

Reduction of uncertainty of hydrological modeling using different precipitation inputs

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Motivation

Watershed models suffer from three major model uncertainties (Abbaspour et al. 2004):

- Conceptual
- Input (data, management)
- Parameterization and calibration

In this study we focus on input uncertainty, especially on precipitation. Because of its high spatial and temporal variability, precipitation is a major source of uncertainty in hydrological modeling. Uncertainty arises from measurement errors, data density and kind of data usage in the model (punctual versus areal information). Using an ensemble of three models with different precipitation inputs we try to minimize uncertainty.

The work is embedded in the project IWAS. One sub-project deals with water quality of the river Western Bug in Ukraine (Fig. 1). Water is highly polluted chemically and biologically. As one part of the system analysis, the water balance of the catchment Kamianka-Buzka (Fig. 2, 2560 km²) has to be assessed.



Fig. 1: Location of the investigation area (encircled).

Data and Methods

We used the hydrological model SWAT (<http://swatmodel.tamu.edu/>). The main parameterization features are:

- Soil and hydraulic parameters were derived from a soil map in the scale of 1:200.000, measurements and expert knowledge.
- Land-use information was derived from images of the satellites Landsat-TM5 and SPOT-1 of the year 1989.
- Three meteorological stations in and nearby the basin had sufficient precipitation data (Fig. 2).

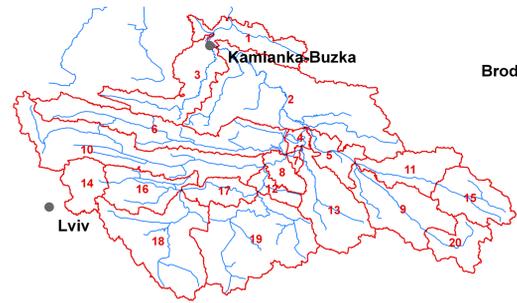


Fig. 2: Sub basins and three precipitation stations.

The spatial representativeness of the existing precipitation stations is often low. We tested three approaches to assimilate precipitation data in the model:

Stations: By default, SWAT incorporates meteorological observations using station data that are nearest to the centroid of each sub catchment.

Regionalized: Data of 20 surrounding stations were regionalized applying kriging methods onto a 3 x 3 km grid.

CCLM: The regional climate model CCLM (resolution 7 km) was set up for the target area (Pavlik et al., 2011). Resulting daily time series were bias corrected.

Grid cells within each of the 20 sub-basins (Fig. 2) were arithmetically averaged to obtain 20 fictive precipitation stations. Radar data were not available for the region, satellite data were disregarded.

Differences between the three precipitation inputs are shown for the whole catchment (Tab. 1) and exemplarily for three sub basins (Fig. 3):

- Yearly and daily means vary little (max. 8%).
- **CCLM** produces too much days with rain (higher median).
- **Regionalized** and **CCLM** data are more balanced than **Station** data on the catchment scale (more days with rain but less strong precipitation events).

Tab.1: Comparison of three precipitation inputs for the whole catchment (1981-1990)

Precipitation input	P (mm/a)	Days/year with P > 0 mm/d	Days/year with P > 10 mm/d	Mean bias to Stations (mm/a)
Stations	665	178	17	-
Regionalized	651	188	14	-1.2
CCLM	676	246	14	+0.9

Before applying alternative precipitation inputs, SWAT was pre-calibrated step by step in a combination of manual and automatic calibration using the meteorological data **Stations**.

Finally, three models with different precipitation inputs were set up and calibrated independently (1981-1990) using the auto-calibration procedure Sequential Uncertainty Fitting (SUF2) which is integrated in the SWAT interface SWAT-CUP (Abbaspour et al., 2004). Models were validated for the period 1971-1980.

An alternative to deterministic predictions of single models are probabilistic predictions on the basis of model ensembles.

Results

Table 2:

- The models **Regionalized** and **CCLM** did not perform better than the default method **Stations** in both periods.
- The performance is better in the validation than in the calibration period. This implies that not all processes in the catchment are fully understood and modeled appropriately.
- Ensemble averaging improved the performance generally in the calibration period. BMA outperformed the others.
- There were no clear superiority of a model or an averaging method in validation period.

Figure 4:

- Differences between three model hydrographs vary much, whereby larger deviations occur with **CCLM** input, because of strongly different monthly precipitation (e.g. in June 1983).
- Not all observed runoff situations could be simulated (e.g. summer 1985).

- There is still high overall uncertainty of modeling (95PPU: 2.5th and 97.5th percentile of modeled uncertainty of calibration parameters)

Tab. 2: Performance of the three models and the ensemble averaging methods. Best performing model or method is marked in red.

