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Quantifying Uncertainty in Simulation of Sewer Overflow Volume

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Abstract: Environmental regulators frequently stipulate the modeling approaches required for water utilities managing sewer networks to demonstrate regulatory compliance. The performance of drainage systems with regard to combined sewer overflow (CSO) discharges is required to be assessed using urban drainage models to prove compliance before large investments can be authorized. However, as far as the authors are aware, the modeling approaches to demonstrate regulatory compliance currently provide no opportunity for considering model uncertainty. This paper therefore addresses a knowledge gap in the role of model uncertainty in environmental compliance studies by describing an objective uncertainty quantification process that enables the water utilities to evaluate and report the uncertainty in their modeling predictions and that is also transparent enough to satisfy regulators. The sewer network was modeled in InfoWorks CS software using a design storm defined by the regulator to test the performance of CSOs. Uncertainty in the model and input parameters was propagated using Monte Carlo simulations with Latin hypercube sampling, and the results were presented to show the trade-off between the infrastructure investment and the risk of spilling. **DOI: 10.1061/(ASCE)EE.1943-7870.0001392.**

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Introduction

Decision making in sewer network infrastructure management is strongly influenced by the desire to comply with regulatory requirements while also attempting to satisfy budgetary constraints. For example, combined sewer overflows (CSOs) intermittently spill wastewater into receiving water bodies due to the lack of sewer capacity during rainfall events. The operation of these overflows needs to comply with the environmental permits issued by regulatory authorities to deliver a defined standard of protection, for example, the *Urban Pollution Management Manual* in the UK, which specifies the allowable frequency and duration of the reduction in the dissolved oxygen (DO) level and of the levels of pollutant concentrations in the receiving water after the CSO spill events (Foundation for Water Research 2012). Frequently, water utilities risk paying financial penalties and/or suffering reputational damage if they fail to comply with regulatory requirements, for example, the outcome delivery incentives set by the Water Services Regulation Authority (OFWAT) in the UK (OFWAT 2014). Compliance risks can be managed by investing in new infrastructure and/or applying new system management strategies, such as real-time control. Investment decisions are based on the assessment criteria that are defined to fairly compare alternative schemes and identify an optimal solution. The assessment criteria are often required to be tested using hydrodynamic network models to simulate the hydraulic performance of alternative schemes (Delelegn et al. 2011). Because the hydrodynamic network models can contain considerable uncertainty (Thorndahl and Willems 2008; Vezzaro et al. 2013), it is understood that uncertainty in the model predictions can affect the outcome of the asset management decision-making process. However, the current methods used by researchers to assess the uncertainty in model simulations are, as far as the authors are aware, not commonly used by modelers simulating the hydraulic performance of schemes for water utilities.

Probability theory has been applied by several researchers to quantify aspects of uncertainty in model calculations. Refsgaard et al. (2007) classified uncertainty in modeling into input data, model parameter, and structure uncertainties. Thorndahl and Willems (2008) studied the impact of the uncertainty in rainfall estimation on the risk of failures of urban drainage systems, Willems (2008) investigated the model input and model structure uncertainty in water quality modeling. There have been few studies on the urban drainage systems where prior parameter distribution was estimated from field measurements representing the measured behavior of the parameter. Freni et al. (2008), Korving et al. (2002), and Vezzaro et al. (2013) assumed that the input and model parameters in urban drainage models followed uniform or normal distributions. This might not reflect reality, but the assumption of a uniform or normal distribution was made due to a lack of the

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relevant data required to statistically quantify the model or the input parameter uncertainty.

There are several methods to estimate model output uncertainty, which differ in their computational requirement and complexity (Vezzaro et al. 2013). Not all these methods are suitable for use by a water utility. Monte Carlo simulation is one method that does not require modifications to the hydrodynamic model structure (and hence can be carried out using commercial software), but it is difficult to implement for computationally expensive models; hence, this technique is usually applied to simplified conceptual models. Korving et al. (2002) quantified the effect of the uncertainty in the sewer-system dimensions on the combined sewer overflow volume using Monte Carlo simulations, in which the sewer system was simplified to a reservoir connected to an external weir and a pump. Model reduction techniques have often been used for complex models to enable uncertainty propagation; for example, Schellart et al. (2010) used a response database before applying Monte Carlo simulations for the uncertainty propagation of water-quality parameters in an integrated catchment model. This model comprised a rainfall generator, a simplified hydrological model, a computationally expensive sewer hydrodynamic model, and a simple river impact model to estimate the water quality failures in a receiving watercourse over an extended time period. Model reduction introduces additional uncertainty in the realization of the physical system on top of the model input and parameter uncertainty.

The applicability of these studies on uncertainty propagation and quantification is very challenging for the water utilities responsible for the management of urban drainage systems. Infrastructure investments, for example, for CSO spill control require adherence to the standard modeling procedures set by the environmental regulators, and in various European countries, there is a standard modeling procedure specified by the regulators to evaluate the CSO performance (Dirckx et al. 2011). CSO performance evaluation by any modeling approach other than the agreed procedure will not comply with the requirements of the regulator. Hence, an uncertainty quantification approach that does not conform to the standard modeling procedure in a transparent and objective way will not be acceptable to a regulator. Countries have professional organizations that promote the best modeling practice, for example, the Wastewater Planning Users Group (WaPUG) code of practice in the UK (WaPUG 2002). However, these guidance documents do not cover uncertainty analysis.

This paper aims to address the practical and conceptual issues associated with the previous uncertainty quantification studies that render them unsuitable for the environmental regulators, either because they do not use the modeling tools that are specified or because the proposed uncertainty assessment procedures are not transparent and objective enough to be accepted by the regulator. This study aimed to quantify objectively the uncertainty in complex sewer network hydrodynamic models to a level that will satisfy environmental regulatory compliance. This study had the following objectives: (1) to develop an objective practical method to quantify the uncertainty in the CSO spill volume using a complex hydrodynamic network model specified by the regulator in Flanders, Belgium; (2) to identify the appropriate tools so that the key parameters that impact uncertainty can be identified unambiguously; (3) to demonstrate the ways in which the uncertainty in the input and model parameters can be robustly defined, either by using the existing knowledge or by performing analysis of the long-term data; and (4) to demonstrate a practical method for propagating the parameter uncertainty in the CSO spill volume predictions and then demonstrate how such information could be used in a regulatory process.

