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Improving Urban Drainage Infrastructure Model Calibration and Reducing Uncertainty in Outputs

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1. Introduction

The design and development of urban drainage infrastructure relies heavily on modeling. It calls for a deep familiarity with fluid dynamics and the hydrologic behavior of the drainage region. Models in the fields of hydrology, hydraulics, and water quality do not provide faithful representations of the real-world processes. Instead, they are approximations of real-world processes that are grounded in either observed data or a system of equations and parameters. Consequently, model calibrations are essential for achieving the desired level of accuracy in the model's output. An assortment of elements determine the uncertainty in the model's output (Freni et al., 2009; Gaume et al., 1998; Giudice et al., 2013; Saltelli et al., 1995; Urbonas, 2007). In modelling literature, numerous publications show that the importance of considering different sources of uncertainties during urban drainage infrastructure modelling (e.g. Bertrand-Krajewski et al., 2003; Kleidorfer et al., 2009b; Overeem et al., 2008), hydrology of natural catchments (e.g. Beven, 2007; Beven and Binley, 1992; Beven and Freer, 2001; Carpenter and Georgakakos, 2004; Engeland et al., 2005; Fang, T and Ball, JE, 2007; Kavetski et al., 2006a), stormwater quality modelling (e.g. Bertrand- Krajewski et al., 2002; Dotto et al., 2009; Haydon and Deletic, 2009; Kanso et al., 2005; Kleidorfer et al., 2009a; Lindblom et al., 2007), rainfall/runoff modelling (e.g. Lei, 1996; Lei and Schilling, 1996), integrated modelling (e.g. Freni et al., 2009a; Harremoës, 2003; Hoppe and Gruening, 2007; Mannina et al., 2006) and urban drainage modelling (e.g. Arnbjerg-Nielsen and Harremoës, 1996; Deletic et al., 2009; Kleidorfer et al., 2009a; Korving and Clemens, 2005; Rauch et al., 1998b; Thorndahl, 2008; Thorndahl et al., 2008).

The characteristics of model parameters can be examined by applying a Bayesian approach (Markov-chain Monte Carlo Simulation). It has the advantage of not only getting one "best parameter set", but also a distribution of the most likely values of the model parameters (Mailhot et al., 1997; Kuczera and Parent, 1998; Kanso et al., 2003; Kuczera et al., 2006), that enables us to recognize „the most" and „the least" important calibration parameters of a model.

There are also a number of tools that can be used in sensitivity analyses of model parameters, which constructs the probability distribution function (PDF) of model parameters using the Markov chain Metropolis-Hastings approach (Doherty, 2003, Metropolis et al., 1953; Hastings, 1970). This kind of approach has already been used by different researchers and consulting companies to examine parameter sensitivity of stormwater models (e.g. Kanso et al, 2003). Model parameters are not the only source of uncertainties in our models. Input data uncertainties have been also recognized as key problem in accurate modeling (Hoppe & Gruening 2007). Recently estimate shows that the influence of uncertainties in the input data already exceeds the effect of error due to observed data. Much work has been done on propagation of these uncertainties through different model frameworks. Recently, a new framework called total error was proposed by Kuczera et al., 2006 indicating all sources of uncertainties should be propagated at the same time, since they can compensate for each other. However, this approach, has only been tested on flow models in non-urban watershed. The methodology is rather complex, and is yet to be tested for water quality or urban stormwater models. (e.g. Bertrand- Krajewski et al., 2003; Haydon and Deletic, submitted; Kavetski et al., 2006; Korving and Clemens, 2005; Kuczera et al., 2006; Lei, 1996; Rauch et al., 1998).

2. Model Uncertainty

Uncertainty is natural in any modelling process and originates from a wide range of sources, ranging from model formulation to the collection of required data. Uncertainties cannot be eliminated, and therefore it is necessary to understand their sources and consequences for model results. However, at least the confidence level of a model‟s predictions should be included in every modelling application of drainage infrastructure design. As pointed out by Beven (2006) there are many sources of uncertainty that interact non-linearly in the modelling process. Nevertheless, it should be mentioned that not all uncertainty sources can be
„quantified‟, and that the fraction of uncertainty sources being
„ignored‟ might be high in environmental investigations (Harremoës, 2003; Thorndahl, et al. 2008). For instance there are many causes why designers may have poor match to observed values in urban drainage infrastructure modeling results:-

Rainfall: - How big is your watershed? More often than not, the characterization of the rainfall in the basin is where the largest error is. The author would argue that unless we have both rainfall gages and Doppler radar reflectivity data for modeling event, we will have very large uncertainties regarding the rainfall temporal and spatial pattern of the watershed for validation events. This is likely to be one of model user largest problem.

Time of Concentration: - Travel time of runoff from the watershed during an infrequent event will have different characteristics in comparison to a smaller more frequent event. This is because larger events produce higher flow rates with larger velocities in the stream reaches in comparison to smaller events. If the modelers are not using a velocity based method and assuming that T_c is the same for all events that will be also a source of error.

