How uncertainty of simulating water resources is affected by different input data information content

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I. Motivation and Objectives

The most widely used tool to investigate water quantity and quality in rural areas is the partly-deterministic Soil and Water Assessment Tool (SWAT). Despite its wide application, it is still debated if complex models such as SWAT are properly used, especially because they demand a large variety of spatial input data. These are commonly available in different resolutions and result from different preprocessing methodologies. Effort is made to apply the most specific data as possible for the study area, which features heterogeneous landscape elements. Most often, modelers prefer to use regional data, especially with fine resolution, which is not always available. Instead, global datasets are considered that are more general. This study investigates how the use of global and regional input datasets may affect the model efficiency and parameter uncertainty.

II. Study area and data: Winseler Catchment

Table 1: Spatial input data description

Code	Data description
D1	DEM 30 meters resolution based on SRTM and ASTER
D2	DEM 5 meters resolution upscaled to 30 meters
S1	Harmonized World Soil Database (one soil type)
S2	Soil GRIDS (three soil types)
L1	CORINE 2006 land use map
L2	OBS Occupation Biophysique du Sol 2007

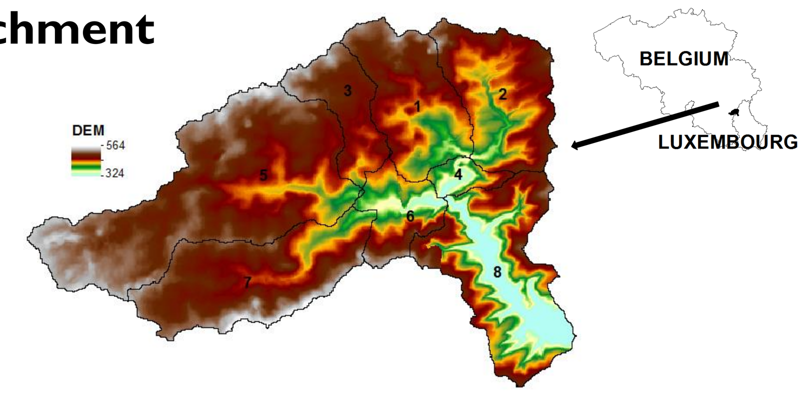
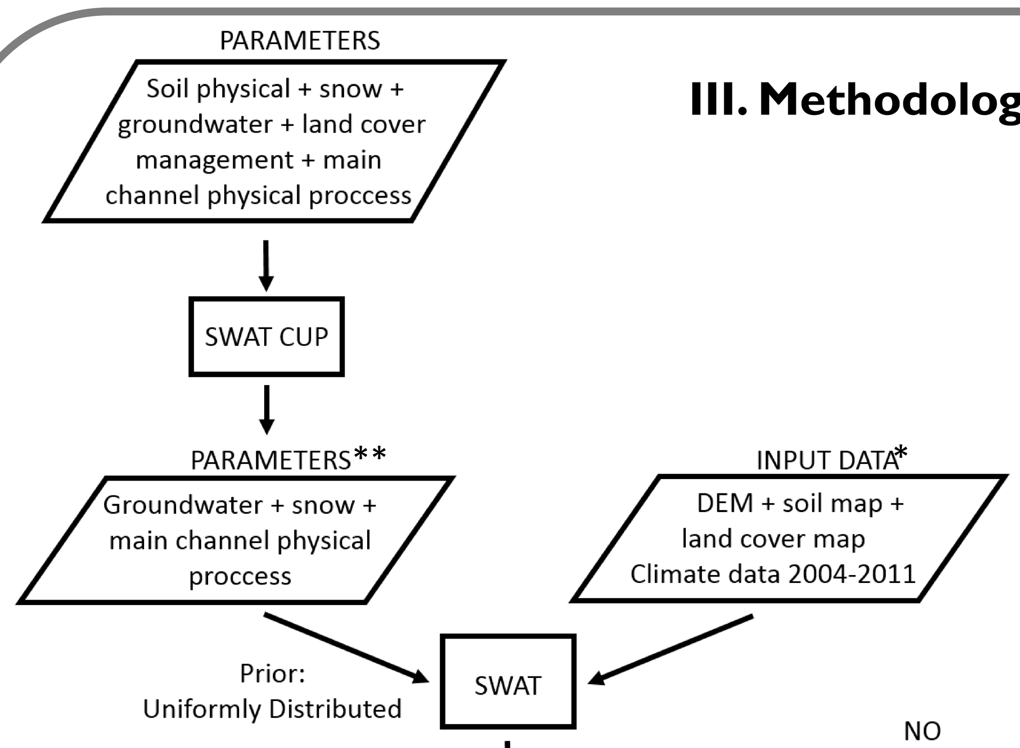


