Towards an uncertainty propagation framework in urban drainage system modelling

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Background

- Most urban drainage models do not pay attention to uncertainty propagation [Mitchell, Duncan, Inman, Rahilly, Stewart, Vieritz, Holt, Grant, Fletcher, Coleman, Maheepala, Sharma, Deletic, and Breen, 2007] [Bach, Rauch, Mikkelsen, McCarthy, and Deletic, 2014].
- Commercial software (in engineering practice) ignore uncertainties because of lack of user-friendly implementations and tools [Schellart, Tait, and Ashley, 2010].

Background (II)

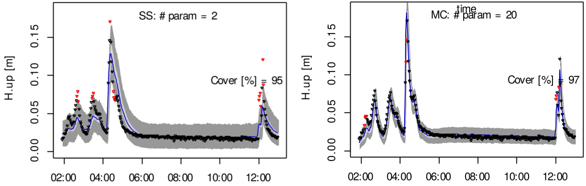
- Input data uncertainties on UDM are far less understood [Deletic, Dotto, McCarthy, Kleidorfer, Freni, Mannina, Uhl, Henrichs, Fletcher, Rauch, Bertrand-Krajewski, and Tait, 2012]

- Research in urban drainage modelling that can trace the propagation of uncertainties is needed [Bach, Rauch, Mikkelsen, McCarthy, and Deletic, 2014].

- We make a contribution to this effort by proposing an uncertainty propagation framework for urban drainage modelling and applying it to the EmiStat-R model.

Background (III)

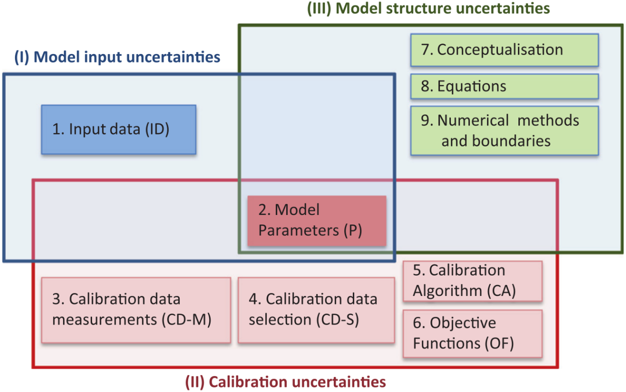
- Generalised Likelihood Uncertainty Estimation (GLUE)
  [Beven and Binley, 1992], [Freer, Beven, and Ambroise, 1996].
- Variance Decomposition Approach
  [Freni and Mannina, 2010]
  - all of the sources of uncertainty (input data, calibration data, model parameters) are independent
  - lumped approach
- Bayesian description of model bias
  [Del Giudice, Reichert, Bareš, Albert, and Rieckermann, 2015].



(illustrations from Del Giudice et al. [2014])

Key sources of uncertainties in UDM

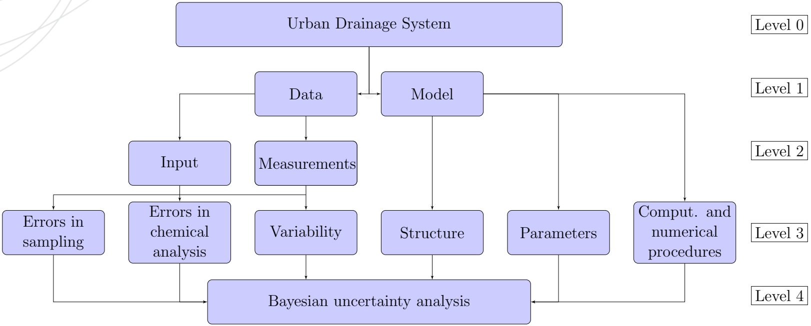
International Working Group on Data and Models (IWA/IAHR Joint Committee on Urban Drainage)



(Illustration from Deletic, Dotto, McCarthy, Kleidorfer, Freni, Mannina, Uhl, Henrichs, Fletcher, Rauch, Bertrand-Krajewski, and Tait [2012])

A new contribution is necessary

A framework for **spatial** uncertainty
in urban drainage models of different complexity



Main goals

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- Optimal complexity of urban drainage system models accounting for **spatial** uncertainty propagation, a step forward of the Water Framework Directive of the European Union.

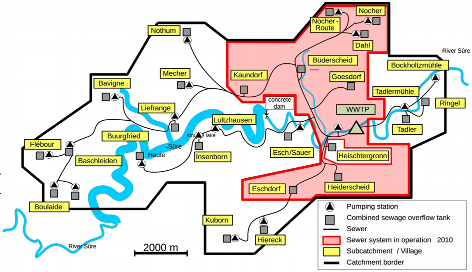
- Uncertainty propagation analysis through the urban drainage system model EmiStat-R.