Spatially Variable Infiltration/Interception Characteristics:- This can be describe as how well do the modeler understand the variability in the watershed characteristics for soils, vegetative cover, vegetative cover density, land use, depression storage, etc. below, table-1 shows some of the example of frequently used formulas and possible sources of uncertainty that can affect the modeling output.

Formula name used	Formula	Affected variable	Range under existing condition	Comment
Rational	$Q = CiA$	*i*	Under study	The value of *i* (in/hr) for the design period driven from IDF curve is based on historical recorded data in region. However with increase precipitation or intensity of rainfall due to climate change historical records will no longer reflect current condition which affect the *i* (in/hr) value also.
		C	0.1-0.99	Ground cover imperviousness factor probably will increase depending on location due to urban development during the past year.
Time of concentration (Kinematic Wave)	$t_c = \dfrac{0.93L^{0.5}N^{0.6}}{i^{0.4}S^{0.3}}$	N	0.011-0.8	Manning's overland flow roughness coefficient expected to decrease due to erosion caused by increase flow. Changes will varies depend on location
		i	2%-10% increase for 1,2,3,6,	Due to climate change
Manning's equation for open channel flow	$V = \dfrac{1.49(R^{2/3}S^{0.5})}{n}$	n	0.01-0.20	Roughness coefficient for aging stormwater pipe infrastructure or drainage open channel expected to decrease due to age, deposition of sedimentation or lack of drainage infrastructure maintenance program
Regional regression equation	$Q = aA^{b_1}S^{b_2}$	a, b1,& b2		The value of a, b1 and b2 are based on historical recorded data in region. However with increase precipitation or intensity of rainfall due to climate change historical records will no longer reflect current condition.

Table 1: Example of Frequently Used Formulas and Possible Sources of Uncertainty That Can Affect the Modeling OutputWhen dealing with complex urban drainage models, calibration may lead to several equally plausible parameters sets, reducing confidence in the modelled results (Kuczera & Parent, 1998)

The concept that a unique parameter set exists should be replaced by the equifinality concept (Beven, 2006), which states that more than one parameter set may be able to provide a good fit between simulated and measured data. Many published studies have dealt with the impact of uncertainties in model parameters, also known as sensitivity analysis (Dotto et al., in press; Kanso et al., 2003; Thorndahl et al., 2008; Umakhanthan, K and Ball, JE, 2002). Some use the results of a model sensitivity analysis to produce parameter Probability Distributions (PDs) which reflect how sensitive the model outputs are to each parameter, while others just use the result to screen parameters. Others use the model sensitivity results to estimate confidence intervals around a model‟s prediction. Impacts of input data uncertainties on urban drainage modelling are far less understood, although their importance is widely studied in other areas (Kuczera et al., 2006). For example, the impact of systematic rainfall uncertainties on the performance of non- urban catchment models are recognized (e.g. Haydon & Deletic, 2009). Some work has been done on the propagation of input data uncertainties through urban drainage models (Bertrand-Krajewski et al., 2003; Korving & Clemens, 2005; Rauch et al., 1998). Deletic et al. 2009) classify uncertainties related to urban drainage modelling in a bit different way as described in table-2 below:

Uncertainties Related To Urban Drainage Mc delling		
Model input uncertainties related	Calibration uncertainties related	Model structure uncertainties related
Measured input data	Measured calibration data uncertainties	Conceptualization errors
Estimated input data	Measured calibration data availability and choices	Numerical methods and boundary conditions
Model parameters	Calibration Algorithms	
Professional skills	Criteria Functions	

Table 2: The General Classification of Model Output Uncertainties Related to Urban Drainage Simulation

3. Model Calibration

Model calibration is the process of estimating the values of the model parameters so that the model responses satisfactorily simulate the behavior of the modelled system. This process is also called “model optimization”, because its scope is the reduction of the model error. It is also defined as “inverse modelling”, since the observations of the model outputs are used to estimate the parameter values, as opposed to direct modelling, in which fixed parameter values are used to estimate the model outputs (Beck 1987; Choi, KS and Ball, JE, 2002; Willmot, 1881).

The process of model calibration involves changing the estimated input variables so that the output variables match well with observed results under similar conditions. The process of checking the model against actual data can vary greatly in complexity, depending on the confidence needed and the amount of data available. In some cases, the only feasible or necessary action may be a simple “reality check,” using one or two data points to verify that the model is at least

providing results that fall within the proper range. In other cases, it may be necessary to perform a detailed model calibration, Whereare the averages of observed and
model goodness-of-fit is judged by the modeler by visual comparison of the simulated responses with the observed variables and/or using classical mathematical measures of model performance such as the root mean squared error, the correlation coefficient and similar (see equation 1-6). Manual calibration method has the disadvantages of being time consuming, and required high degree of expert knowledge of the model as well as the system. Automatic calibration is more effective and efficient procedures and is based on numerical optimization methods (Ball, JE, 2009, Bertrand et al. 2003, Korving, & Clemens, 2005).simulated measurements at space-time point n, calculated from all available data (observation and multiple simulation run). These two statistics are most useful when applied separately to measurements at each time–space point rather than to all measurements jointly. This way they provide insight to the spatial and temporal distribution of errors and help identify deficiencies in the model.

