Towards an uncertainty propagation framework in urban drainage system modelling

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Abstract
This paper introduces an uncertainty analysis framework in urban drainage modelling and focuses on the application of the EmiStat model which simulates the volume and substance flows in urban drainage systems (UDS). EmiStat aids the planning and design of UDS without the requirement of extensive simulation tools. An implementation of EmiStat as an R-version, the EmiStat-R model, was realised. EmiStat-R can make use of R functionalities, such as time series analysis, modelling and visualisation. Uncertainty is often ignored in urban drainage modelling. Commercial software used in engineering practice typically ignores uncertainties and uncertainty propagation, among others because of lack of user-friendly implementations. This can have large impacts, such as the wrong dimensioning of UDS and the inaccurate estimation of pollution in the environment. The paper presents the EmiStat-R model and illustrates its use with a case study from the Haute-Sûre catchment in Luxembourg for 10 rainfall events. An accuracy assessment of the model predictions with independent observations was performed. The case study results indicate that model predictions and independent observations of volume in the combined sewer overflow tank (CSOT) for rain events without and with combined sewer overflow (CSO) agree overall on the temporal pattern. However, the inflow to the CSOT and accordingly the activated storage volume is overestimated by the model in events without CSO. The results of the simulations of rain events with CSO showed that the volume in the CSOT curve is not well simulated, having more volume than the observed curve. The causes are model input, model parameter and model structure uncertainty, while uncertainties in observations and the conversion of validation data explain part of the deviation between simulated and observed time series. An important aspect is, to compare simulations and observations at the same temporal support. In order to analyse the contributions of the various sources of uncertainty, we propose a formalised uncertainty framework for UDS modelling.

Keywords
accuracy assessment, uncertainty propagation, urban drainage modelling, EmiStat-R, support, CSO

INTRODUCTION
Most urban drainage models do not pay attention to uncertainty propagation (Mitchell et al. 2007) (Bach et al. 2014). In particular, commercial software packages as used in engineering practice typically ignore uncertainties due to lack of user-friendly software implementations (Schellart et al. 2010). However, uncertainties can be substantial and ignoring these may affect decision making. In particular, end users should be aware of uncertainties so that they can take more robust decisions. In addition, the current state of knowledge regarding uncertainties in urban drainage modelling is poor (Deletic et al. 2012). Thus, research into uncertainty propagation in urban drainage modelling and development of operational systems that can trace the propagation of uncertainties is needed (Bach et al. 2014). In this paper we make a contribution to this effort by proposing an uncertainty

propagation framework for urban drainage modelling using the EmiStat-R model. Before addressing the uncertainty propagation framework, first the EmiStat-R model is presented and applied to a case study from the Haute-Sûre (Obersauer, in German) catchment in Luxembourg. In a first step of an uncertainty analysis, we focus on the assessment of the overall accuracy of the EmiStat-R predictions using independent observations and perform the comparison at the same temporal support (Leopold et al., 2006)

MATERIALS AND METHODS

The EmiStat model

The EmiStat model is an XLS based model which provides a fast estimation of combined waste water emissions. It supports the planning and design of urban drainage systems, without the requirement of extensive simulation tools (Klepiszewski & Seiffert 2013). The EmiStat model includes six main components to simulate combined sewage discharges of a catchment. 1) **Dry Weather Flow (DWF)**: EmiStat assumes a constant DWF resulting from specific water consumption per population equivalents (PE) and specific discharge of infiltration inflow per hectare of contributing impervious area to combined sewage flow; 2) **Pollution of DWF**: specific load contribution per PE and day of substances of interest. No pollutant contribution of infiltration inflow is taken into account; 3) **Rain runoff volume and Rain Weather Flow (RWF)**: complete runoff of rainfall on impervious catchment area contributing to combined sewage flow. The RWF is discharged instantaneously to the sewer outlet or Combined Sewer Overflow (CSO) structures downstream of the catchment, i.e. the flow time in the sewer system is not taken into account; 4) **Pollution of RWF**: constant surface runoff concentrations of substances under observation. EmiStat assumes complete mixing of pollutants in simultaneously flowing volume components and tank structures; 5) **Combined sewage flow (CSF) and pollution:** contributions of DWF and RWF to combined sewage flow and consequent pollution load; 6) **CSO volume and pollution**: flow diverted towards the receiving water body that takes place when the overflow weir level in the CSO tank (CSOT) is exceeded. The pollution is measured as concentrations given a certain load.

The sewer system under investigation includes a tank structure to store first flush pollutant peaks. After filling of the storage volume a combined sewage overflow structure discharges, to the receiving water, volume and pollutant load inflows exceeding the structure flow to the Waste Water Treatment Plant (WWTP). In EmiStat a simple volume balance taking into account inflow volume, present storage capacity and outflow to WWTP is implemented to simulate the tank structure. In case of an overflow the pollutant concentrations in the CSO are equivalent to the combined sewage inflow concentrations of the structure.