Study area: Haute-Sûre catchment, Lux.

Catchment	Abbreviation
Boulaide Bauschelbusch	BAU
Boulaide Boellerbuch	BOE
Eschdorf	ESD
Goesdorf	GOE
Kaundorf	KAU
Nocher-Route	NOR

Data available 2010 – 2011

Location	Type of measurement
GOE	Rainfall Water level CSO and tank, outflow rate WWQ Campaign
KAU	Rainfall Water level, flow velocity, temperature WWQ Campaign
NOR	Rainfall Water level, flow velocity WWQ Campaign



(With kind permission of Kai Klepiszewski)

Research questions

- Are some inputs and/or parameters **spatially** and/or **temporally distributed**?

... attention must be paid to spatial and temporal correlations of the uncertainty.

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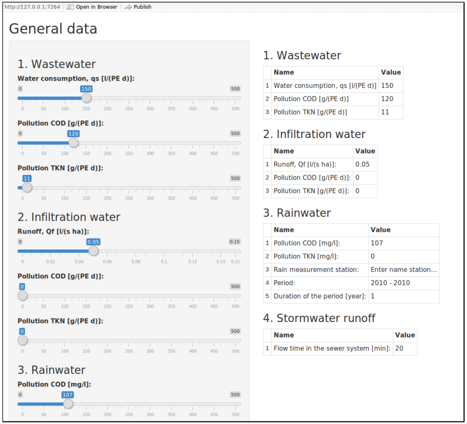
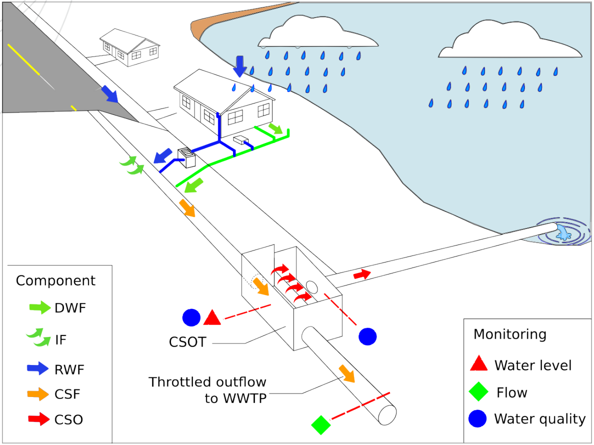
The EmiStat-R model

- Is a R implementation based on the XLS EmiStat model by Klepiszewski and Seiffert [2013].
- It provides a fast estimation of combined waste water emissions.
- It can aid the planning and design of hydraulic properties and pollutant handling, without the requirement of extensive simulation tools.
- Conceived as an evaluation tool for the water authorities.



Graphical User Interface (GUI) of the EmiStat-R model. R interface for capturing the input data.

Conceptual model: main components



1) Dry Weather Flow (DWF) including Infiltration Flow (IF); 2) Pollution of DWF; 3) Rain Weather Flow (RWF); 4) Pollution of RWF; 5) Combined Sewage Flow (CSF) and pollution; and 6) Combined Sewer Overflow (CSO) and pollution.

EmiStat-R; input data

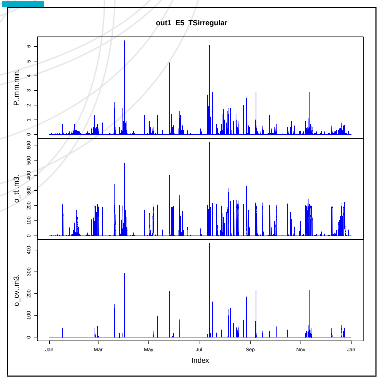
General input data

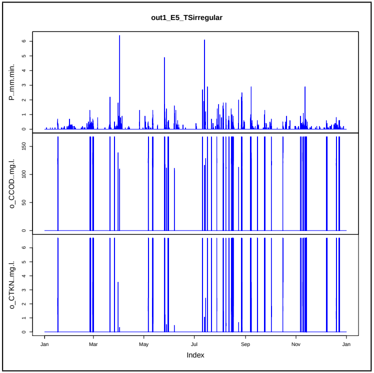
Category	Variable
Wastewater	
	Water consumption (qs)
	Pollution COD (CODs)
	Pollution NH_4 (NH4s)
Infiltration water	
	Inflow (qf)
	Pollution COD (CODf)
	Pollution NH_4 (NH4f)
Rainwater	
	Pollution COD (CODr)
	Pollution NH_4 (NH4r)
	Precipitation time series (P)
	Period
Storm water runoff	
	Flow time in the sewer system (tf)