Another measure that provides information on the relative error are the Coefficient of Determination (r^2), and Nash- Sutcliffe efficiency (NSE)

4. Statistical Model Validation

The general simulation literature includes a large number of for the statistical validation of simulation models.
efficiency of lower than zero indicates that the mean value of the observed time series would have been a better predictor than the model.

5. Model Accuracy

6. In spite of improvements in models, model interfaces, and model math engines, accurately and reliably modeling stormwater runoff (i.e. hydrology and hydraulics) and related phenomena remains a challenge (Freni et al. 2009, Gaume et al. 1998, Nix, 1994). Computer models are being used for planning, designing, maintaining, and making decisions on massive drainage infrastructure projects that are worth billions of dollars (Giudice, et al. 2013, Urbonas, 2007). The author and many of his colleagues acknowledged that while most models include some degree of uncertainty, there are several important factors that contribute to this uncertainty in urban infrastructure drainage design models. These include the expertise of the user or modeler, the difficulty in choosing the right model, the availability of reliable calibration data, and many more (Bertrand k. and Bardin, J. P. 2002; Frey, H. C. and Rhodes, D. S. 1998; Helge, D. 2006; Omlin, M. (2000); Reichert, P. and Borsuk, M. E. 2005). In addition, there is a

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Vol-07 Issue-01 Feb 2012

lack of data on the following: how accurate and dependable are the output results? Where does uncertainty come from, and how big is it? Uncertainty in model outputs: how to mitigate it? When less experienced experts are engaged in the modeling and analysis of the results, there are issues with the accuracy of the models. Do people who use models want their models to be accurate and calibrated? It is common practice to compare the model's outputs to the chosen observations for validation and calibration in order to ascertain the model's accuracy.

7. Types of Urban Drainage Models General

Modeling in urban drainage system serves various purposes such as the overall assessment of drainage area response as a part of strategic and master planning to the detailed network and providing necessary support to primary activities such as elements design, assessment of pollution, operational management, real time control and analysis of interactions among sub-systems. The type of model applied depends on the goal of Modeling, spatial coverage, data and technology availability. There are a number of empirical hydrologic methods that can be used to estimate runoff characteristics for the drainage areas. The most commonly used stormwater models can generally be classified as either hydrologic, hydraulic, or water quality models (Giudice, et al. 2013, Gironás, et al. 2010, McColl, & Aggett, 2007, Saltelli, et al. 1995, Umakhanthan, K and Ball, JE, 2005, Zarriello, 1998) and, the general description of those models are as follows:-

Hydrologic models: - are models used to simulate runoff volumes, peak flows, and the temporal distribution of runoff at a particular location resulting from a given precipitation of an event. Hydrologic models are also used to simulate how the drainage area parameters will cause runoff either to flow relatively unhindered through the system to a point of interest, or to design a detention or retention system to route runoff hydrographs through storage areas or channels (Looper, et al.

2012, McColl, & Aggett, 2007, Melching, et al. 1990, Nix, 1994).

Hydraulic models:- are models used to simulate the water surface elevations (HGL), energy grade lines, flow rates, velocities, pipe size and other flow characteristics throughout a drainage network that result from a given runoff hydrograph or steady flow input. The hydraulic model also used for various computational routines such as to route the runoff through the drainage network, which may include channels, pipes, control structures, and storage areas (Mannina & Viviani, 2010, Thorndahl, et al. 2008, Urbonas, 2007).

Water quality models: - are models used to evaluate the effectiveness of an agency recommended best management practices (BMPs), simulate water quality conditions in a lake, stream, or wetland, and to estimate the loadings to water bodies. Often the goal is to evaluate how some external factor (such as a change in land use or land cover, the use of best management practices (BMPs), or a change in lake internal loading) will affect water quality. Parameters that are frequently modeled include total phosphorus, total suspended solids, and dissolved oxygen (Gironás, et al. 2010, Mailhot, et al. 1997, Mannina, & Viviani, 2010, Vaze, & Chiew 2003).

8. Selection of Appropriate Design Model

Models are range from very basic tools with minimal data input requirement, to complex tools that require expertise. In general, the selection of appropriate urban drainage infrastructure models are depends on a number of factors (Mailhot, et al. 1997, Saltelli, et al. 1995, Urbonas, 2007, Zarriello, 1998). Including:-

Desired output (outflow hydrograph, peak runoff rate and volume, pollutant removal, infiltration loss, etc.):- some models can be used to estimates peak runoff rates, but cannot be used to simulate total runoff volumes (Rational Method). In the contrary, other methods can only estimates total runoff volumes. While others, such as the natural resources conservation service (NRCS) model for example, can be used to simulate both total runoff volume and peak rate, and runoff hydrographs.

Scale of project and Drainage Area Size: -because of their assumptions and/or theoretical basis, some models can only use to simulate runoff volumes or rates for drainage areas less than 20 acres, while other methods can be applied for a larger drainage area of 20 square miles or more 9 (Vaze, & Chiew 2003).