In order to comply with the local regulations, a complex hydrodynamic model of the sewer system was required to be used with a specified design storm. Hence, any uncertainty propagation method that failed to use a complex hydrodynamic model was not appropriate. Therefore, to estimate the uncertainty in the model output, a small subset of dominant input/model parameters that could explain the model output variance was selected (Wainwright et al. 2014). The dominant processes were identified by ranking the parameters using global sensitivity analysis (GSA). This reduced the computational cost by including only the significant parameters in the uncertainty analysis. The Monte Carlo technique was selected to propagate the uncertainty over other available techniques, such as differential analysis using a Taylor series approximation and response surface–based techniques, because it does not require modification in the model structure and provides a direct estimation of the probability distribution of the simulated model outputs (Helton and Davis 2003). Because it is a sampling-based technique, using an efficient sampling method such as the Latin hypercube sampling (LHS) can ensure a full coverage of the sample space. Helton and Davis (2003) and Melching and Bauwens (2001) maintained that LHS provided a faster convergence than a random sampling applied to Monte Carlo simulations. LHS is also easier to implement than the stratified sampling method because it does not require the definition of strata in the sample space and the corresponding strata probabilities (Helton and Davis 2003). Hence, in this study, LHS was applied to generate samples from the parameter space.

Although the methods applied for sensitivity and uncertainty analyses are not new, their application to a modeling study satisfying environmental regulatory guidelines is new. As far as the authors are aware, GSA methods such as the Morris screening method (Morris 1991) and Monte Carlo simulations with Latin hypercube sampling (Helton and Davis 2003) have not been applied to simulation results obtained from a detailed sewer hydrodynamic network model. The methodology to quantify uncertainty in the CSO spill volume laid out in this study can be implemented by water utilities for other regulatory guidelines with a different rainfall input.

Methodology

This study was conducted in three steps. First, the Morris screening approach was used to identify the input/model parameters that contribute the most to the uncertainty of the predicted sewer overflow volume in an urban catchment in Flanders, Belgium. Second, the uncertainty in the estimation of the shortlisted input/model parameters was quantified. For one of the input/model parameters, the process of estimating the prior parameter distribution using the available field measurements was demonstrated. In the third step, the uncertainty in the CSO spill volume was quantified by propagating the shortlisted input/model parameter uncertainty through Monte Carlo simulations on the output from a detailed hydrodynamic sewer network model. LHS was used to draw realizations of model inputs and parameters from their distributions, which resulted in a set of the CSO spill volume values. This set of model output values could be considered random samples of its distribution (Uusitalo et al. 2015). Although the GSA provided information about the significant parameters for a selected model output, this information was also assessed for the contribution of each of the important parameters to the overall model output uncertainty.

Catchment Model

The hydrodynamic model used in this study was a subsystem of an InfoWorks CS model for the municipality of Herent in Belgium. It served around 2,100 inhabitants with a total contributing area of about 87 ha. The urban residential sewer system was gravity-driven; 60% of its pipes had a slope from 0 to 2% and a small number of pipes (around 3% of the total number of pipes) had a slope of 10% or higher. The pipes with a high slope were usually short-length pipes connecting adjacent manholes. The catchment was selected for this study because of the available 5- and 10-year-long flow survey data that enabled the calculation of uncertainty in the pipe hydraulic roughness. The sewer network and catchment model was a detailed model built and calibrated using InfoWorks CS; this software was selected because it is the standard modeling procedure agreed upon by Aquafin and the environmental regulators in Flanders, Belgium. The sewer network and catchment model could be built using alternative software, such as MIKE URBAN or the storm water management model (SWMM). As the underlying hydrological and hydraulic principles are the same, any of these software packages should be able to provide similar predictions of the CSO spill volume when they are appropriately calibrated. However, the aim of this study was to demonstrate an objective uncertainty quantification process that enabled the water utilities to evaluate and report the uncertainty in their modeling predictions and that was transparent enough to satisfy the regulators. The uncertainty quantification process demonstrated in this study is independent of the choice of the model.

Individual physical components of the sewer system, such as manholes, pipes, weir, and so forth, were well represented in this model, as were the runoff processes from the catchment. In the InfoWorks CS model, the runoff volume after the initial losses was calculated by applying a fixed runoff coefficient, and the double linear reservoir (Wallingford) model (Sarginson and Nussey 1982) was used to model the runoff routing. Due to the lack of the measured data required to calibrate a catchment scale runoff routing model, the double linear reservoir (Wallingford) model available in InfoWorks CS was selected, as per the Aquafin's internal modeling code of practice (Aquafin 2017). The modeling of sewer hydraulics was governed by the equations of de Saint-Venant as described by Yen (1973). InfoWorks CS used a Kindsvater and Carter equation (Kindsvater and Carter 1959) to model the flow over the weir.

Sensitivity Analysis

Several methods have been used for performing sensitivity analyses; they can be broadly classified as GSA or local sensitivity analysis (Saltelli et al. 2000). Local sensitivity analysis studies the effect of small input perturbations on the model output and is performed around a point in the parameter space, whereas a GSA is performed over the whole parameter space of the model inputs (Borgonovo and Plischke 2016; Gamerith et al. 2013; Iooss and Lemaître 2014). A GSA should be performed if the objective is to identify the important input/model parameters influencing the model output under uncertainty (Borgonovo and Plischke 2016). GSA is performed using various approaches, for example, the standard regression coefficients (SRC) (Saltelli et al. 2008), the extended FAST method (Saltelli et al. 1999), the Morris screening method (Morris 1991), and the Sobol indices (Sobol 2001). Vanrolleghem et al. (2015) preferred the extended FAST over the SRC and Morris screening method for water quality simulations using a conceptual model, and stated that the extended FAST method provided an overall better compromise between the computational burden and the results' reliability. However, for a water quantity output, they concluded that the Morris screening provided the same results as the extended FAST method with approximately 57% fewer simulations required for convergence, satisfying a 3.5% precision threshold band. Kroll et al. (2016) further demonstrated that the Morris screening performed on a par with the extended FAST method in ranking the influence of parameters on the CSO volume.