The pollutants typically taken into account are total Chemical Oxygen Demand (COD) and Ammonium (NH_4). The variable COD is the standard used in the framework of the dimensioning of CSO structures. NH_4 represents a diluted substance which can have a significant impact on surface water quality due to possible transformation to Ammonia (NH_3).

At the CSOT structure a simple volume balancing takes place: 1) substance and volume flows are stored and discharged to the WWTP if the storage volume is not completely filled up; 2) if the storage volume is completely filled up the proportion of the volume inflow which is not discharged to the WWTP goes to the CSO. The CSO pollutant concentration is equivalent to the combined sewage inflow concentration.

Figure 1 depicts the underlying processes simulated by EmiStat and the locations where monitoring is typically done. Details regarding the conceptual and mathematical model of the EmiStat model are given in Torres-Matallana and Klepiszewski (2015).

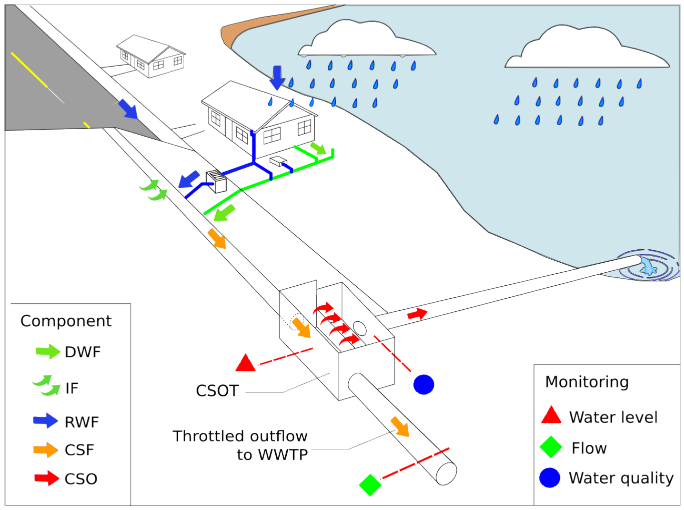

Figure 1. Main components of the EmiStat model: 1) Dry Weather Flow (DWF) including Infiltration Flow (IF); 2) Pollution of DWF; 3) Rain Weather Flow (RWF); 4) Pollution of RWF; 5) Combined Sewage Flow (CSF) and pollution; and 6) Combined Sewer Overflow (CSO) and pollution. (Background adapted from: Sanitary-District, 2015).

Emistat-R: Implementation of EmiStat in R

The EmiStat-R model takes the EmiStat model a step further, by implementing EmiStat as modular R functions. This enables to add new functionalities through the R framework. Furthermore, EmiStat-R was implemented with an interactive user interface with sliders and input data exploration.

The R Language for statistical computing and graphics (Ihaka & Gentleman, 1996; R Development Core Team, 2013) is a versatile and open source programming language influenced by S (Becker et al. 1988) and Scheme (Steel & Sussman 1975). R is very similar in appearance to S, but the underlying implementation and semantics are derived from Scheme (Ihaka & Gentleman 1996). R supports various types of statistical analysis, from basic types of analysis to highly specialized, due to the large number of specialized add-on packages that have been developed over the years and that can be installed together with R. Being open source and cross-platform software, R is ideally suited for performance of standardized tests, comparison of models, and analysis of reproducibility of methods and results (Andrews et al., 2011). R provides generic functionality for urban drainage modelling. This includes basic data manipulation, handling and analysing time series data, spatial data and spatio-temporal data, implementation of flow equations, basic plotting and high quality visualisation (Torres-Matallana & Pebesma 2013).

Figure 2 illustrates the Graphical User Interface (GUI) of the EmiStat-R model for capturing input data. The model input data can be grouped into four main categories (Table 1): 1) wastewater production data, i.e. water consumption in Population Equivalent (PE) and characterization of the pollution load of wastewater in terms of COD and NH_4 concentrations in PE; 2) runoff and specific pollutant load contribution per population equivalent and day (COD and NH_4 concentrations) of infiltration water; 3) precipitation data, i.e. time series of rainfall and rainfall runoff pollution in terms of concentrations of COD and NH_4; 4) storm water runoff characteristics given as the maximum flow time in the sewer system to mimic attenuation effects in systems with a maximum flow time higher that 20 minutes.