Figure 1: Winseler catchment (104 km²) location including Digital Elevation Map (DEM) and subbasins

III. Methodology



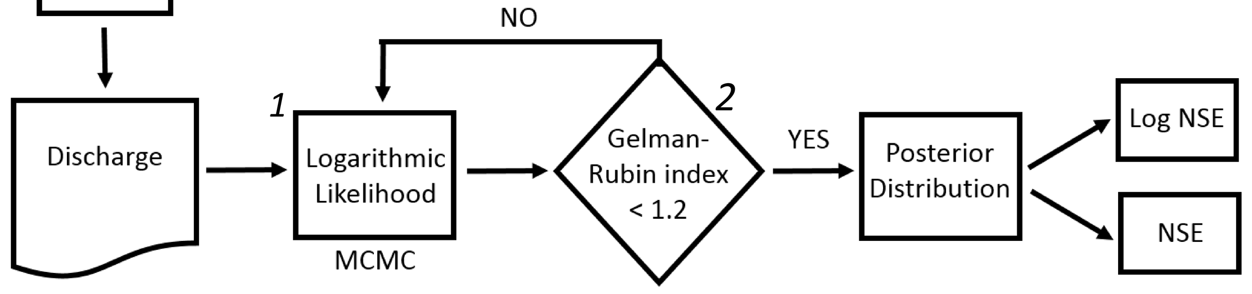


***Table 2: Different input data combination and the number of HRUs per watershed**

Model set up	Number of HRU's
D1S1L1	90
D1S1L2	99
D1S2L1	173
D1S2L2	199
D2S1L1	89
D2S1L2	100
D2S2L1	174
D2S2L2	200

****Table 3: SWAT parameter description, lower and upper bound**

Parameter name	Parameter definition	Parameter factor	Lower bound	Upper bound	Units
SFTMP	Snowfall temperature	replace	-5	5	°C
SMTMP	Snow melt base temperature	replace	-5	5	°C
CH_N2	Manning's roughness coefficient n	replace	0.01	0.25	mm/h
CH_K2	Hydraulic conductivity of channel	replace	0.01	150	mm/h
ALPHA_BF	Baseflow alpha factor	replace	0.001	0.99	-
GW_DELAY	Groundwater delay time	replace	0	31	days

