 5000 sample sizes generated by $DREAM_{(zs)}$

## The SWAT parameter uncertainty

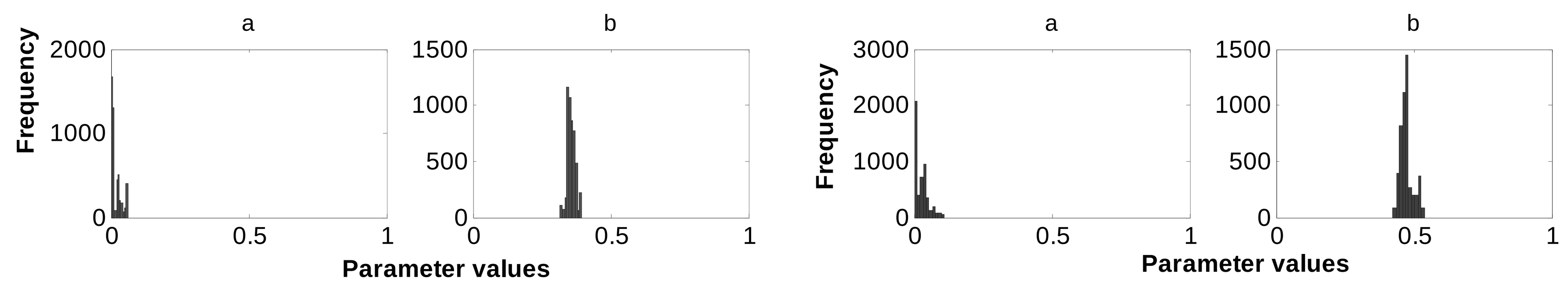
- CN2, Alpha-Bf, Ch-N2, Ch-K2, Surlag, Gw-Delay, Gw-Revap, Sol-Awc, Revapmn, ESCO and Gwqmn are the most important parameters for the upstream part of the basin.
- Most of the SWAT parameters are well defined by $DREAM_{(zs)}$ within their prior ranges.




The marginal posterior distributions of the SWAT parameters with rainfall multipliers (left) and without rainfall multipliers (right)

## The flow uncertainty

The posterior distributions of the flow uncertainty parameters show that the flow data is uncertain




The marginal posterior distributions of the flow error parameters with rainfall multipliers (left) & without rainfall multipliers (right)

## Conclusions

The approach of using rainfall multipliers to account for the rainfall uncertainty in a complex model like SWAT is feasible. The rainfall uncertainty has an impact on the marginal posterior distributions of the SWAT and on the flow error model parameters.

### References

1. Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large-area hydrologic modeling and assessment: Part I. Model development. *J. Am. Water Resour. Assoc.* **34**(1), 73-89.
2. Schoups, G., Vrugt, J.A., 2010. A formal likelihood function for parameters and predictive inference of hydrologic models with correlated, heteroscedastic and non-Guassian errors. *Water Resour. Res.* **46**(W10531).
3. Vrugt, J.A., ter Braak, C.J.F., Clark, M.P., Hyman, J.M., Robinson, B.A., 2008. Treatment of input uncertainty in hydrologic modeling: Doing hydrology backward with Markov chain Monte Carlo simulation. *Water Resour. Res.* **44**(W00B09).
4. Willems, P., 2009. A time series tool to support the multi-criteria performance evaluation of rainfall-runoff models. Environ. Modell. Softw. **24**(3), 311-321.