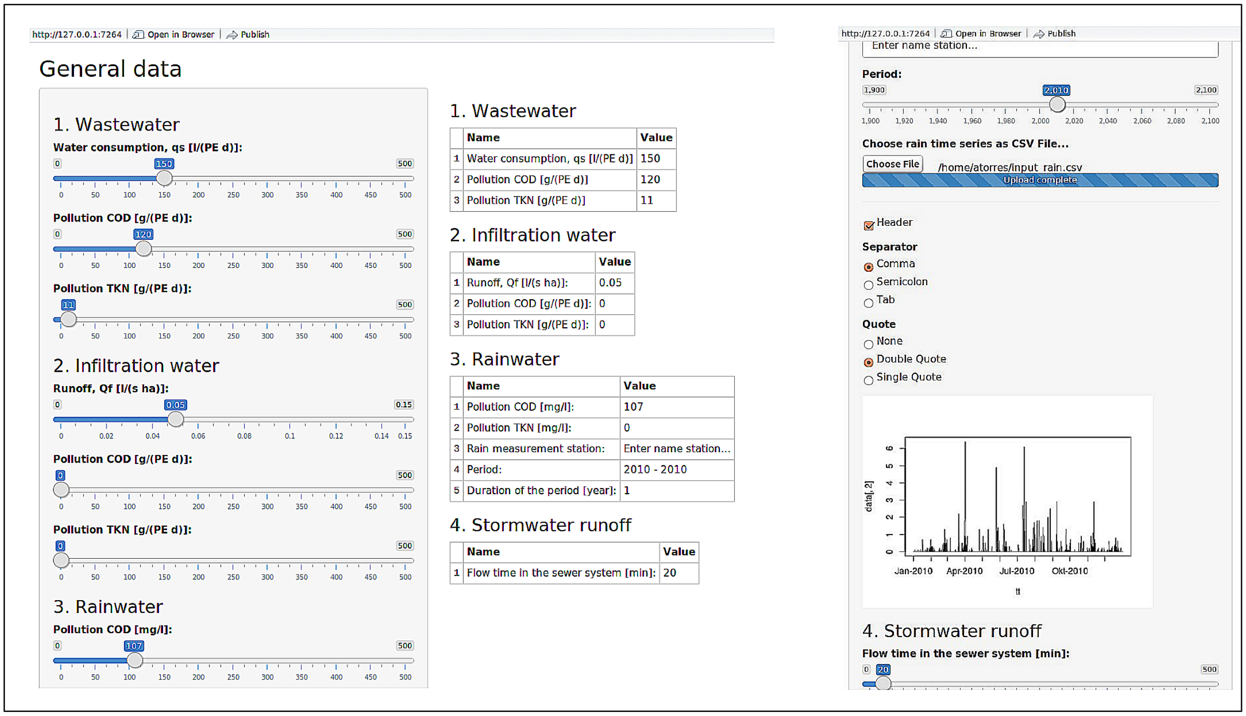

Figure 2. Graphical User Interface (GUI) of the EmiStat-R model. R interface for capturing the input data.

Table 1. General input variables of the EmiStat-R model.

Category	Variable	Units	Value
Wastewater	Water consumption	[l/(PE^{+} d)]	150
	Pollution COD*	[g/(PE d)]	120
	Pollution NH_4^{**}	[g/(PE d)]	5
Infiltration water	Inflow	[l/(s ha)]	0.05
	Pollution COD	[g/(PE d)]	0
	Pollution NH_4	[g/(PE d)]	0
Rainwater	Pollution COD	[mg/l]	107
	Pollution NH_4	[mg/l]	0
	Precipitation time series	[mm/min]	P1
	Period	[year]	2011
Storm water runoff	Flow time in the sewer system	[min]	20

* COD = Chemical Oxygen Demand; ** NH_4 = Ammonium ; $^{+}$PE= population equivalents.

The general input variables of the CSO structure distinguishes two main components (Table 2): 1) catchment data, i.e. data concerning the name of the municipality, name and number of the catchment, land use (residential, commercial, industrial), the total area of the catchment, the impervious area, and the population equivalents connected to the sewer system; and 2) structure data, i.e. data regarding the throttled outflow diverted to the WWTP and the total storage volume of the CSOT.

The main interest of simulation with EmiStat-R is the emission of overflows in individual CSO structures. Therefore, no aggregation of catchments is done because the interest is in the behaviour of individual structures. The model predictions were compared to InfoWorks® ICM (Innovyze) predictions for this study area obtained previously for different scenarios (Klepiszewski et al. (2014).

Study area

The study area is a sub-catchment of the Haute-Sûre catchment in the north-west of Luxembourg. The combined sewer system of the sub-catchment drains the three villages of Goesdorf, Kaundorf and Nocher-Route. In the local sewer system downstream the villages, three CSOTs are located to store pollutant peaks in the first flush of combined sewage flows. Table 2 shows the general characteristics of each CSOT and its associated sub-catchment. Figure 3 depicts their locations and the delineation of the catchment.