Input data of the CSO structure

Category	Variable
Identification	
	ID of the structure
	Name of the structure
Catchment data	
	Land use
	Total area (Ages)
	Reduced area (Ared)
	Flow time structure (tfS)
	Population equivalents (pe)
Structure data	
	Throttled outflow (Qd)
	Volume (V)

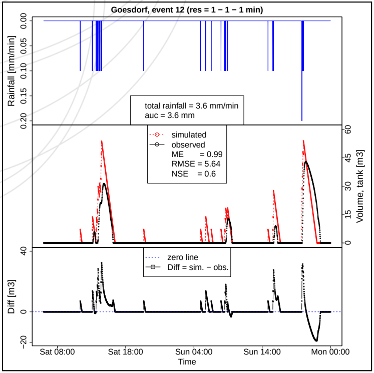
Results: EmiStat-R; typical output

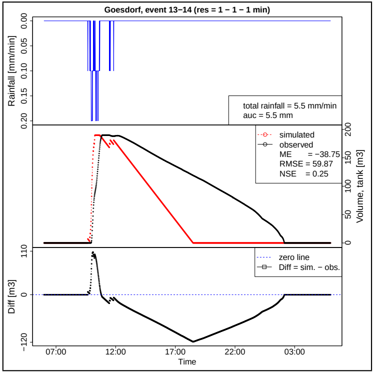




Typical output of the EmiStat-R model for the year 2011 at Goesdorf station simulating volume in the CSOT and CSO volume (left) and COD and NH_4 concentrations in the CSO

EmiStat-R; validation (Goesdorf, 2011)

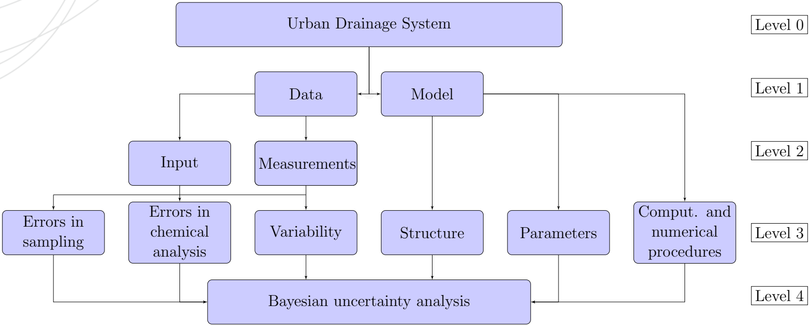




Accuracy assessment of the EmiStat-R model simulating volume in the CSOT for rain events with CSO at Goesdorf station: (left) event 12, rain from 31/05/2011 00:00:00 to 01/06/2011 12:00:00; (right) event 13-14, rain from 22/06/2011 06:00:00 to 23/06/2011 06:00:00.

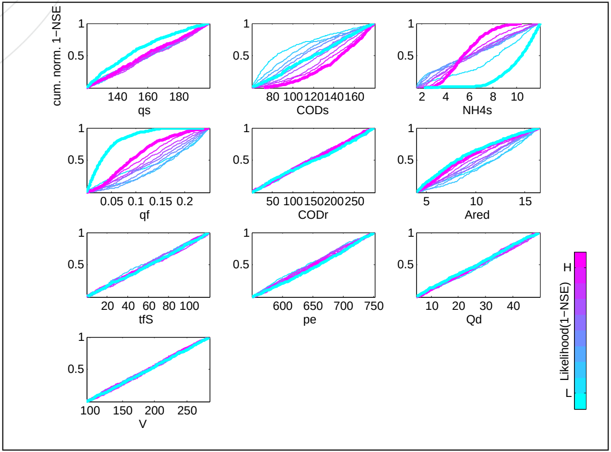
A new contribution

A framework for **spatial** uncertainty
in urban drainage models of different complexity



Regional sensitivity analysis

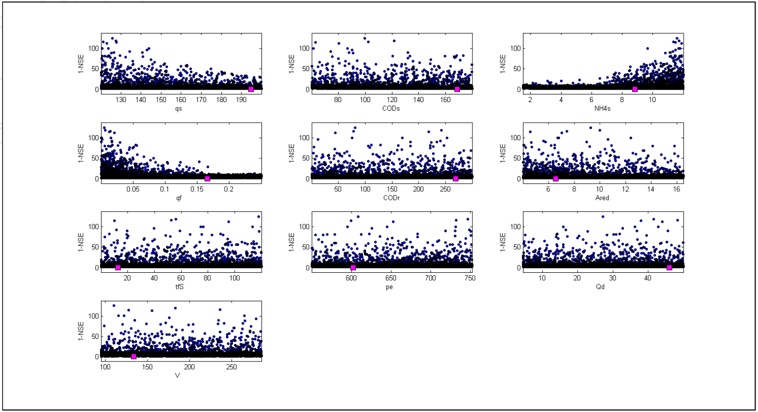
[Spear and Hornberger, 1980] [Wagener, Wheater, and Lees, 2004]



RSA plot according to 1-NSE for volume and water quality

for 5,000 simulations of Monte Carlo.

