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Impact of input uncertainties on predictions of a distributed hydrological model

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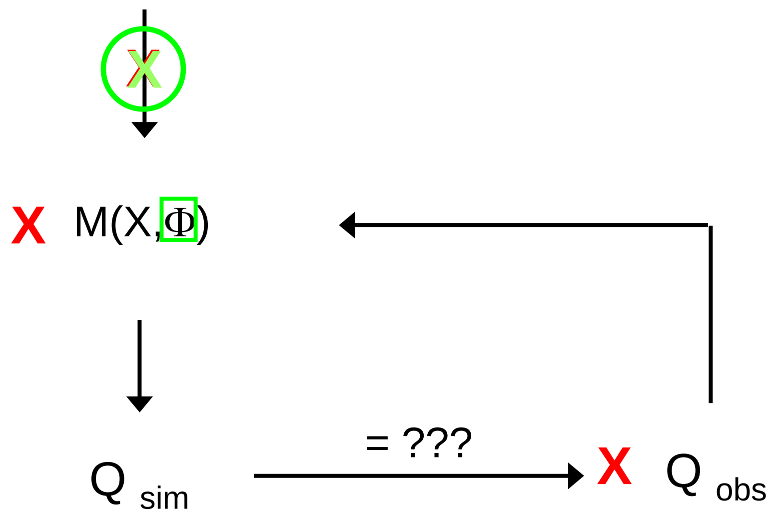
Outline

- Motivation and Objectives of the study
- Methodological approach
- Case Study
- Results
- Conclusions

Motivation



X: Input variables

Φ: Model parameters, state variables

Q : Discharge [m³/s]

Detailed process descriptions

Detailed representation of catchment characteristics

Limited predictive capability

Necessity to calibrate

Performance for validation events often disappointing

Uncertainties disturb parameter estimation

Motivation

- Least Squares Parameter estimation scheme is based on clear assumptions about error characteristics
- Uncertainties in input data provoke compensation effects in calibration which reflects in distortion of parameters
    - Spatial averaging (intensity, depth,…)
    - Temporal averaging

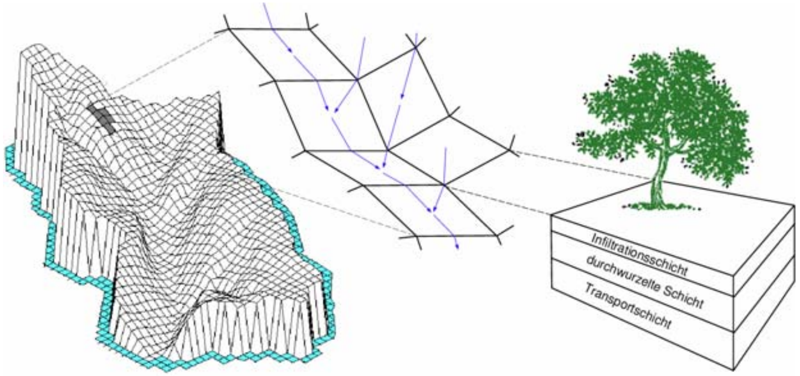
…but, little is known about the structure of errors