IV. Results

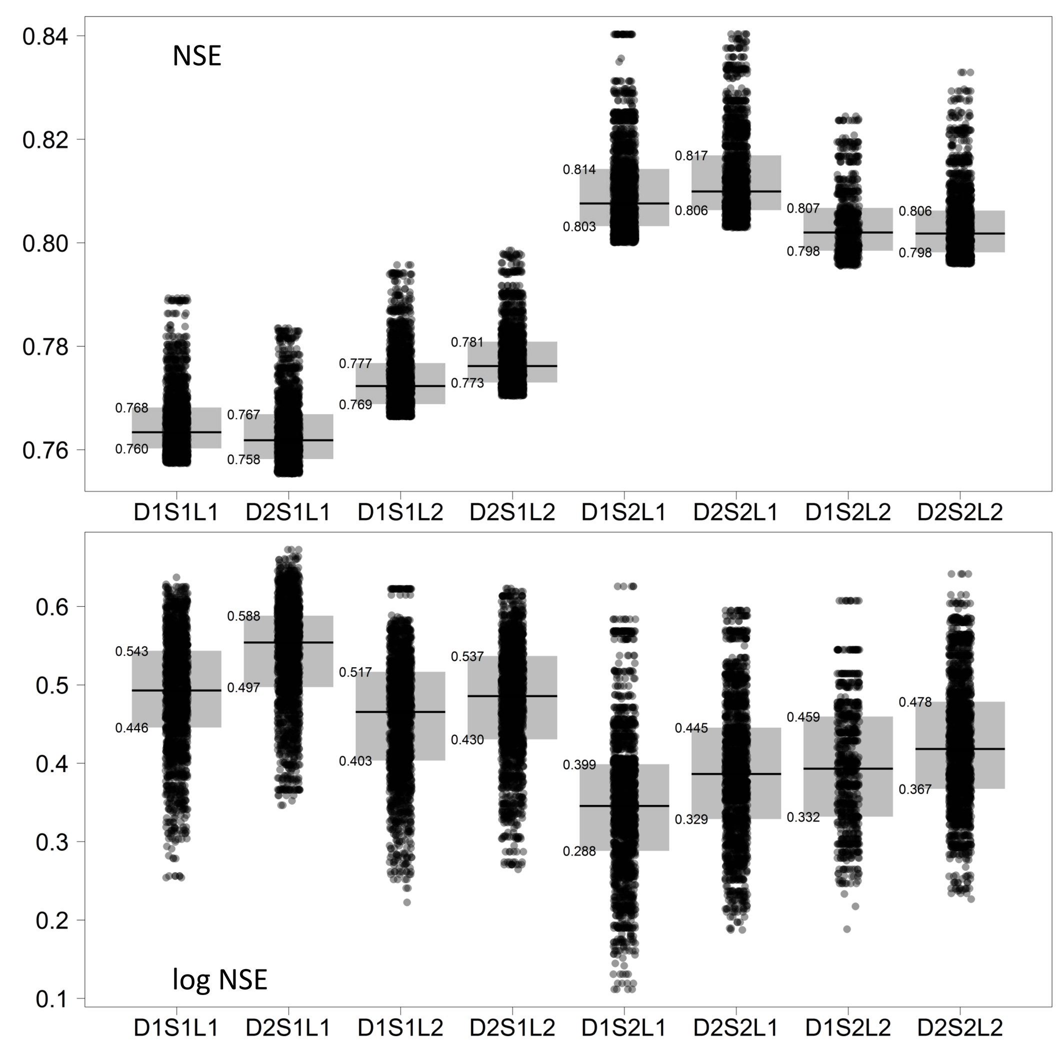


Figure 2: Box plot of NSE and log NSE for each model set up

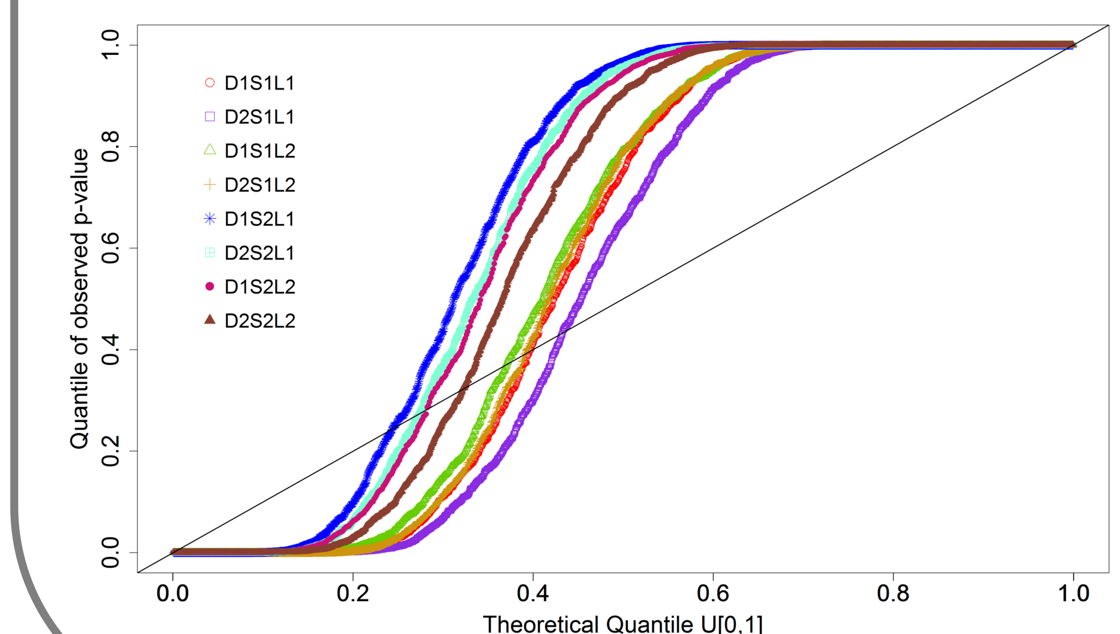