The availability of various model input parameters (soil type, topographic etc): - Simple models, such as the modified rational methods, require basic data such as rainfall intensity, runoff coefficient and drainage area, while other, more sophisticated methods have extensive data requirement, including long-term rainfall and temperature data etc.

Level of professional expertise required to perform modeling:

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Vol-07 Issue-01 Feb 2012

- the level of expertise required to perform modeling is the most important factor for both theoretical and practical reasons, compare to less trained professionals in knowledge,

model output analysis, decision-making, and a range of other capabilities.

9. Demonstration Case Study

To demonstrate the project area of this study is located in Astoria Heights more commonly called “Upper Ditmars" a district of the New York City borough of Queens. The study total area is approximately 8.2 ha. Fig.-1 and 2 below shows the general location and drainage map of the study area.

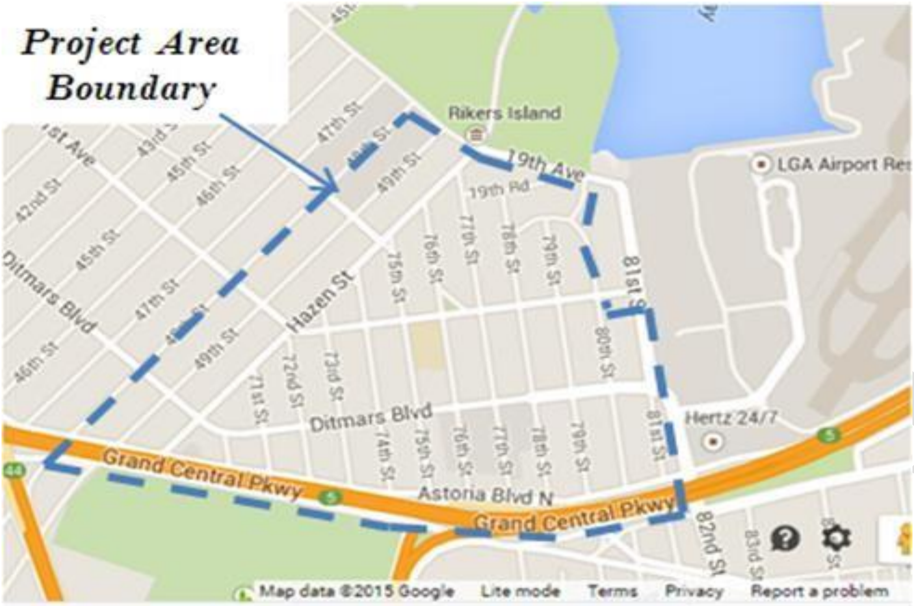

Figure 1: General Location of Study Area

10. Methods and Modeling Approach

Analyzing the configuration of the drainage networks including existing stormwater drainage network; existing stormwater storage and peak flow reduction facilities; and sub-basin drainage delineation was the first stage of the modeling approaches; followed by defining model scenarios and hydrologic characteristics identification such as land use, soil, and roughness coefficient applied for the modeled sub- basins. With the same rainfall event applied to each scenario, the resulting stormwater performance could be compared for the various campus conditions and measured against designated benchmarks. The runoff curve number method was selected for infiltration modeling as the CN values (primary parameter for the curve number method) can be determined more readily, compared to Horton or Green-Ampt parameters, from the land cover and soil maps available for the watershed.

Computer-based SWMM modeling software with Geographic Information System (GIS) add on was used so that land uses and vicinity map locations on the project area were spatially referenced within the modeling environment. Pipes, nodes, and stormwater storage components were input into the model as point and line features with the attributes (i.e. inverts, sizes, and geometry) populated using record drawings that were obtained from previous projects.

The research model calibration involves the adjustment of the primary drainage network model parameters and changing the estimated input variables so that the model output match well or fall within the proper range of observed results (i.e. observed peak flow and water surface elevation data) under similar conditions before and after Model calibration. The study total drainage area is divided into six sub-drainageareas with 97 % impervious. For simulation purpose, the 10 year 24hr rainfall event in accordance with the NYSDOT Highway Design Manual is used. The existing storm runoff is conveyed via a road side curve and gutters through 315mm, 450mm, 560mm, 900mm and 1600mm (12”, 18”, 22”, 36 and 66”) concert pipes.

11. Calibration Strategies

The calibration process adopted for this study involves adjustment of the primary model parameters until the model results of peak flow and water surface elevations at each junction point approximately close to the actual observed value as designed under

International journal of imaging science and engineering

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Vol-07 Issue-01 Feb 2012

similar condition. After the model result and the observed values are in reasonable agreement, and identify which parameters have the most significant impact on the model result output, and thereby identify potential parameters for subsequent final fine tuning through micro-level calibration.

12. Calibration Parameters

For calibration and model output uncertainty analysis a total of 11 SWMM-5 runoff parameters were considered. The values of these parameters are varying from sub-area to sub- area depending on soil, land use, imperviousness, topography and/or other characteristics of the total drainage area. The values of these parameters for each sub-area have been taken from the existing drawing and maps obtain from the department of design and construction NYC. Table -1 indicates some of the representative design formulas and Calibration Parameters used that passible affect the modeling output.