It can be concluded that Morris screening is an appropriate method for performing the GSA because it is computationally cheap and it performs at a level similar to more computationally expensive methods. The Morris screening method uses multiple one-at-a-time (OAT) perturbations of the inputs/parameters to derive the sensitivity measures. Morris screening as a GSA method can be used to identify the inputs/parameters affecting the model output variance, which can greatly reduce the uncertainty in the model output. In addition, it allows fixing the values of those inputs/parameters that are noninfluential and do not affect the model output uncertainty if they are varied across their uncertainty range.

Data: Global Sensitivity Analysis

The input/model parameters selected for the GSA were the initial loss value, fixed runoff coefficient for impervious surfaces, Colebrook-White (CW) roughness in the pipes, headloss coefficient in the pipes, the primary and secondary discharge coefficients of the weir, the weir crest level, and the weir width in the CSO. These parameters were selected because they were expected to influence the flow quantity from the catchment surfaces, the flow in the pipes, and the flow over the weir at the CSO structure, thus overall affecting the estimation of the CSO spill volume.

A GSA using the Morris screening method for this catchment was first outlined in Sriwastava et al. (2016). The frictional hydraulic losses in the pipes were represented by the CW roughness (k_s). In this study, the upper bound was set at 6 mm (Lind 2015), but the roughness may reach higher values due to the sediment deposition or major pipe defects [discussed in CW roughness (k_s)]. During the GSA, the CW roughness values of all the pipes were varied simultaneously. Because the measured data on the initial losses to runoff in the Herent catchment were not available, these values were obtained from studies that modeled the runoff from residential urban catchments. Thorndahl et al. (2006) reported a range of 0.4–1.0 mm for initial loss values, whereas Vanrolleghem et al. (2015) considered a range of 0.22–1.5 mm. A conservative estimate of the uncertainty in the initial loss values from Vanrolleghem et al. (2015) was used for the Herent catchment. The calibrated model had its fixed runoff coefficient set at 0.8 for the impervious surfaces, which was found to be in accordance with the runoff coefficient values for streets and roofs (BASMAA 1999; McCuen 1998). Because the fixed runoff coefficient represents the effects of a natural random process, it was assumed to have a symmetrical variation around the value of 0.8, which resulted in a physical upper limit of 1.0 and a lower bound of 0.6. In InfoWorks CS, the extra headloss due to the angle of approach of a pipe to a manhole was represented by a headloss coefficient. The default value of this multiplying factor was 1, which meant no additional headloss due to the angle of approach. The headloss coefficient values could increase up to 6.6 for an angle of approach at 90° to the flow direction, which was taken as its upper bound, with the lower bound set at 1.0. The experimentally determined values for the weir discharge coefficient from the British (BS) and International (ISO) standards [BS ISO 1438:2008 (BS EN 2008)] were used to define a range for the primary discharge coefficient of the weir at the CSO structure. The InfoWorks CS model used an additional discharge coefficient, termed a secondary discharge coefficient, when the water level reached the roof of the CSO. The authors considered a symmetrical range of ±50% for the secondary discharge

Table 1. Morris screening results and ranking of input/model parameters

Parameter	Absolute mean (μ^*)	Standard deviation (σ)	Rank
Fixed runoff coefficient	0.974	0.055	1
Weir crest level	0.196	0.019	2
CW roughness	0.098	0.048	3
Headloss coefficient	0.019	0.008	4
Primary weir discharge coefficient	0.001	0.002	5
Weir width	0	0	6
Initial loss value	0	0	7
Secondary weir discharge coefficient	0	0	8

coefficient, as it included the discharge coefficient values given in the British, European (EN), and International standards [BS EN ISO 5167-2:2003 (BS EN 2003)]. The weir crest level and width were varied by ± 10 cm to account for potential measurement errors.

For the GSA, the parameter values were sampled from a uniform distribution within their respective ranges.

Morris Screening Results

Table 1 presents the results of the Morris screening in the form of the Morris screening sensitivity measures, the absolute mean (μ^*), and the standard deviation (σ) (Campolongo et al. 2007). Higher values of μ^* suggest a higher influence of the model parameters on the model output, and a high value of σ suggests a nonlinear relationship or interactions with other parameters. The ranking of the parameters was based on their respective μ^* values. The fixed runoff coefficient was found to be the single most important parameter; it also had a high standard deviation, suggesting a dependence on other parameters. The weir crest level was identified as the second most significant parameter, followed by the CW roughness, which also had a relatively higher standard deviation. The model output was found to be insensitive to the remaining parameters.

Previous studies (Vanrolleghem et al. 2015) have defined a cutoff threshold of $\mu^* = 0.1$ in selecting the important parameters to be included in the uncertainty analysis. On the basis of this guidance, the fixed runoff coefficient, weir crest level, and CW roughness were selected for inclusion in the uncertainty quantification and propagation analysis.

Characterization of Uncertainty in Input/Model Parameters

This section describes the process of uncertainty quantification for the selected significant input/model parameters.

Fixed Runoff Coefficient (Impervious Surfaces)

The calibrated model calculated runoff from the impervious surfaces using a fixed runoff coefficient of 0.8 to represent the runoff losses. This value was in accordance with McCuen (1998), which recommended a value of 0.85 for roofs, 0.80 for brick pavements, and 0.85 for asphalt and concrete pavements. McCuen (1998) suggested the typical ranges of the runoff coefficient to be 0.75–0.95 for roof surfaces and 0.70–0.95 for asphalt and concrete pavement. It was stated that these values were applicable for events with 5- to 10-year return periods and that higher values of the runoff coefficient should be considered for less frequent, higher-intensity events.