Figure 3: Quantile-quantile plot[3] for each model set up

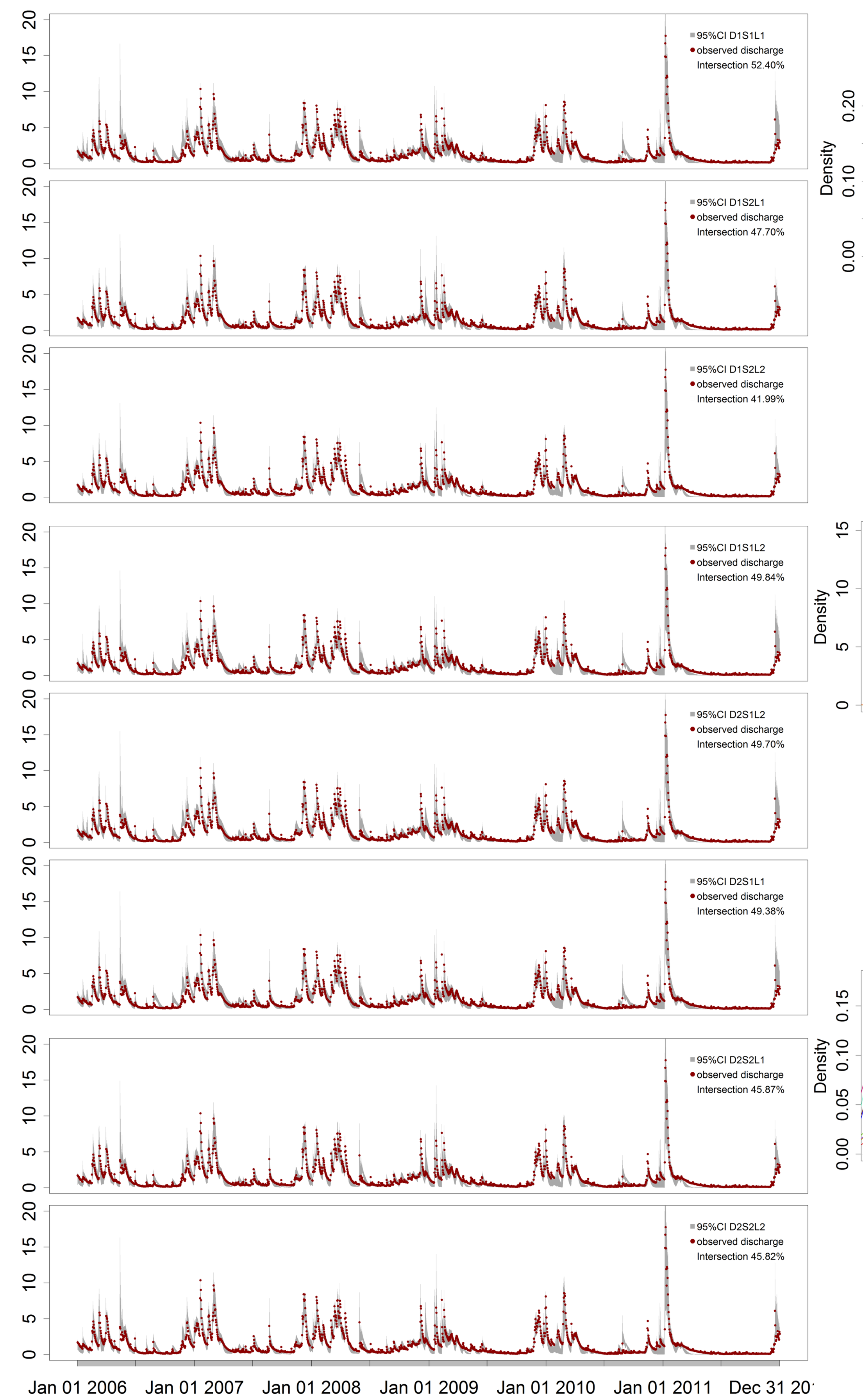


Figure 4: Observed and simulated daily discharge, including 95% confidence interval.