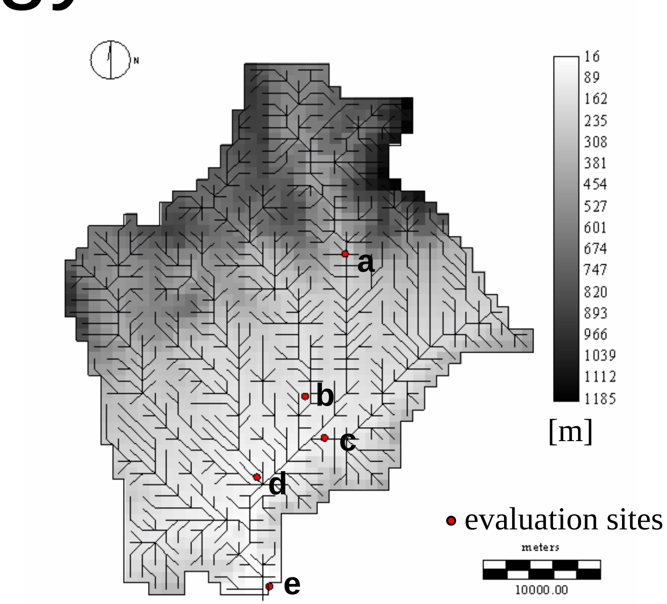
Objectives

- What kind of errors in model predictions are induced by simplified representation of rainfall field?
- What general characteristics can be revealed and do they conform with assumption of LS estimation?
- What are important features of errors?
- How could the calibration scheme and in turn predictive performance of the model be improved?

Methodology

M(X,Φ)





Application of a Distributed hydrological model (WBr^{2}M) to the Besòs catchment (1024km^2):

- Representation of spatial variability of soil, landuse and rainfall
- Detailed soil moisture modelling in a grid column

Assumptions

Semi-synthetic work environment:

Corrected and adjusted radar images represent the ‘true’ rainfall field

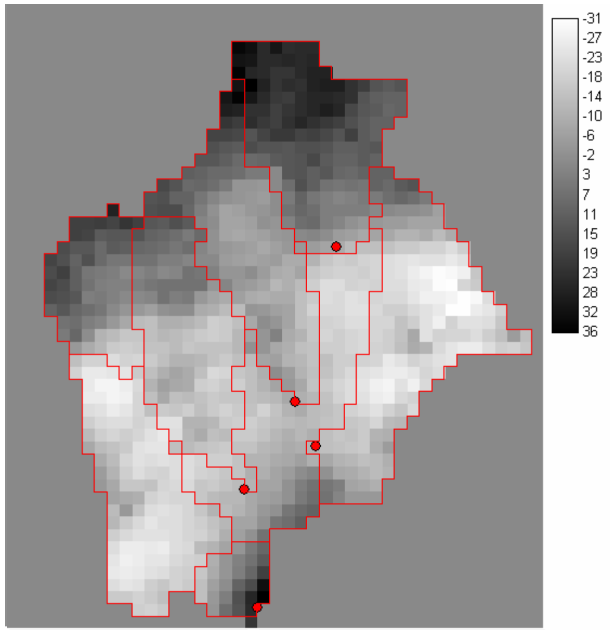
- Calibration of WBr^{2}M with ‘true’ rainfall
- Generation of ‘true’ reference hydrographs for a set of observed events