13. Sensitivity Analysis

The problem in calibration of models is the large number of parameters. For this reason, methods for reducing the number of parameters in the course of sensitivity analysis are very important (Mailhot, et al. 1997, McCuen 2005, Melching, et al. 1990, Van Griensven, et al. 2006). The main target of sensitivity analysis is to detect insensitive parameters and to exclude them from the calibration process. In this study the analysis has been accomplished by varying different model parameters by different amounts so that the model output match well or fall within the proper range of the observed results (Savic, & Walters, 1995, Sun, et al. 2014, Thorndahl, et al. 2008).

14. Result Analysis

Generally, the goal of urban drainage infrastructure system modeling is to provide a reasonable prediction of the way the catchment area considered for design will respond to a given set of conditions. Recognizing the high degree of error or uncertainty in many aspects of modeling can help the efforts to encourage model users to pursue accuracy and model calibration. The modeling goal may be to precisely predict this response or to compare the relative difference in response between different numbers of scenarios. Therefore, the best way to verify that a model fulfills this need to the required degree of accuracy is to check it against actual monitoring

data or observations.

This paper illustrated a basic practical approach and relatively simple to implement for urban drainage infrastructure model calibration to minimize output uncertainty, which can be used but ignored during storm water simulation and analysis using Astoria-Heights watershed, a heavily urbanized area located in New York City. For comparison purpose, the following values were simulated and analyzed:

I. The peak flow with the best fitted calibrated model of the mean flow of 0.33m^3/s or 11.63 cfs (measured 0.32m^3/s or 11.44cfs) and a peak flow of 0.47m^3/s or 16.59 cfs (measured 0.46m^3/s or 16.42 cfs) with standard deviation of 2.9 calibrated (2.85 measured) and correlation between measured calibrated 99.6%. Calibration runs was confirmed by the inspection of the resulting ranges in parameter values and in model output. Table-3 shows a summary of measured, calibrated, and un-calibrated model output statistical analysis.

Table 3: Summary of Measured, Calibrated and Un- calibrated Model Output Runoff in cfs Statistical Analysis for 10 yrs. 24hr Storm Runoff

	Runoff Uncalibrated and Calibrated Model Comparison		
	Measured	Uncalibrated model	Calibrated model
Max	16.42	13.55	16.59
Mean	11.44	10.04	11.63
SD.	2.85	2.07	2.9
Variance	8.12	4.24	8.41
Corrolation		70.00%	99.61%

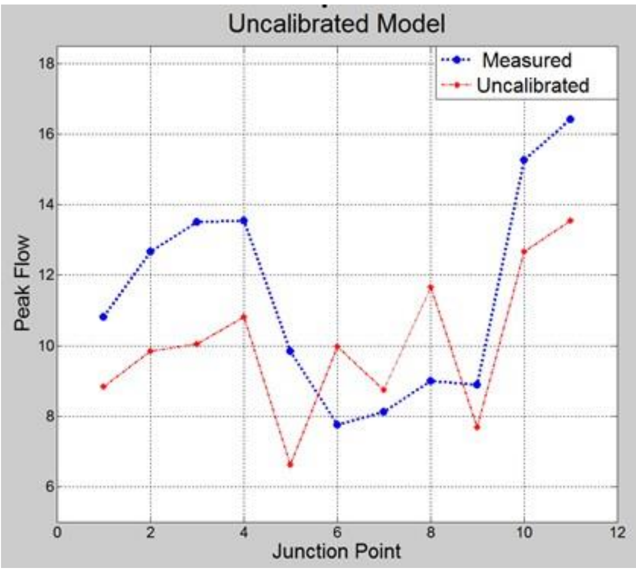

Figure 2: Un calibrated Model Result of Measured vs Modeled Output Value of Peak Flow (cfs)

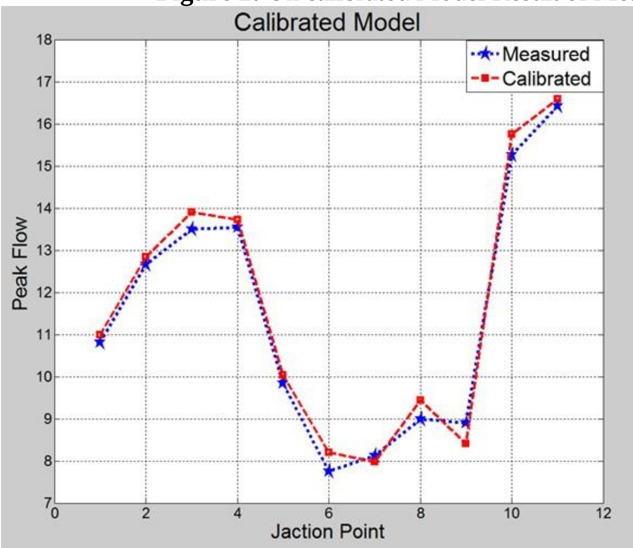

Figure 3: Celebrated Model Result of Measured Vs Modeled Output Value of Peak Flow (cfs)

II. Relative water surface elevation (HGL) also simulated with the best fitted calibrated model of a mean HGL of 27.97m or 91.75ft. (Measured 27.90m or 91.52ft),and a max of water surface elevation (HGL) 30.63m or 100.49 ft. (measured30.626m or 100.48 ft.) with standard deviation of 6.504 calibrated (6.503 measured) and correlation between measured calibrated is almost 100%. Calibration runs was confirmed by the inspection of the resulting ranges in parameter values and in model output. Table-4 shows a summary of measured and calibrated and uncalibrated model output statistical analysis for water surface elevation.