In the absence of field measurements, any continuous probability distribution type can be assumed to represent the uncertainty in the fixed runoff coefficient. Because runoff from the catchment surfaces is a natural process and there was no available information about the mode of the distribution, a symmetrical normal distribution with the mean value of 0.8 was selected. The assumed normal distribution was truncated at the upper physical limit for the fixed runoff coefficient, that is, 1. Because the composite design storm used in this study had a much lower return period than 5- to 10-years, values smaller than 0.70 should be taken into account in the fixed runoff coefficient. A standard deviation of 0.1 was assumed, with the mean of the normal distribution set at 0.8. The normal distribution was truncated with a lower bound 0 and upper bound 1.

Weir Crest Level

The absolute weir crest level was set at 35.35 m (at 1.6-m elevation with respect to the bottom of the pipe upstream to the weir) in the calibrated model based on survey data. The measurement errors in surveying the weir crest level can be assumed to have a random variability. Hence, a symmetrical normal distribution was used to represent the uncertainty in the measurement of the weir crest level. The standard deviation of the normal distribution was chosen on the basis of a range of ± 10 cm for the potential error in estimating the weir crest level, so that $3\sigma = 10$ cm.

Colebrook-White Roughness (k_s)

The uncertainty in the CW roughness was quantified using long-term flow survey data. This data set was used to estimate the probability distributions of the CW hydraulic roughness parameter.

Colebrook-White Equation. The CW equation for flow in partially filled circular pipes (Swaffield and Bridge 1983) can be written

$$\frac{1}{\sqrt{f}} = -2\log_{10}\left[\frac{k_s}{14.83R} + \frac{2.52}{\mathsf{R}\sqrt{f}}\right] \quad (1)$$

where f = Darcy-Weisbach resistance constant; k_s = CW roughness parameter (m); R = hydraulic radius (m); and R = Reynolds number. For partially filled circular pipes, the hydraulic radius R can be calculated using the diameter of the pipe D and the measured flow depth h. If a cross section of the circular pipe was considered with θ as the angle made by the intersection of the water surface and the circumference of the pipe at the center of the circular cross section, the hydraulic radius R can be expressed (Barr 1986)

$$R = \frac{D(\theta - \sin\theta)}{4\theta} \quad (2)$$

The Darcy-Weisbach resistance constant f was calculated using the Chezy equation given in Swaffield and Bridge (1983), which argued that it can be applied for moderately smooth channels. The f can be expressed

$$f = \frac{8gRS}{V^2} \quad (3)$$

where V = mean velocity of flow (m/s); S = hydraulic gradient; and g = acceleration due to gravity (m/s^2). The slope of the pipe was taken to be the hydraulic gradient, as uniform flow conditions were assumed at the measurement locations during the dry-weather period. For wet-weather conditions, the rapidly changing nature of the flow would result in a nonuniform flow. This would also mean that the assumption underlying the CW equation would be invalid. The Reynolds number was calculated

$$\mathsf{R} = \frac{4VR}{\nu} \quad (4)$$

where ν = kinematic viscosity of water (m^2/s). The inclusion of R in this equation made the calculation of R suitable for partially filled circular pipes. The year-round average temperature of wastewater in the Flanders region was taken as 15°C on the basis of the in-sewer temperature observations collected in the study by Abdel-Aal et al. (2015). The value of the kinematic viscosity of water ($v = 1.139 \times 10^{-6}$ m^2/s at 15°C) was used for the wastewater.

Data. There were long-term measurements of the flow depth (m), velocity (m/s), and derived flow rate (m^3/s) from 9 different locations in the catchment. Table 2 presents a summary of the data set. The data set was filtered to identify the suitable monitoring locations and periods for the calculation of the hydraulic roughness, as defined in Eq. (1). Eq. (3) assumed that the pipe slope was equal to the hydraulic gradient and hence selected the monitoring locations needed to have uniform flow conditions. On the basis of this criterion, the data from locations M1 and M6 were found to be unsuitable because the invert levels of the two connecting pipes were different. M2 and M109 were discarded due to 0 or near-0 pipe slope values; M4 was discarded due to the presence of a pipe junction (making nonuniform flow likely); and M8 and M9 were discarded due to slope and pipe diameter changes close to the measurement section.

For the locations M3 and M5, a data-filtering procedure was followed to remove the erroneous data and extract only the dry-weather flow measurements. The process for data selection consisted of the following steps.

1. Ensuring reliable flow measurements: The data was filtered to remove water depths less than 0.02 m (the minimum submerged depth of the sensor) and the negative velocity readings caused by backflow or probe malfunction.
2. Removing wet-weather flow periods: The calculation of the CW roughness requires estimation of the hydraulic gradient in the sewer pipe [Eqs. (1) and (3)]. In a hydraulic resistance equation such as the CW equation, the key assumption is a uniform flow, that is, S has the same value all along a pipe. Hence, only dry-weather flow measurement data was used, with an assumption that flow in the pipe would be uniform during dry weather. This enabled using the slope of the pipe as a proxy for the hydraulic gradient. For wet-weather conditions, the rapidly changing nature of the flow would result in nonuniform flow. This would also mean that the assumption underlying the CW equation would be invalid. A regular survey of these measurement locations in the sewer network indicated little evidence of sedimentation. Hence, it was anticipated that the calculation of CW roughness using dry-weather flow measurements would not be an overestimation in this particular case. Dirckx et al. (2009) reported a threshold of the 70th percentile to identify the number of rain days through a standardized cumulative curve of daily inflow. The rain days were described as the days with a surface runoff contribution. Because the study by Dirckx et al. (2009) was also based in Flanders, Belgium, where the catchment from the current study is located, a threshold of the 70th percentile on the daily average flow depth values was assumed to remove the wet-weather days. In order to apply the threshold, percentiles of the daily average flow depth values were obtained for the whole duration of the flow survey.
3. Identifying blockage of the sensors: Blockage of the sensors can result in fluctuations in errors. These can be identified through substantial variations in the daily average flow trend. These variations remain stable for some time ranging from a few hours to 1–2 days. These anomalies along with the instrumentation errors were identified using the covariance values between the flow depth and the velocity.
4. Outlier detection: Outliers were identified and removed using a covariance method between the flow velocity and the flow depth values. In uniform flow conditions, the water depth and flow velocity in the pipes are expected to have a positive correlation. Flow measurements displaying any discrepancy in this relationship might arise from a blockage or malfunctioning of the sensors.