Input Uncertainty

Interpolation techniques based on rain gauge observations

Uncertainty about true spatial rainfall field

- Uniform
- Thiessen Polygon
- External Drift Kriging
- Spline



Distribution of rainfall error

Error Definition

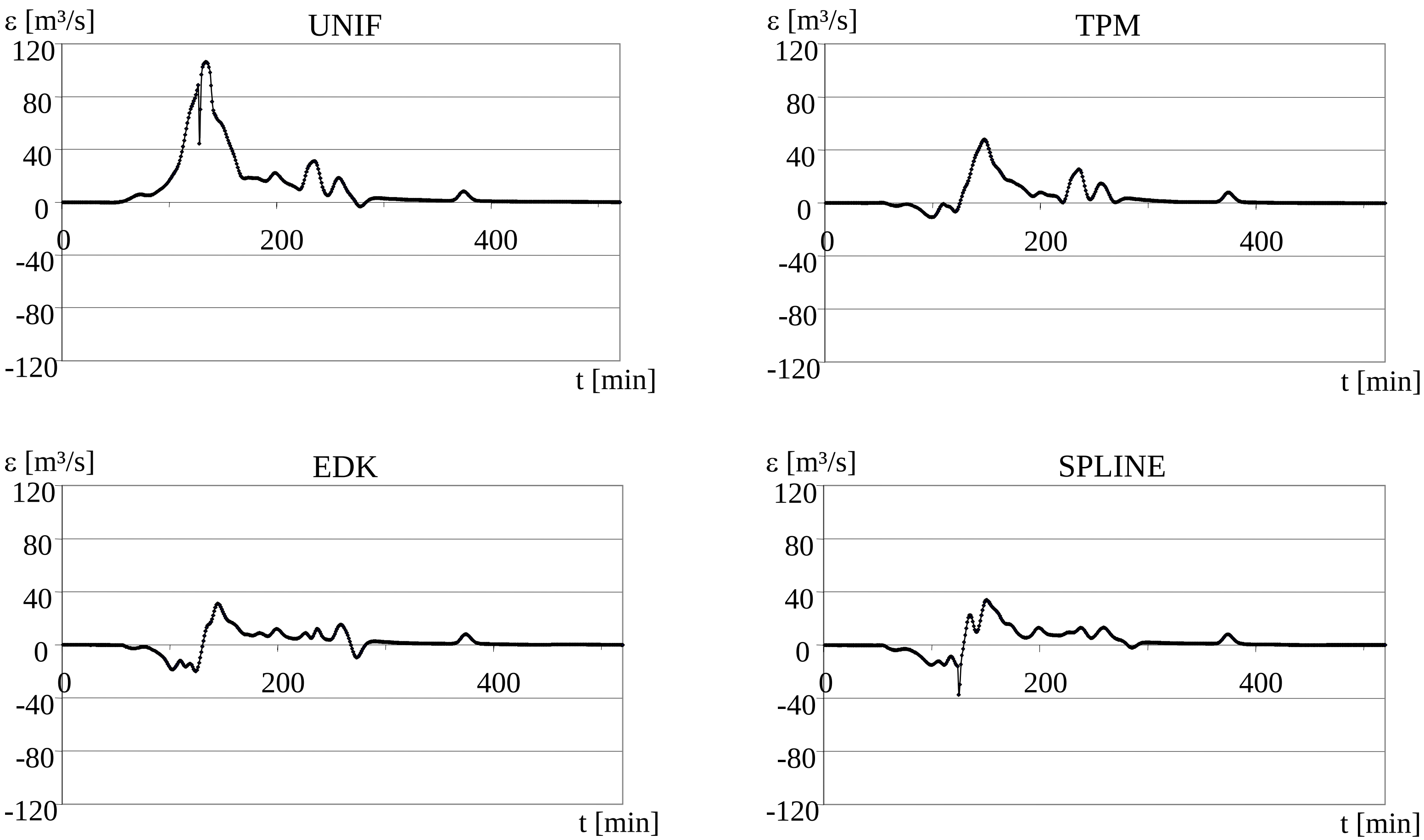
Residuals: $\varepsilon_i = Q_i\text{ref} - Q_i\text{sim}$