Table 4: Summary of Measured, Calibrated and Un calibrated Model Output Statistical Analysis for 10 yrs. 24hr Storm Water Surface Elevation (HGL in ft.)

	HGL Uncalibrated and Calibrated Model Comparison		
	Measured	Uncalibrated model	Calibrated model
Max	100.48	100.30	100.49
Mean	91.75	89.90	91.75
SD.	6.503	5.640	6.504
Variance	42.29	31.78	42.30
Corrolation		93.00%	99.00%

Figure 4: Un calibrated Model Result of Measured vs Modeled Output Value of water surface Elevation (HGL in ft.)

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Vol-07 Issue-01 Feb 2012

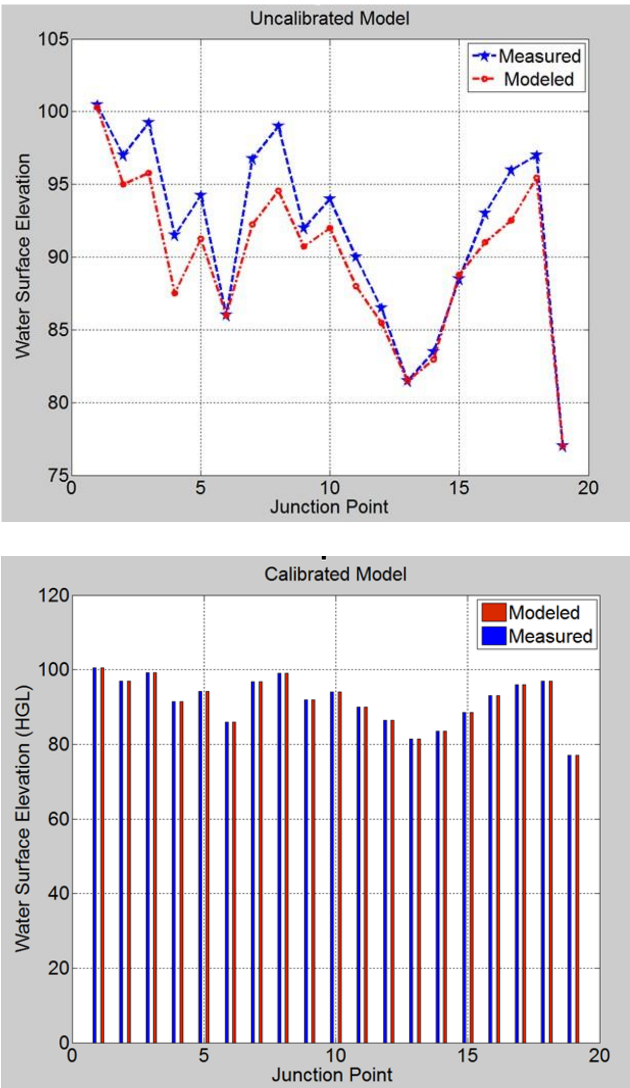

Figure 5: Celebrated Model Result of Measured vs Modeled Output Value of water surface Elevation (HGL in ft.)

15. Conclusions

In conclusion, incorporating what is known about the uncertainty into input parameters and variables used in optimization and simulation models can help in quantifying and minimizing the uncertainty in the resulting model predictions of the model output. This case study demonstrated that it is very crucial to establish model output calibration standards before preceding the final design stage of any urban drainage infrastructure. Finally, the author recommends model users to pursue accuracy and model calibration during drainage network analysis and simulation for reliability model output result.

References:

[1]When there are enough data, testing statistical hypotheses about several factors becomes more difficult, Abraham W. 1943 Vol.54, pp. 426-482, Transactions of the American Mathematical Society.
[2]As of 1996, Arnbjerg-Nielsen and Harremoës were published. Modern urban storm drainage models for ungauged small catchments and the significance of their inherent uncertainties. Volume 179, Issues 1-4, Pages 305–319, Journal of Hydrology, Pages 5, 53
the thirdA discussion on the article "Automatic calibration of the US EPA SWMM Model for a Large Urban Catchment" by Barco, J, Wong, KM, and Stenstrom, MK, ASCE, was published in the Journal of Hydraulic Engineering in 2009 and can be found on pages 1108-1110.
[4]Beck MB. Uncertainty analysis in water quality modeling: a literature survey. Chapter 23 of Water Resource (1987): 1393–442.
[5]Concerning volumes and pollutant loads in a storage and settling tank, Bertrand-Krajewski and Bardin (2002) assessed uncertainty in urban hydrology. Technol. Wa¬ ter Sei, 45(4-5), 437-444.