The topography of the area is characterised by a hilly landscape. The elevations around Goesdorf are between 390 m and 490 m, around Kaundorf between 370 m and 464 m, and in the area of Nocher-Route the elevations vary between 400 m and 485 m. The main land use types in the villages are residential, smaller industries and farms. Outside of the villages forest as well as agricultural arable and grassland are the dominating land uses. The receiving water bodies at CSO structures Goesdorf, Kaundorf and Nocher-Route are tributaries of the river Sûre (Sauer, in German) (Figure 3).

Table 2. General input variables of the CSO structures of the EmiStat-R model. The data used for simulation is of the year 2010.

Variable	Goesdorf	Kaundorf	Nocher-Route
Sub-catchment data			
Land Use [-]	Residential/Industrial	Residential/Industrial	Residential/Industrial
Total area [ha]	16.5	22.0	18.6
Impervious area [ha]	7.6	11.0	4.3
Population equivalents [PE]	611	358	326
Flow time structure [min]	10	10	10
Structure data			
Throttled outflow [l/s]	9	9	4
Volume [m^3]	190	180	157

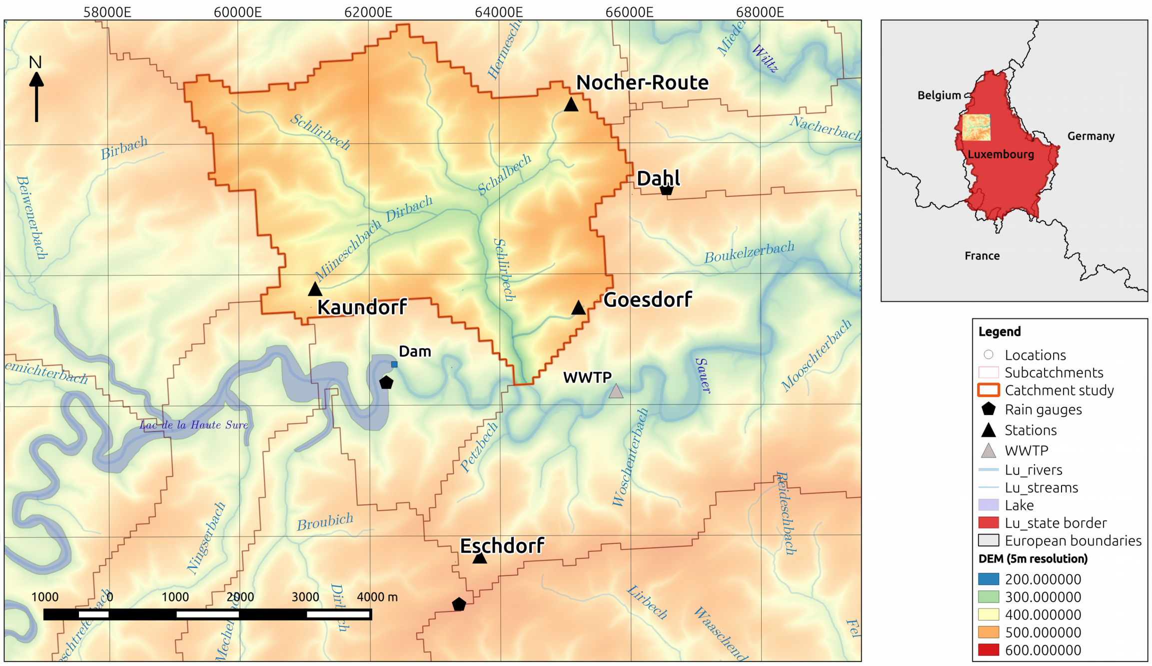

Figure 3. The Haute-Sûre (Obersauer, in German) sub-catchment. CSO structures are located in Goesdorf, Kaundorf and Nocher-Route.

Data

The input data used to run the EmiStat-R model are shown in Tables 1 and 2. The simulated precipitation time series represent 11 events from 28/04/2011 to 22/06/2011 at 1 minute time intervals: one in DWF conditions, eight in rain conditions and two CSO events. The events correspond to time periods at which measurement campaigns of waste water quality were carried out. The hydraulic variables measured were outflow rate (discharge towards WWTP) in [m^3/h], water level in the CSO structure and in the CSOT [cm]. The temporal resolution of the measurements is 30 seconds. The following Waste Water Quality (WWQ) measurements were monitored: total COD, biochemical oxygen demand, total nitrogen, NH4, nitrate, total phosphorus, phosphate, total suspended solids, pH, Conductivity, water temperature. The temporal resolution of the WWQ variables was two hours of composite samples for characterising DWF and between 2 to 30 minutes to grab samples during rain events.

Accuracy assessment method

The above measurements were used as independent observations to assess the accuracy of the model predictions. We aggregated the observations to 1 minute resolution to assure the same temporal support of simulations and observations for the comparison. As accuracy assessment measures we usedMean Error (ME), Root Mean Squared Error (RMSE) and the Nash-Sutcliffe model efficiency coefficient (NSE).