The study used the robustcov function available in MATLAB R2016a software. The robustcov function uses the minimum covariance determinant (FAST-MCD) method (Rousseeuw and Van Driessen 1999) to generate robust estimates of bivariate location and scatter. Nguyen and Welsch (2010) and Peña and Prieto (2001) argued that the FAST-MCD method provides a better estimate of multivariate location and scatter than other classical methods such as the maximum likelihood estimation-based methods, because such methods rely on the assumption of normality in the data and the presence of outliers induces a bias to such estimators. In order to detect outliers, the Mahalanobis distance values were calculated using the robust covariance estimates that follow a chi-square distribution (Filzmoser et al. 2005). In this bivariate case, the Mahalanobis distance values had two degrees of freedom and the outliers were identified by setting a cutoff of the 97.5% quantile of the chi-square distribution. The data validation resulted in an approximately 55% removal of data for measurements taken at the location M3 and a 41.6% removal of data at the location M5.

Distribution of Calculated k_s Values. The k_s values are calculated from the filtered data at the locations M3 and M5 using Eq. (1). Figs. 1(a and b) show the histograms of the k_s values calculated at the locations M3 and M5. It was clear that the k_s values at these locations followed a heavy-tailed probability distribution (Fig. 1). Hence, a variety of continuous heavy-tailed distribution types such as gamma, generalized pareto, loglogistic, lognormal and Weibull distributions were tested to identify the most appropriate distribution type to describe the CW roughness. Because the flow survey durations at the two locations were different, the best-fitted probability distributions were obtained independently for each location. The R software package fitdistrplus was used to fit these distributions using the maximum likelihood estimation (Delignette-muller

Table 2. Details of flow survey data

Location name	Measurement start date	Measurement end date	Pipe shape	Pipe dimensions (mm)	Pipe material	Pipe slope (m/m)
M109	August 25, 2015	January 24, 2016	Circular	1,000	Concrete	0.00011
M9	January 9, 2009	September 16, 2015	Circular	800	Concrete	0.00094
M8	January 9, 2009	January 24, 2016	Circular	500	Concrete	0.00135
M6	November 22, 2007	January 9, 2009	Circular	800	Concrete	0.00074
M5	August 10, 2005	January 25, 2016	Circular	600	Concrete	0.00088
M4	August 17, 2005	January 9, 2009	Circular	1,000	Concrete	0.00250
M3	March 14, 2005	January 8, 2009	Circular	1,400	Concrete	0.00389
M2	March 14, 2005	August 10, 2005	Circular	500	Concrete	0.00000
M1	March 14, 2005	May 30, 2005	Circular	970	Concrete	0.00133

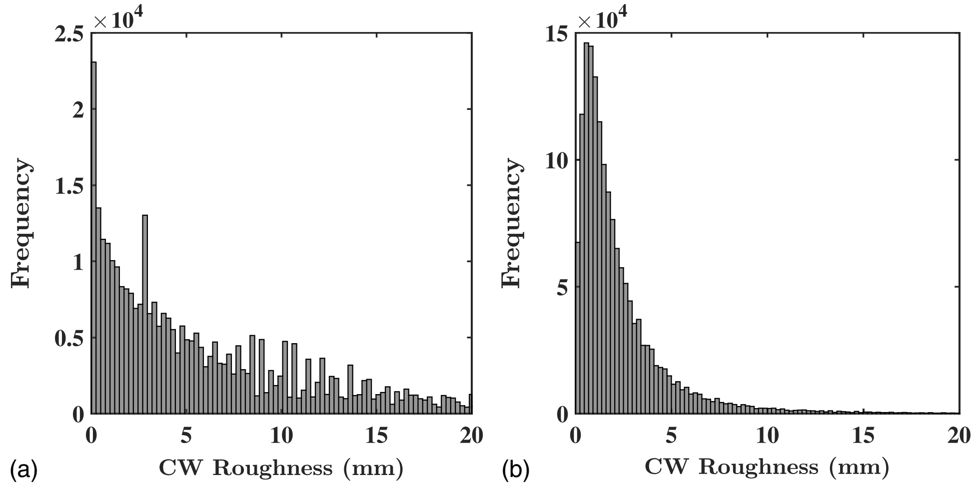

Fig. 1. Histograms of k_s calculated at location: (a) M3; and (b) M5.

and Dutang 2015). The Bayesian information criterion (BIC) was used as the goodness-of-fit statistic because the BIC avoids overfitting by penalizing distributions with a greater number of parameters and also because the use of the maximum likelihood as the estimation method is consistent with the BIC because it is based on the log-likelihood (Vose 2010). A lower BIC value was considered a better fit. Table 3 provides the results of the distribution fitting for the two locations, with the rank in parentheses. For both M3 and M5, the loglogistic distribution provided the best fit with the lowest value of the goodness-of-fit statistic BIC (Table 3). This suggested consistency in the form of the uncertainty for the CW roughness parameter. However, in order to propagate this uncertainty in InfoWorks CS simulations, a single probability density function (PDF) for k_s was needed. Between the two locations, the loglogistic distribution parameters obtained for the location M5 were assumed to represent better the uncertainty in the CW roughness due to the considerably longer flow survey (10 years) at this location.

However, in reality, the CW roughness of each pipe may follow a loglogistic distribution with different parameters, similar to the M3 and M5 locations. Table 4 provides the parameters of the loglogistic distribution for the CW roughness values calculated at M3 and M5. The PDF of the two-parameter loglogistic distribution can be written

$$f(x;\alpha,\beta) = \frac{\left(\frac{\beta}{\alpha}\right)\left(\frac{x}{\alpha}\right)^{\beta-1}}{\left(1+\left(\frac{x}{\alpha}\right)^{\beta}\right)^2}, \qquad x > 0 \tag{5}$$

where $\alpha > 0$ was the scale parameter and represented the median of the distribution; and $\beta > 0$ was the shape parameter.