This information is sourced from Bertrand-Krajewski et al. (2003). The monitoring of urban drainage systems must take into consideration the uncertainties associated with sensor calibration, data validation, measurements, and samples. Water Science & Technology, volume 47, issue 2, pages 95–102. 4.
[7]Barraud, S., Bertrand-Krajewski, J. L., & Bardin, J.-P. (2002). Concerns about stormwater infrastructure, key performance indicators, and decision support tools! Part 4: Urban Water, 163–179.Croom-Hammer, London, 1986, H.H. Crokell, "Specialization and International Competitiveness," in Managing the Multinational Subsidiary, edited by H. Etemad and L. S. Sulude. such as in a book chapter
NSGA II, "A Fast Elitist Non-dominated Sorting Genetic Algorithms for Multiobjective Optimization," KanGAL report 200001, Indian Institute of Technology, Kanpur, India, 2000, by K. Deb, S. Agrawal, A. Pratab, and T. Meyarivan. (formatted as a technical report)
[9]According to J. Geralds's report in vnunet.com from January 31, 2001, "Sega Ends Production of Dreamcast," para. 2, the publication was defunct. [On the web]. You may get this at: http://nl1.vnunet.com/news/1116995. Retrieved on September 12, 2004. (Universal web page)
Even (2007) [10]. Uncertainty, data, and learning via modeling: towards ubiquitous integrated environmental models. Articles 460–467 in the journal Hydrology and Earth System Sciences, volume 11, issue 1. 58, 4, [11]Written by Beven and Binley in 1992. Forecasting uncertainty and calibrating distributed models: the way forward.
Volume 6, Issue 3, Pages 279–298. Published by Hydrological Processes. 2, 54, 56 [12]August 2001 by Beven and Freer. Mechanistic modeling of complicated environmental systems utilizing the GLUE methodology: equifinality, data assimilation, and uncertainty estimation. Pages 11–29 of Journal of Hydrology 249 (1-4). 3, [13]In 2004, Carpenter and Georgakakos published a paper. Uncertainty in parametric and radar rainfall effects on a distributed hydrological model's ensemble streamflow predictions. The published version of the article is Journal of Hydrology 298, 202–221, 4, 43 [14].Proceedings of the 9th International Conference on Urban Drainage, Portland, Oregon, USA, issued on a CD, in which Choi, KS and Ball, JE (2002) investigate the impact of model complexity and structure on the calibration process.
[15]This sentence is a citation for a 2009 paper by Deletic et al., with co-authors Dotto, Fletcher, McCarthy, Bertrand-Krajewski, Rauch, Kleidorfer, Freni, Mannina, and Tait. Uncertainty definition for urban drainage system modeling. Volume 8, Issue 5, Pages 42–46, Pages 53–118, 8th International Conference on Urban Drainage Modelling, Tokyo, Japan, 2008.In 2009, the authors Dotto, Deletic, and Fletcher published a paper. Examination of the unpredictability of stormwater model parameters pertaining to flow and quality. Published in the journal Water Science & Technology, volume 60, issue 3, pages 717–725. 67, 4, and 16With Gottschalk, L. and Engeland, K. (2005). Analyzing the conceptual water balance model's uncertainty using Bayesian approach. Journal of Hydrological Sciences, 50(1), 45–63, 64
[17]It was written by Fang and Ball in 2007. Journal of Hydro-informatics, 9(3), 163–173, "A Genetic Algorithm Application for Evaluating Spatially Variable Control Parameters in a Complex Catchment Modeling System." The publication has the DOI of 10.2166/hydro.2007.026,
[18] inThe authors of the 2009 work are Freni, Mannina, and Viviani. Modeling urban stormwater quality with uncertainty: how the GLUE methodology's probability measure formulation affects the outcomes. Publication: Science of the Total Environment, Volume 408, Issue 1, Pages 138–145.
The year 19Publication: 2009a by Freni, Mannina, and Viviani. Evaluate the level of uncertainty in a model for integrated urban drainage.
Volume 373, Issues 392–404, Journal of Hydrology, pages 58
In [20],A study conducted by Frey and Rhodes (1998) examined the effects of distribution choice, variability, uncertainty, and parameter dependency on the characterization and simulation of uncertain frequency distributions. Environmental Health Risk Assessment, 4(2), 423-468.
[21]This sentence was written by Gaume, Villeneuve, and Desbordes in 1998. Evaluate the calibrated parameter values of an urban storm water quality model and analyze the uncertainty associated with them. Hydrology Journal, 210, 35–50.
[22] is aJoaquín Gironás, Luis Roesner, Luis Rossman, and José Davis (2010). A revised guide for using the SWMM to manage storm water. Page numbers 813–814 of the Environmental Modeling & Software journal article.
[23] TheIn 2013, Giudice, Honti, Scheidegger, Albert, Reichert, and Rieckermann published a paper. Enhancing the assessment of uncertainty in urban hydrological modeling using the statistical description of bias. The scientific journal Hydrology and Earth System Sciences, volume 17, issue 10, pages 4209-4225.
[24]Using automated calibration with different goals for parameter estimation in distributed hydrological catchment models (Madsen, 2003), Recent Developments in Water Resources, 26:205-216
[25] TheArremoës, P. (2003). Integrated urban water modeling and the impact of uncertainty in practice. The IMUG Conference was held in Tilburg, Netherlands. 5
[26]The authors of the 2009 article are Haydon and Deletic. An uncertainty in the input data might affect the model's output when it is paired with a disease indicator and a hydrologic catchment. "Environmental Modelling & Software" (volume 24, issue 3, pages 322-328). no. 4"Parameter uncertainties in modeling urban wastewater systems" is the title of Helge's 2006 PhD thesis, which was completed at Zürich.
[28] in"Hoppe and Gruening 2007" The importance of caveats in the data used for integrated wastewater system design. Included in: Novatech, 6th International Conference on Sustainable Techniques and Strategies in Urban Water Management, Lyon, France, pp. 1607-1614. 2,3,4,5, [29]Published in 2005 by Kanso, Tassin, and Chebbo. An industry standard approach to reducing