Model	Calibration period			Validation period		
	R ²	NSE	Diff *1	R ²	NSE	Diff *1
Stations	0.66	0.57	2.01	0.79	0.69	3.86
Regionalized	0.57	0.53	-1.44	0.71	0.65	-0.20
CCLM	0.55	0.54	-0.69	0.39	0.38	1.31
Ensemble averaging method						
Arithm. mean	0.67	0.67	-0.04	0.73	0.66	1.65
R ² -weight	0.67	0.67	0.08	0.76	0.69	1.81
NSE-weight	0.67	0.67	0.05	0.75	0.69	1.76
BMA	0.69	0.68	0.00	0.75	0.69	1.63

*1 difference between mean observed and mean simulated/averaged runoff [m³/s]

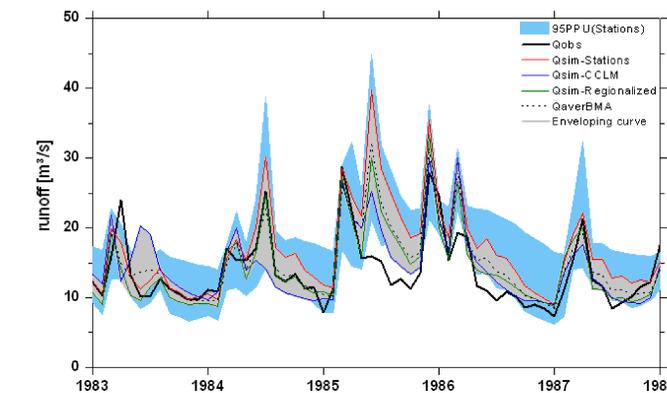


Fig. 4: Observed and modeled hydrographs of three models, their enveloping curve, BMA and the uncertainty band of the model **Stations** (95PPU) for the calibration period.

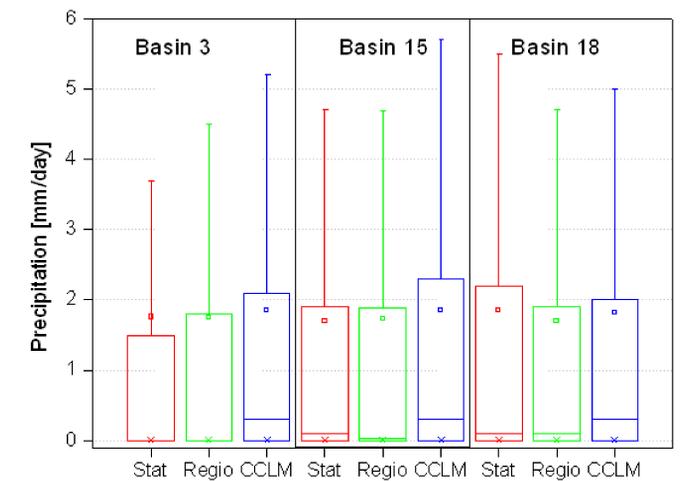


Fig. 3: Box plots of daily data (1981-90) for the three precipitation inputs for three sub basins. Shown are 25 and 75% percentile, median (line), arithmetic mean (square) and 1.5* interquartile range (whiskers). Outliers are not shown for the sake of clarity.

We applied four **ensemble averaging methods**:

- **Arith.mean:** Arithmetic mean of simulated monthly runoff.
- **R²-weight:** Weighted mean regarding the coefficient of determination.
- **NSE-weight:** Weighted mean regarding the Nash-Sutcliffe model efficiency coefficient.
- **BMA:** Bayesian model averaging (Raftery et al., 2005): The weight of each considered model corresponds to the degree of agreement between the PDFs of each modeled and the observed runoff.

Conclusions

- Uncertainty that results from input data could be reduced.
- The alternative inputs **CCLM** and **Regionalized** did not perform better than **Stations**.
- Bayesian Model Averaging was superior to the other averaging methods in the calibration period.
- In the validation period no clear advantage of using ensemble averaging was recognizable.
- Uncertainty in precipitation data couldn't be reduced completely, which is due to low station density and low representativeness of stations. But also, uncertainty that results from model concept, model parameters, boundary conditions, and very probable also from the observed runoff is still high.
- A possible approach to deal with uncertainty of precipitation could be to calibrate the precipitation data as well.

References

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.

Pavlik, D., Söhl, D., Pluntke, T., Mykhnovych, A., & Bernhofer, C. (2011). Dynamic downscaling of global climate projections for Eastern Europe with a horizontal resolution of 7 km. *Environmental Earth Sciences*, doi: 10.1007/s12665-011-1081-1.

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

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