- Positive error: under prediction
- Negative error: over prediction

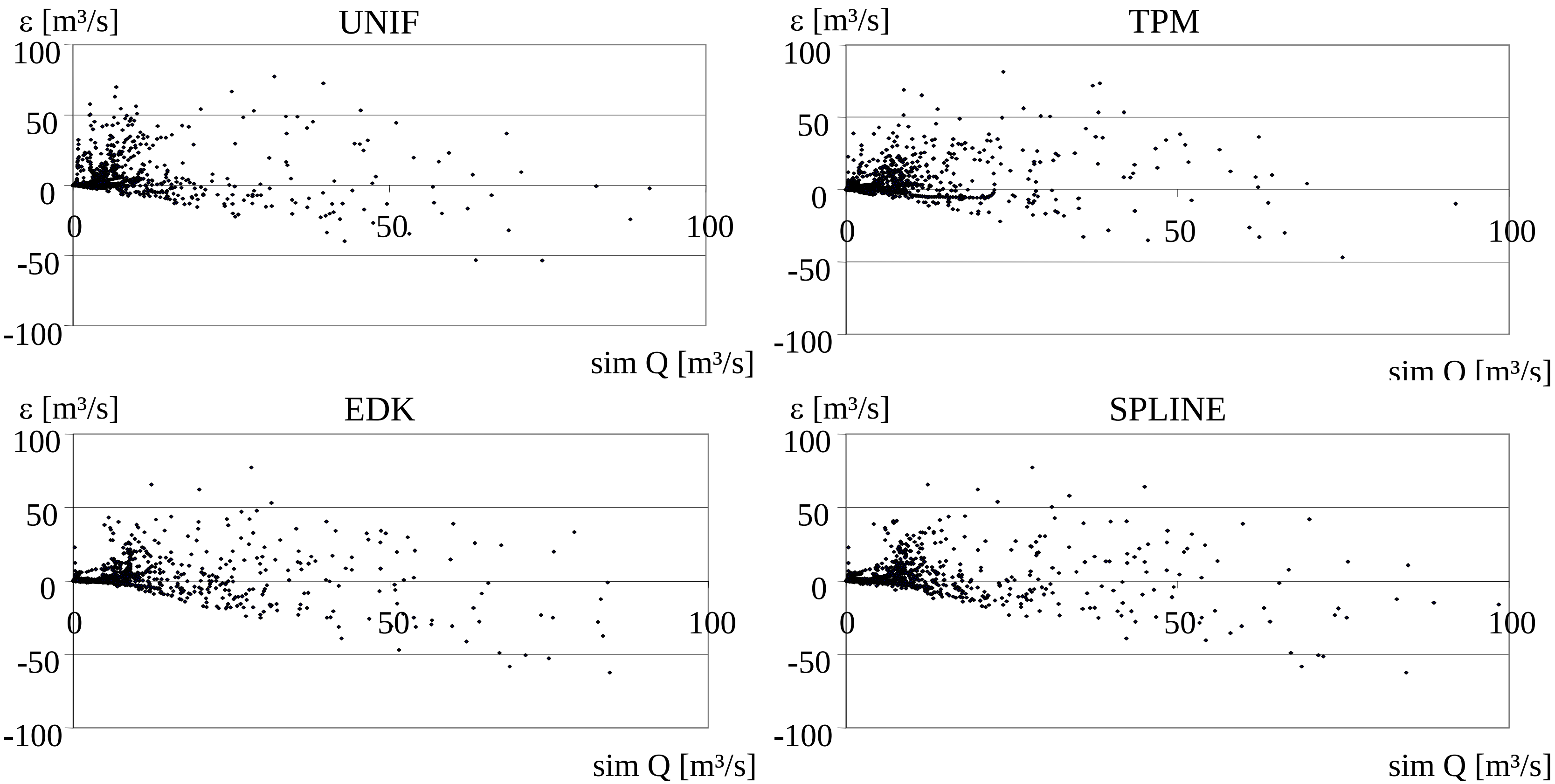
Analysis of error characteristics (check of LS-estimation assumptions)

- Normally distributed
- Zero mean (non biased) constant variance
- independent of each other and predictions

Residual time plots



Errors vs. predictions



Resumé

- Interpolation methods introduce uncertainty about ‚true‘ precipitation field: also in real application cases?!
- Examined by means of a semi-synthetic case study

  (control uncertainty to attribute errors to specific source)
- Diagnostic plots: residual time plots, error scatters (residual vs. prediction)
- LS assumptions violated – adaptation of error model for parameter estimation
- Systematic error induces bias in parameters due to compensation characteristics of the model
- Spatial variation of rainfall field error induces spatial variation of runoff error

Results

- What has to be expected in ‚real‘ application case?
  - What do we really know about uncertainties?
- How can inevitable uncertainty be considered?
- Which estimator is appropriate?
- Which estimation scheme is appropriate?

Conclusions

- Case and data dependence
- Data transformation (stabilise error variance)
- Time series models for auto-correlation
- Descriptive model (representing important general features) for input uncertainty to consider in calibration
- Systematic bias (multiplication model)
- Multi site calibration scheme, tailored error models
- Spatial distribution of rainfall is crucial information for runoff generation processes

Thank You!

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