Table 3. Distribution fitting BIC values for k_s

Probability distribution(s)	Bayesian information criterion	
	M3	M5
Gamma	3,239,694 (5)	5,764,741 (3)
Generalized pareto	3,098,093 (2)	5,792,316 (5)
Loglogistic	3,097,110 (1)	5,705,864 (1)
Lognormal	3,110,213 (3)	5,745,767 (2)
Weibull	3,157,747 (4)	5,787,913 (4)

Note: Ranking of distributions for fitting k_s values is provided in parentheses.

Uncertainty Propagation

The PDF of the output CSO spill volume can be calculated via propagation of the input/model parameter distributions defined in the previous sections through Monte Carlo simulations. In Flanders, the design criteria for the CSO include a threshold on the annual overflow frequency (Dirckx et al. 2011). A composite design storm f7 was selected as the rainfall input instead of the historical rainfall data in order to reflect the design guidelines set by the Flanders Environment Agency (VMM) (Coördinatiecommissie Integraal Waterbeleid 2012). The VMM regulations for CSO structures state that the CSO should not spill for the specific design storm f7. The composite design storm event f7 had an average frequency of occurrence of 7 times per year. The composite storm was developed by Vaes et al. (1996) using a historical rainfall series from 1967 to 1993 with a time step of 10 min measured at the rain gauge at Uccle in Belgium. For a frequency of 7 years, all intensity/duration relationships were included in the single composite f7 design storm.

Monte Carlo simulations with LHS were performed considering the parameter distributions of the fixed runoff coefficient (rc), weir crest level (wc), and CW roughness (k_s) and keeping other parameters constant as defined in the calibrated model. To draw n samples using the LHS method, the uncertain range of each input/model parameter was divided into n intervals of equal probability. This was followed by drawing a random sample from each of these n intervals. Assuming that the input/model parameters were independent of each other, the n samples for the individual input/model parameters were combined randomly to generate the sample space (Helton and Davis 2003). For the Latin hypercube sampling, the function randomLHS in the R package lhs was used to draw the samples.

The sufficiency of the sample size was tested by analyzing the convergence of the respective sample mean, standard deviation, scale, and shape parameter estimates (Fig. 2). Figs. 2(a, b, d, and e) show the convergence in the sample mean and the sample

Table 4. Parameters of fitted loglogistic distribution

Location	α (mm)	β
M3	6.035	0.926
M5	1.490	1.749

standard deviation for the fixed runoff coefficient and the weir crest level; the sample size was increased from 50 to 2,000. Figs. 2(c and f) show a plot of the variation in the sample scale and shape parameter, respectively, for the loglogistic distribution fitted for CW roughness. It was evident that a stable convergence (0.5% of the maximum variation) was achieved with a sample size of 1,000 for all three parameters. Hence, a sample size of 1,000 using Latin hypercube sampling was considered sufficient.

The uncertainty propagation was performed in two steps. First, the uncertainty in the three selected parameters was propagated through 1,000 simulations, resulting in 1,000 values of the model output CSO spill volume for the defined design storm. In the second step, the contribution of the individual parameters toward the overall uncertainty in the CSO spill volume was assessed by propagating the uncertainty in only two parameters and keeping the third parameter constant. Here, the term *overall uncertainty* means the uncertainty in the CSO spill volume caused by the uncertainty in all three parameters.

Results and Discussion

Overall Uncertainty

Fig. 3(a) shows the PDF of the CSO spill volume obtained as a result of propagating the uncertainty in the fixed runoff coefficient, weir crest level, and CW roughness. The calculated CSO spill volume values were described by a normal distribution truncated at 0 as the lower bound [Fig. 3(a)] with the mean 117.9 m^3 and standard deviation 50.8 m^3. The exceedance probability (EP) curve [Fig. 3(b)] gives the information about the probability that the CSO spill volume exceeded a certain value with the f7 design storm. The slope of the EP curve can be used to find the rate of reduction in the risk from spills when additional storage capacity was planned upstream of the CSO. The benefit of adding extra storage capacity was less for the plot regions where the slope of the EP curve was high. As shown in Fig. 3(b), there was a 50% probability that the CSO spill volume would exceed 116.9 m^3; however, to ensure that the system capacity was exceeded with a probability of only 10%, the total required basin storage volume was only 184.4 m^3. This meant that the practitioner was likely to reduce the probability of a CSO spill from 50 to 10% by investing in additional basin storage in a quantity as small as 67.5 m^3. Therefore, by incorporating uncertainty into the model-based performance evaluation of the CSO, the practitioners could achieve greater protection against the risk of CSO spills with efficient investment.

Contribution of Individual Parameters

Additional Monte Carlo simulations were performed to propagate the uncertainty in any two out of the three selected parameters. The value of the third parameter was kept constant, as in the calibrated model. This resulted in three distinct scenarios: the fixed runoff coefficient + CW roughness ($rc + k_s$), the fixed runoff coefficient + weir crest level ($rc + wc$), and the weir crest level + CW roughness ($wc + k_s$). Fig. 4 shows the PDFs obtained for the CSO spill volume in the three cases and the PDF representing the overall uncertainty shown in Fig. 3(a). Although the PDFs shown in Fig. 4 represented an underestimation of the overall true uncertainty in the CSO spill volume, they provided very useful insights for decision making. For example, comparing the PDFs from the two-parameter uncertainty propagation with the PDF from the three-parameter uncertainty propagation [Fig. 3(a)] gives information on how much each parameter affects the overall uncertainty in the modeled CSO spill volume.