RESULTS

Application and accuracy assessment of the EmiStat-R model to the Haute-Sûre case

Presentation and analysis of results are concentrated to the model simulations of volume in the sub-catchment of the Goesdorf CSOT. In total 11 events at Goesdorf CSOT were analysed in 2011 (events 4 to 14). Events 1 to 3 belong to another period of analysis (2005-2006) and are not taken into account in this paper. Figure 4 shows the comparison of model predictions with independent observations of volume in the CSOT for rain events without CSO: (a) event 6, rain from 19/05/2011 00:00:00 to 21/05/2011 00:00:00; (b) event 12, rain from 31/05/2011 00:00:00 to 01/06/2011 12:00:00. Figure 5 shows the comparison for rain events causing a CSO: (a) event 7, rain from 18/06/2011 06:00:00 to 20/06/2011 00:00:00, the event 8 was the CSO; (b) event 13, rain from 22/06/2011 06:00:00 to 23/06/2011 06:00:00, the event 14 was the CSO. Table 3 presents the accuracy measures for all events.

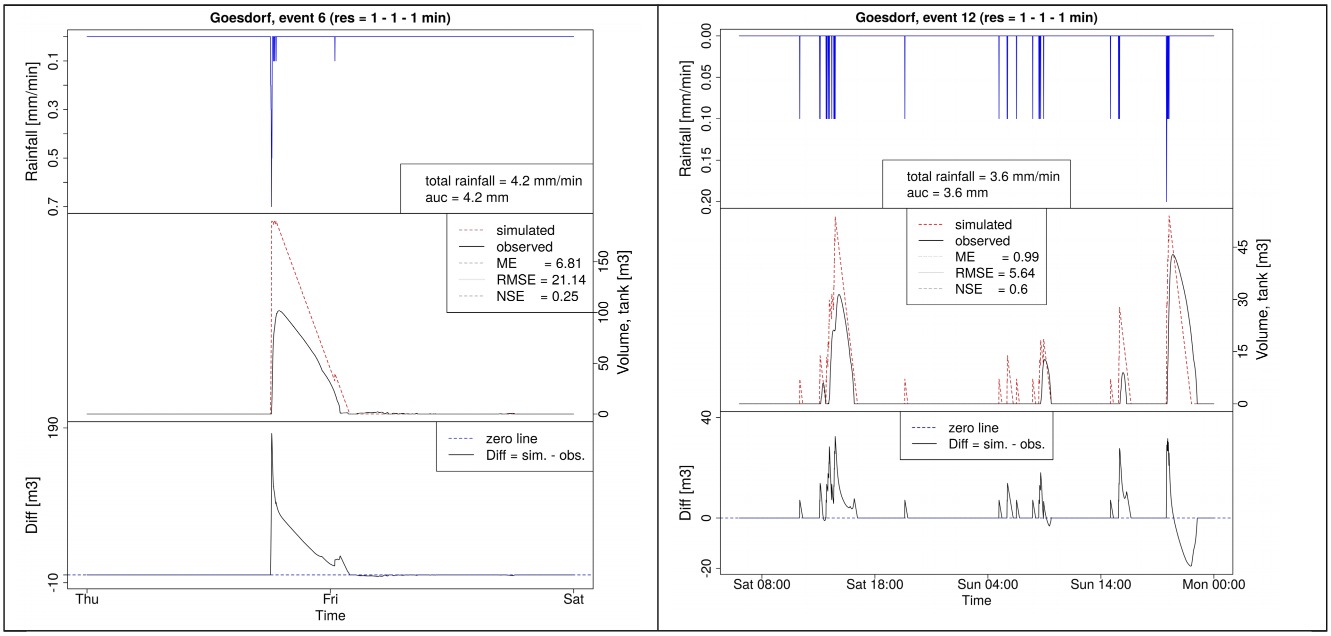

Figure 4. Accuracy assessment of the EmiStat-R model simulating volume in the CSOT for rain events without CSO at Goesdorf station; (a) event 6, rain from 19/05/2011 00:00:00 to 21/05/2011 00:00:00; (b) event 12, rain from 31/05/2011 00:00:00 to 01/06/2011 12:00:00.

For the events presented in Figures 4 and 5, values of the ME and RMSE are [m^3], whereas the NSE is dimensionless. The NSE ranges from -Inf to 1. Essentially, the closer to 1, the more accurate the model is. NSE equal to 1, corresponds to a perfect match of modelled to the observed data. NSE equal to 0, indicates that the model predictions are as accurate as the mean of the observed data. -Inf < NSE < 0, indicates that the observed mean is better predictor than the model. The graphs and accuracy measures given in Figures 4 and 5 indicate a moderate representation by the model of the volume in the CSOT at Goesdorf for the rain events. In general, during events without CSO the model over-predicts the volume in the COST, while during CSO events the model tends to let the volume drop much more quickly over time than observed in reality. Table 3 summarises the accuracy measures obtained.