Parameters analysis

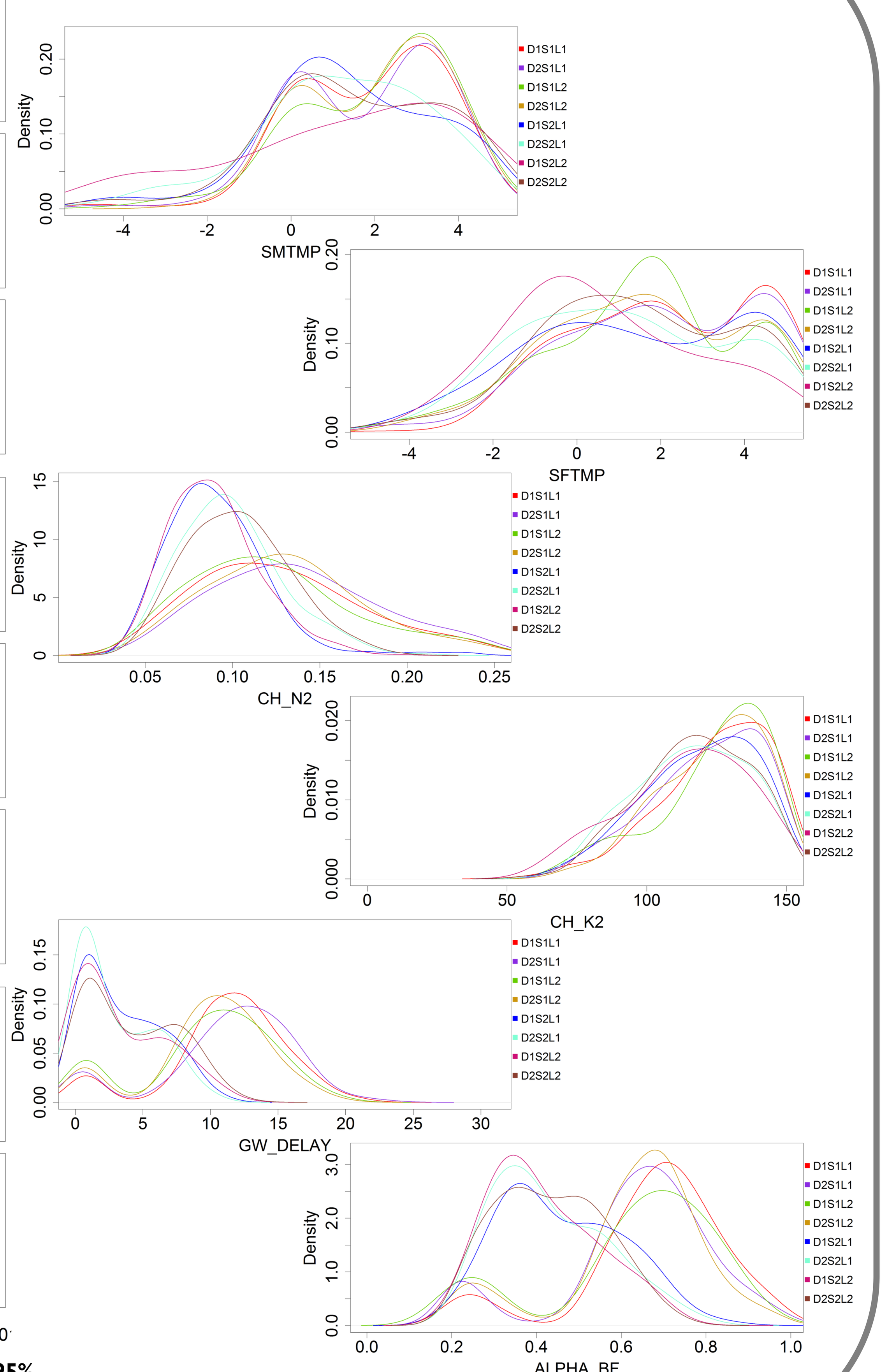


Figure 5: Posterior density distribution of model parameters

V. Discussions and Conclusions

- Considering an evaluation criteria that provides more weight to high flows (NSE, figure 2), the model is little affected by the input data resolution resulting in performance varying between 0.76 and 0.84. However, when considering a measure of fit with high weight in low flows (log NSE, figure 2), the model performance varies between 0.10 and 0.65 and the best performances are obtained when using the regional DEM (D2) and global soil map (S1). It suggests that SWAT is sensitive to small topographic changes but cannot necessarily make use of additional soil information if they are not substantially effecting soil hydrological fluxes.
- All set-ups have similar uncertainty on the output and higher uncertainty for low flow prediction. The q-q plot (figure 3) suggests that these predictive uncertainties are being underestimated.
- We notice a constrained behavior of all calibrated parameters (figure 5), highlighting the model sensitivity to these parameters. The parameters GW_DELAY, ALPHA_BF, CH_N2 and CH_K2 presented a posterior distribution similar according to the soil map used, indicating smaller parameters values for regional soil map (S2) setups.

VI. Future research

- Validate the analysis for 2012 and 2013.
- Expand the analysis for a different catchment using the same spatial input data.
- Analyze also water quality as output of the model.

VII. Acknowledgement

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