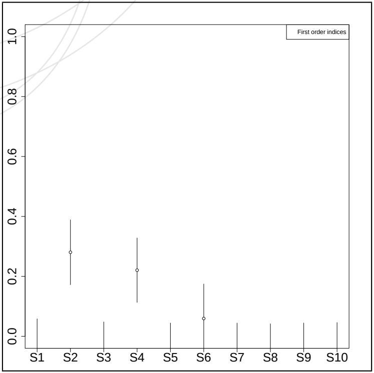
Surface response

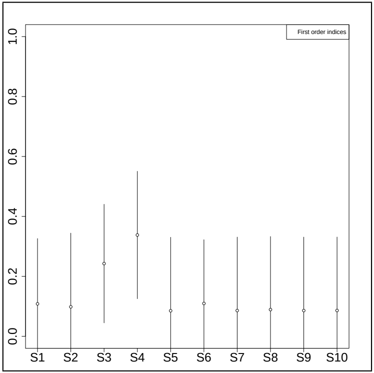


10 parameter distribution according to 1-NSE for volume and water quality for 5,000 simulations of Monte Carlo.

Global sensitivity analysis (Sobol's indices)

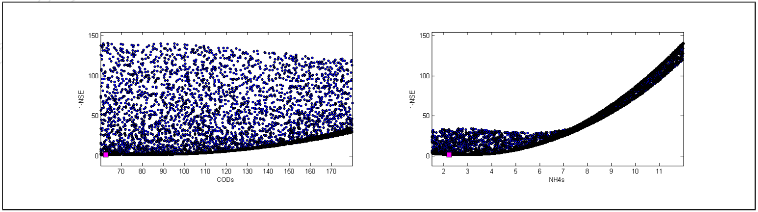
[Monod, Naud, and Makowski, 2006],
[Janon, Klein, Lagnoux-Renaudie, Nodet, and Prieur, 2014]





First order Sobol's indices according with RMSE (left), and NSE (right).
S2 = CODs; S4 = qf; S6 = Ared; S3 = NH4s. (3,300 Monte Carlo simulations).

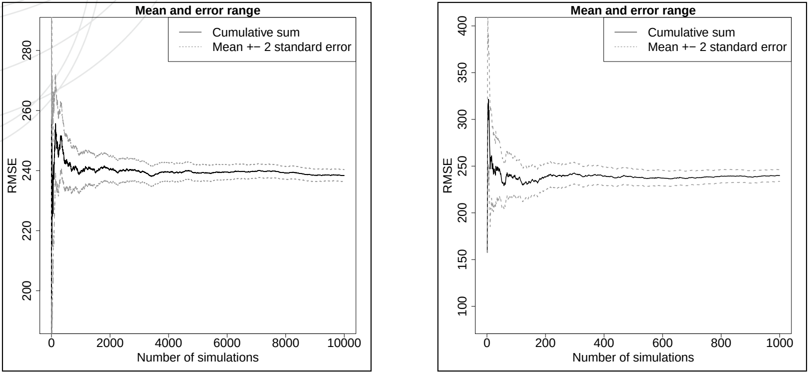
Surface response



Two parameter distribution according to 1-NSE for volume and water quality for 5,000 simulations of Monte Carlo.

Monte Carlo efficiency

Conditioned Latin hypercube sampling [Minasny and McBratney, 2006]



Mean $\pm$ two standard errors against iterations for a single sequence of simulations. Simulations for volume and water quality analysis. Traditional MC (left); conditioned Latin hypercube sampling (right).

Further steps

- Extension of routines for semi-distributed modelling, accounting for spatial distribution of inputs and analysis of spatial uncertainty.

- A formal Bayesian uncertainty framework to analyse what are the contributions of various uncertainty sources to the overall uncertainty i.e. identification of the input, total, model parameters and model structure uncertainties.

- Application of the methodologies developed to other modelling approaches (SIMBA and Infoworks ICM)

Thank you!

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