Figures 4 and 5 present the graphical measure (i.e. plot of both predicted and observed in one plot against time).

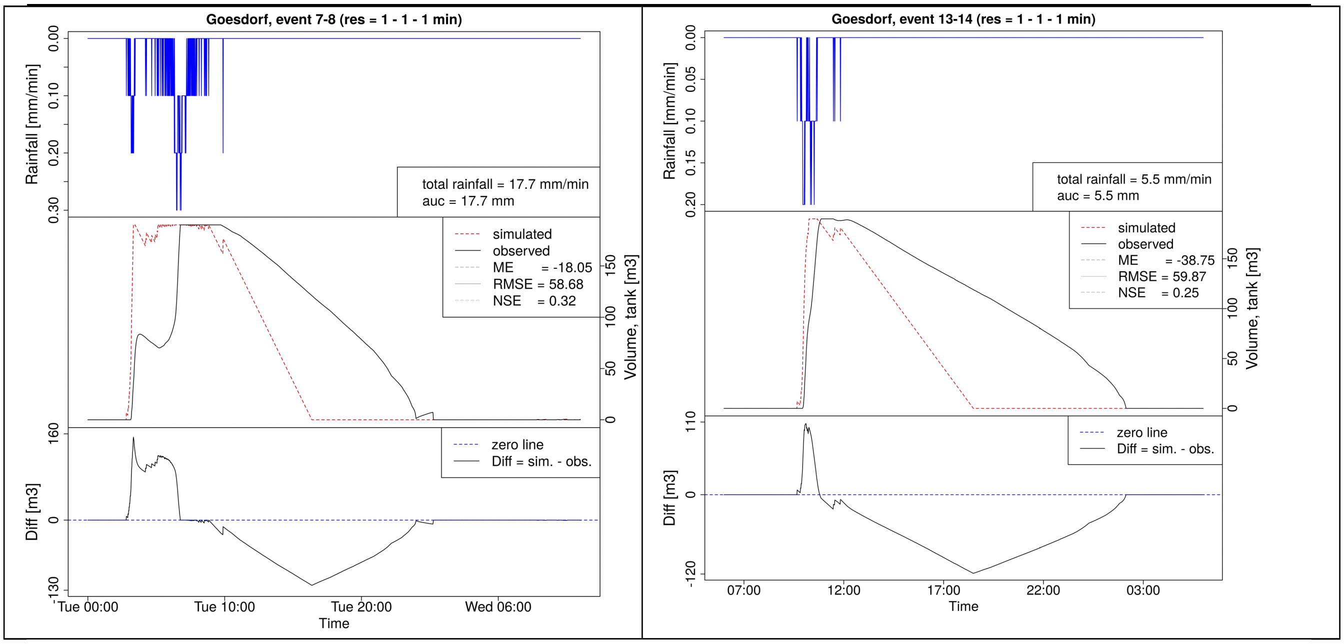

Figure 5. Accuracy assessment of the EmiStat-R model simulating volume in the CSOT for rain events with CSO at Goesdorf station: (a) event 7-8, rain from 18/06/2011 06:00:00 to 20/06/2011 00:00:00; (b) event 13-14, rain from 22/06/2011 06:00:00 to 23/06/2011 06:00:00.

Table 3. Accuracy measures for 11 events.

Event	ME [m^3]	RMSE [m^3]	NSE [-]
4, rain event	3.69	10.1	-8.57
5, dry weather flow	-0.37	0.81	-0.26
6, rain event	6.81	21.14	0.25
7, rain event with CSO	-18.05	58.68	0.32
8, rain event (CSO)	-18.05	58.68	0.32
9, rain event	13.11	34.57	-6.94
10, rain event	22.56	46.53	-10.8
11, rain event	26.56	42.02	-0.56
12, rain event	0.99	5.64	0.60
13, rain event with CSO	-38.75	59.87	0.25
14, rain event (CSO)	-38.75	59.87	0.25

DISCUSSION

Implementation of EmiStat in R

The implementation of EmiStat in R has as a main advantage the possibility to make use of Graphical User Interfaces (GUIs) and plotting functionalities of R. This implementation saves time in the set-up of the model. Implementation in R is also attractive because EmiStat-R can easily be extended with R routines, such as ensuring compatibility of input and output time series with geospatial functionalities implemented in R, e.g. through R package spacetime (Pebesma 2012). Moreover, the R environment allows implementation of routines for parallel computing and multicore tasks, e.g. packages snowfall (Knaus, 2015) and doParallel (Weston 2015).