Similarly to the overall uncertainty in the CSO spill volume [Fig. 3(a)], the uncertain pairs $rc + k_s$ and $rc + wc$ resulted in a

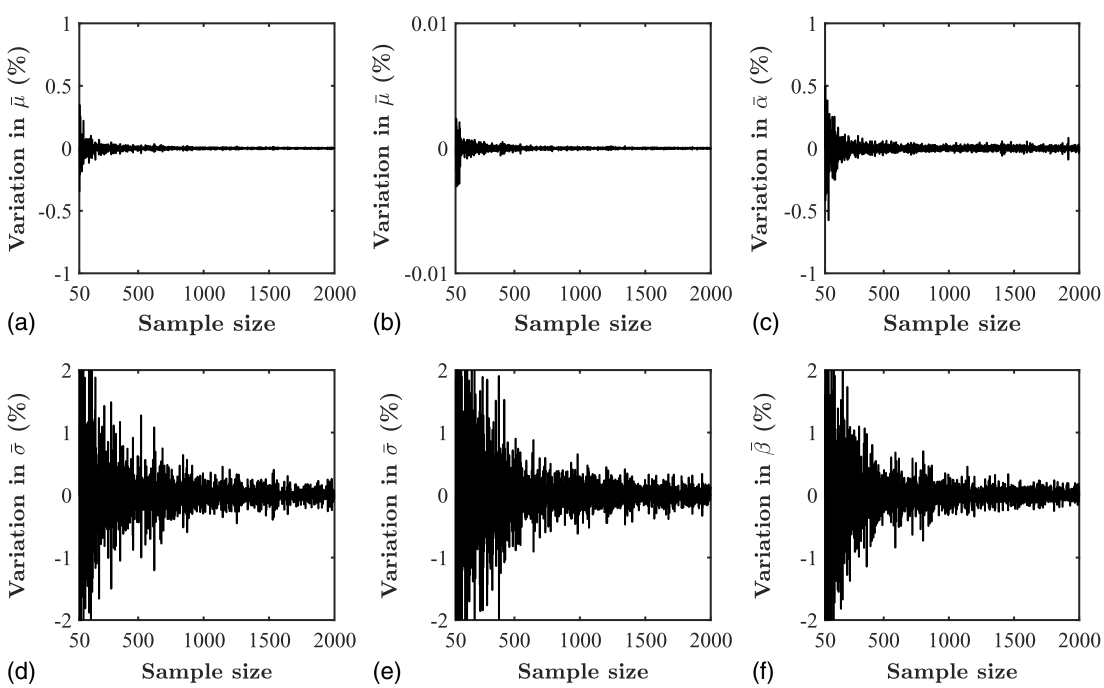

Fig. 2. (a and b) Variation (expressed in percentage) in the sample mean for fixed runoff coefficient and weir crest level; (c) sample scale parameter $\bar{\alpha}$ (median) for CW roughness; (d and e) sample standard deviation for fixed runoff coefficient and weir crest level; and (f) sample shape parameter $\bar{\beta}$ for CW roughness with increasing sample size.

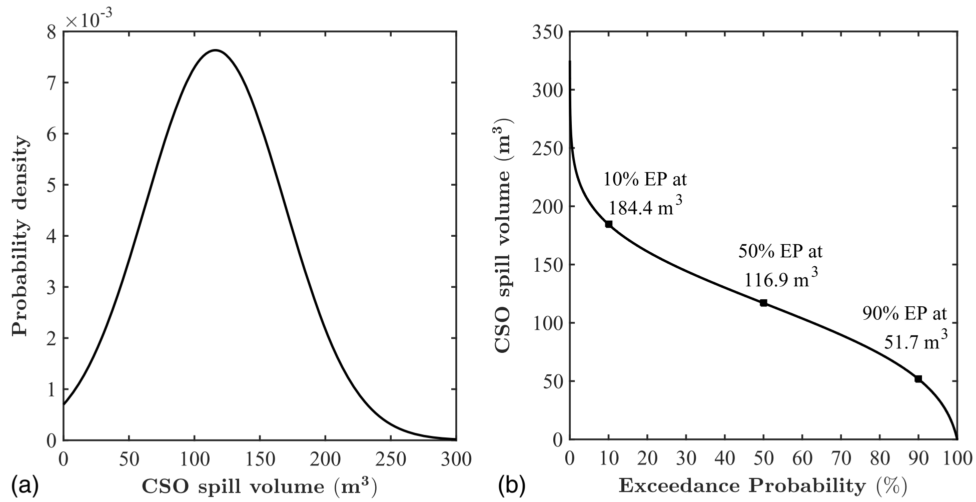

Fig. 3. (a) Probability density curve of CSO spill volume representing the overall uncertainty; and (b) exceedance probability curve for CSO spill volume.

normally distributed CSO spill volume with the left tail truncated at 0; however, the uncertainty in the CSO spill volume caused by the pair $wc + k_s$ was found to be best described by a Weibull distribution. Table 5 presents a summary of the results of these three scenarios and the overall uncertainty, in the form of the mean and standard deviation obtained for the CSO spill volume. The PDF of the CSO spill volume with a constant weir crest level, $rc + k_s$, was almost identical to the overall uncertainty PDF, which suggested that the effect of uncertainty in the estimation of the weir crest level was negligible on the overall uncertainty in the CSO spill volume. Similarly, when the uncertainty in the CW roughness was introduced, its contribution to the uncertainty in the CSO spill volume was found to be insignificant. Therefore, it can be deduced that the contribution of the CW roughness to the overall uncertainty was of a similar magnitude to that of the weir crest level. This meant that the ranking obtained as a result of the Morris screening was not clearly evident in the uncertainty quantification results for the input/model parameters with low Morris sensitivity measures. In the GSA, only the absolute mean μ^* was used to rank the parameters. The sensitivity measure, standard deviation σ, of the CW roughness in the GSA analysis was higher than that of the weir crest level, which indicated that roughness had a nonlinear relationship with the CSO spill volume and/or it interacted with other parameters to a higher degree than the weir crest level did. Therefore, the significance of σ as an indicator of the contribution of input/model parameters to the output uncertainty needs to be investigated further, so that the relative importance of the input/model parameters with low sensitivity measures, such as the weir crest level and CW roughness, can be quantified.

It was evident from Fig. 4 and Table 5 that the fixed runoff coefficient was the largest contributor to the overall model uncertainty in the CSO spill volume. Assuming that the true value of the fixed runoff coefficient was known, the CSO spill volume followed a Weibull distribution with a considerably smaller standard deviation. In this case, there was a 50% probability that the CSO spill volume would exceed 119.4 m^3, which was close to the value of 116.9 m^3 at a similar probability in the case of the overall uncertainty. However, to reduce the risk of CSO spills from 50 to 10%, additional storage of at least 14.3 m^3 was required. This required additional storage was significantly smaller than the required additional storage of around 67.5 m^3 when the overall uncertainty was considered for decision making.