EmiStat-R implements EmiStat which is a simplified, aggregated model that makes many simplifications. For instance, it does not take spatial distribution of inputs, specifically rainfall and impervious areas, into account. Also, the simulation of the volume and CSO volume, and henceforth the pollutants concentration as Chemical Oxygen Demand (COD) and Ammonium (NH_4), as linear combinations of DWF and RWF is a gross simplification or reality. Finally, the model does not take into account additional processes, such as washoff, first flush, emptiness flush and hydrodynamics in the sewer network. All these simplifications and limitations indicate that the model is not perfect and that model simulations depart from reality, as confirmed by comparison of model simulations with independent observations.

Case study results

Figures 4 and 5 illustrate observations of the monitoring campaign and EmiStat-R simulation results for the CSOT Goesdorf. The rain events taken into account include events causing a loading of the tank and events causing a CSO. For rain events without CSO, i.e. Figure 4, the volume curve is considerably well simulated, i.e. similar temporal patterns. Nevertheless, the peaks in volume in the CSOT are overestimated in the model simulations. Therefore an important component of the uncertainty is related to the representation of inflow to the tank and consequently the peak volume in the CSOT.

The simulation results of rain events with CSO, i.e. Figure 5, show that the volume in the CSOT is not well simulated over time, having more volume than the observed curve. This behaviour could be attributed to the fact that during intense rain events, when CSO takes place, the contribution of the surface runoff is not only due to the contribution of the impervious areas to the sewer system but also to the contribution of surrounding green and pervious areas in Goesdorf and beyond the urban catchment of Goesdorf. This indicates an additional source of uncertainty related to the model inputs.

Other main sources of uncertainty regarding the input variables and the physical processes modelled, i.e. uncertainty in input and model structure, are related to the fact that 1) a runoff coefficient that accounts for effective precipitation and direct runoff is not taken into account. Therefore, all runoff due to impervious areas is directly proportional to the total amount of precipitation, without discounting losses of effective precipitation due to land processes as interception, wetting of soil, infiltration, subsurface flow and saturated zone. As a consequence, the overestimation of the peak volume in the CSOT takes place in all simulations of rain events without CSO; and 2) we used just one rain gauge per structure located at the CSO structure, which may not be an accurate representation of the "real" rainfall in the catchment. Heterogeneity in the rainfall field is expected and as a consequence the spatial variation of precipitation should be taken into account to reduce uncertainty. Similarly, other sources of uncertainty due to measurement errors in the observed data that must be considered are: the observed volume of the tank is derived from *in-situ* measurements of the water level in the CSOT through a volume curve that has imperfections as well. The volume curve is uncertain due to the fact that an under estimation of the storage capacity of the CSOT is done because backwater effects in the upstream sewer system are not taken into account in the model. Discrepancies between simulated and observed are not only due to uncertainties in the simulations, but can also partly explained by uncertainties in the observations.

Hence, a Monte Carlo analysis could add a comparison of observation *versus* simulations accounting for observational and simulation uncertainty. This would enable us to check whether observed and simulated values differ statistically significant (see Leopold et al. 2006).

Support issues

Most model inputs and outputs have a specific temporal *support*, which is defined as the time interval over which measurements and predictions are averaged. For instance, rainfall is expressed as average rainfall over a specific time period, e.g. one minute, ten minutes, or one hour. Likewise, the tank CSO has a temporal support, because it is calculated as an average over a given time interval. The model input data must be supplied at the right support, which, in the case of EmiStat-R, equals the model time step. Also, comparison of model outputs with independent observations must be done at the same temporal support. This may require a change of support, i.e. disaggregation or aggregation. When addressing uncertainty and uncertainty propagation, it is important to take support issues and change of support into account because uncertainties are support-dependent (e.g. Leopold et al., 2006).

Sources of uncertainty

The accuracy assessment results show that model simulations of the volume in the CSOT at Goesdorf for rain events with and without CSO are far from perfect, i.e. the model is not very accuracy. This leads to an important question: what are the causes of the poor performance of the model? The discussion above clarified that the causes are input, model parameter and model structure error/uncertainty, while measurement and conversion errors in the validation data also explain part of the deviation between simulated and observed time series shown in Figures 4 and 5. In order to analyse the contributions of the various sources of uncertainty, we propose a formalised uncertainty analysis framework.

Framework for uncertainty analysis

All the model inputs are subject in some degree to uncertainty. As suggested by Neumann (2007) when designing CSO Detention, it is important to distinguish between the effects induced from model inputs, such as rainfall variability, and effects due to model parameter uncertainty. Figure 6 illustrates the proposed framework for uncertainty analysis in urban drainage modelling. At level 1 two main components are distinguished, the Data and the Model. Data refers to two main components: model input data and observations, where the latter are used for accuracy assessment of model outputs through validation (Level 2). Data are prone to uncertainty due to various reasons, e.g. measurement, sampling and interpolation error (Level 3). The Model uncertainty can be divided in three main components: structure, parameters, and computational uncertainty, where the latter includes uncertainty due to numerical procedures (Level 3). Quantification of the Model uncertainties may be achieved using a Bayesian statistical approach (Beven & Freer, 2001; Vrugt et al., 2008; Chandra et al., 2015; Del Giudice, 2015) (Level 4). In total we distinguish six sources of uncertainty in urban drainage modelling. The proposed framework uses the Taylor series approximation and Monte Carlo techniques in order to propagate the uncertainty through the EmiStat-R model.

It is important to separate the contributions of the various sources of uncertainty. Uncertain input data comprise rainfall, the size of the impervious area, the flow time to the structure and the population equivalent served by the system. Additional data inputs which are less subject to uncertainty are the throttled outflow derived towards the wastewater treatment plant (WWTP) and the storage volume of the structure. Upon quantification of uncertainties in model inputs and parameters by probability distributions, the propagation of these uncertainties through the environmental urban drainage model EmiStat-R can be calculated. For this, the use of Monte Carlo simulation is proposed. In principle, propagation of model parameter and model structure error can also be analysed in this way, although quantification of these uncertainty sources by means of probability distributions is more difficult. Here, the advantage of an R-implementation becomes eminent, because the R-environment provides numerous tools for (spatial) uncertainty analyses. The software is currently tested for the Haute-Sûre case study and further developments of the EmiStat-R model are envisioned where the concept of semi-distributed modelling is applied, so that spatial variability of inputs, such as rainfall, can be accounted for in the modelled system.

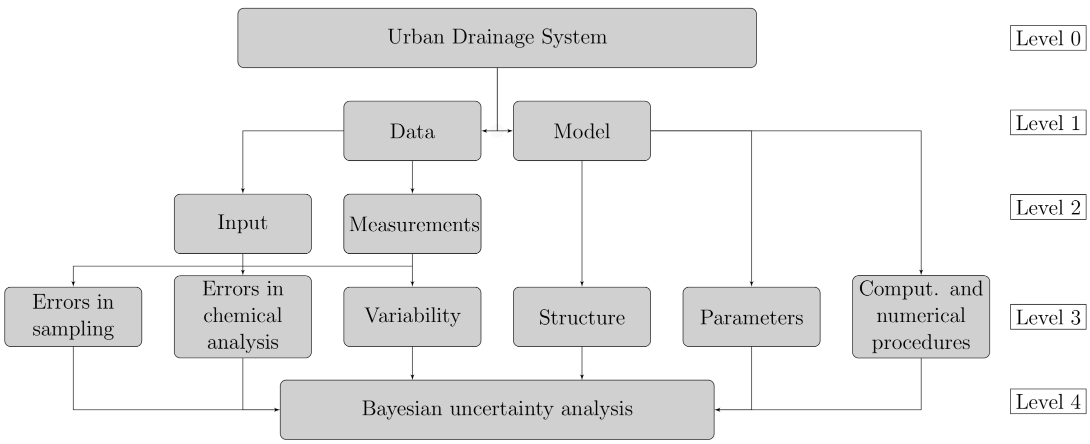

Figure 2. Proposed framework for uncertainty analysis in urban drainage modelling.

CONCLUSIONS

The EmiStat-R model was built as an implementation of the EmiStat urban drainage model in R. It works well, has an interactive user-interface and can present outputs in accessible plots. Another important advantage of EmiStat-R is that it opens up possibilities to make use of the large body of R functionalities, such as compatibility of input and output time series with geospatial functionalities and the implementation of Monte Carlo techniques for uncertainty propagation. Although, this has not been done yet, a framework has been designed and implementation is envisioned in the near future.

The case study results indicate that model predictions and independent observations of volume in the CSOT for rain events without and with CSO agree moderately. However, the inflow to the CSOT and accordingly the activated storage volume in the CSOT is significantly overestimated by the model in events without CSO. This indicates that an important component of the uncertainty is related with the flow rate to the CSOT. The results of the simulations of rain events with CSO showed that the recession limb of the volume in the CSOT curve is not well simulated, having more volume than the observed curve. This behaviour could be attributed to the fact that during intense rain events, when CSO takes place, the contribution of the surface runoff is not only due to the contribution of the impervious areas to the sewer system but also to the contribution of surrounding green and impervious areas in and beyond the urban catchment of Goesdorf.

The causes of uncertainty in model outputs are related with input, model parameter and model structure error/uncertainty, while measurement errors in the accuracy assessment data also explain part of the differences between simulated and observed model outputs. Differences in temporal support of predictions and observations may also lead to discrepancies, and hence it is important that upscaling and/or downscaling techniques are use to ensure that both the simulations and observations have the same temporal support. In order to distinguish the different sources of uncertainty, an uncertainty analysis framework is required which accounts for all possible uncertainty sources. It will allow to apportion the different sources of uncertainty to the overall uncertainty. For this, a framework was designed which will be implemented in R and applied to the EmiStat-R model.

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