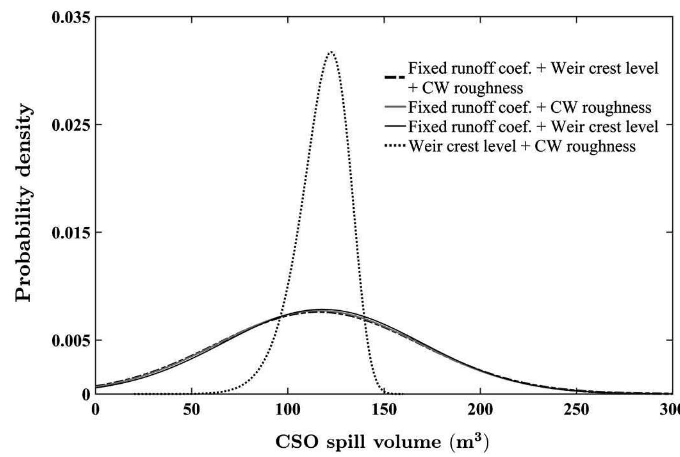

Fig. 4. PDF curves of CSO spill volume representing the uncertainty in the combinations of the fixed runoff coefficient, weir crest level, and CW roughness; fixed runoff coefficient and CW roughness; fixed runoff coefficient and weir crest level; and weir crest level and CW roughness.

Table 5. Summary of uncertainty analysis results

Parameter	Probability distribution type	Mean (m^3)	Standard deviation (m^3)
Weir crest level + CW roughness	Weibull	117.9	13.4
Fixed runoff coefficient + CW roughness	Truncated normal	117.9	50.3
Fixed runoff coefficient + weir crest level	Truncated normal	119.5	49.6
Fixed runoff coefficient + weir crest level + CW roughness	Truncated normal	117.9	50.8

With this additional available information on the individual contributions of the input/model parameters, a practitioner might evaluate the trade-offs between investing resources in reducing the uncertainty in the estimation of important parameters and investing in larger basin storage to cope with the overall uncertainty. For example, the uncertainty in the estimation of the runoff coefficient could be reduced by gathering more information on the runoff surfaces through a survey campaign. The usefulness of such a campaign could be assessed by comparing the cost of the survey and the benefit gained as a result of the smaller basin storage required.

Conclusion

This paper demonstrated a methodology to incorporate probabilistic uncertainty in a standard modeling procedure used by a water utility to conform to regulatory guidelines. The physical characteristics of different subprocesses such as rainfall-runoff, in-sewer flow, and weir flow were represented as potential sources of model uncertainty. Morris screening identified the fixed runoff coefficient, the weir crest level, and the CW roughness as the most significant parameters. Following the Morris screening, the authors were able to propagate the uncertainty in the three most significant parameters through Monte Carlo simulations using Latin hypercube sampling and to quantify the uncertainty in the CSO spill volume. Both Morris screening and LHS based Monte Carlo simulations proved to be reliable methods and easy to implement within the constraints of the modeling guidelines. Because the InfoWorks CS model and the rainfall input used in this study satisfied the regulatory modeling guidelines, any random sample from the probability distribution of the CSO spill volume obtained as a result of the uncertainty propagation could be used to represent the performance of a compliant CSO.

For the CW roughness, this paper demonstrated a process to quantify the parameter uncertainty using extensive flow survey data. The CW roughness values were found to have a heavy-tailed distribution, and a loglogistic distribution was found to be the best fit. This study is the first in which the uncertainty in the CW roughness for sewer pipes has been defined on the basis of in situ field measurements. It is expected that the probability distributions obtained for the CW roughness in this paper are representative and that their distribution shape and spread can be used in future studies.

The resulting uncertainty in the CSO spill volume indicated that the impact of uncertainty in the fixed runoff coefficient was much higher in comparison with the other parameters, which was in agreement with the results obtained from the global sensitivity analysis. It is imperative that the uncertainty in such dominating parameters should be carefully defined and quantified, as it was demonstrated in this study that the shape of the probability density function for the fixed runoff coefficient largely influenced the shape of the uncertainty in the model output CSO spill volume.

After the uncertainty in the CSO spill volume has been quantified, the results can be processed to be used for decision-making purposes. For example, the information available from the exceedance probability curve for the CSO spill volume can be used to develop a trade-off analysis between the provision of additional storage volume and the consequent risk of predicted spill volumes given this additional storage volume, while considering any budget constraints. In this study, the risk of the predicted spill volume's exceeding the storage capacity could be reduced from 50 to 10% by increasing the provision of additional storage from 116.9 to 184.4 m^3.

However, it should be noted that the uncertainty in the CSO spill volume obtained through this study is still an underestimation of the overall modeling uncertainty in the CSO spill volume, as only a small number of the more significant sources of uncertainty were considered. This study used a single design rainfall event in order to follow the requirements of the local environmental regulator; however, to capture the dynamics of the rainfall-runoff process, the spatial and temporal variability of the rainfall should also be represented in the uncertainty propagation. This would require changes in the current regulatory framework. Furthermore, the runoff from the permeable areas is not taken into account; it is assumed that it infiltrates the soil, but this may not be the case when there have been extensive antecedent wet weather conditions. Therefore, this is another source of uncertainty not taken into account in the current modelling approach; as stated, the paper aimed only to quantify uncertainty in the current approach.

Another possible future line of investigation could be the use of analytical probabilistic urban drainage models (Adams and Papa 2000) as an alternative to the practice of computationally expensive urban drainage models. This would require a change in the way water utilities are regulated in Belgium and other European countries where, as far as the authors are aware, the regulatory framework does not permit the use of probabilistically based modeling approaches. Therefore, it is expected that the water utilities may be able to adopt the methodology demonstrated in this paper to account for model uncertainty as they comply with the modeling requirements of their regulator.

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