ISSN: 1934 -9955www.ijise.net

Vol-07 Issue-01 Feb 2012

risk in urban runoffFirst Theory of Bayesian Analysis of Uncertain Inputs to Hydrological Models by Kavetski, Kuczera, and Franks, 2006a. Journal of Water Resources 42: W03407, pages 70–72 [30]The effect of unknown input data on the parameters of urban stormwater models (Kleidorfer et al., 2009a). Chapters 4, 5, and 7 of Water Science & Technology [31]Methods for optimizing measurement campaigns to calibrate a conceptual sewage model (Kleidorfer et al., 2009b). Publishing in the journal Water Science & Technology, volume 58, issue 8, pages 1523–1530. #4, #7 [32]Korving and Clemens (2005) worked together. Effects of unpredictability in dimensions and calibration of models on evaluation of sewage systems. Publication: Water Science & Technology, Volume 52, Issue 5, Pages 35–42.

(5) [33]In Headwater Control VI: Hydrology, Ecology and Water Resources in Headwaters, presented at the 2005 IAHS Conference in Bergen, Germany, Krause and Flugel conducted integrated study on the hydrological process dynamics from the Wilde Gera watershed.

on page 34Parent, E., and Kuczera, G. (1998). Evaluation of conceptual catchment models' parameter uncertainty using the Metropolis algorithm: a Monte Carlo study. Hydrology Journal, 211, 69–85.

[35] inJ. H. Lei, 1996. Evaluation of urban rainfall uncertainty - runoff simulations. Thesis, Norwegian University of Science and Technology–Norway. 4

[36]This is from 1996 by Lei and Schilling. Assessing the predicted uncertainty of hydrologic models requires preliminary uncertainty analysis. Journal of Water Science and Technology, 33, 79–90. 1.

[37]In 2007, Lindblom, E., Madsen, H., and Mikkelsen, P. Research comparing GLUE with grey-box modeling for assessing the uncertainty of copper loading in stormwater systems. In Water Science & Technology, volume 56, issue 6, pages 11–18, pagination 58

[38]In 2012, Looper, Vieux, and Moreno published a work. Evaluating how precipitation bias affects the accuracy of calibration and predictions made by distributed hydrologic models. Hydrology Journal, 418, 110-122.

in the text.An article published in 1997 by Mailhot, Gaume, and Villeneuve. Examining the Metropolis Monte Carlo algorithm's calibration parameter values for an urban storm water quality model: uncertainty analysis. Journal of water science and technology, 36(5), 141-148.

In 2010, Mannina and Viviani published a study. The creation of a stormwater quality model for urban drainage systems and the measurement of associated uncertainty. Hydrological Journal, 381(3), 248-265.

[41] TheG. Aggett and C. McColl (2007). better land-use decision-support via the combination of hydrologic models with land-use forecasts. Pages 494-512 in the Journal of Environmental Management, volume 84, issue 4, published in 2014.

[42]R.H. McCuen (2005). Evaluating peak discharge models for accuracy. The citation is from the Journal of Hydrologic Engineering, volume 10, issue 1, pages 16-22.

[43]In 1990, Melching, Yen, and Wenzel published a paper. Accurately estimating reliability in watershed runoff models. Publication: Water Resources Research, Volume 26, Issue 10, Pages 2275–2286.

[44]"Nix, S. J." in 1994. Urban stormwater modeling and simulation. Press of CRC.

[1] Omlin, M. (2000). "Uncertainty analysis of model predictions for environmental systems concepts and application to lake modelling", PhD thesis. Zürich.

[2] Overeem, A., Buishand, A., Holleman, I., 2008. Rainfall depth-duration-frequency curves and their uncertainties. Journal of Hydrology 348 (1-2), 124 – 134. 4

[3] Rauch, W., Harremoës, P., 1998b. On the application of evolution programs in urban drainage modelling. In: Fourth Conference on developments in Urban Drainage Modelling. London.

[4] Reichert, P. and Borsuk, M. E. (2005) Does high forecast uncertainty preclude effective decision support? Environmental Modelling & Software 20, 991-1001.

[5] Saltelli, A., Andres, T.H., Homa, T., 1995. Sensitivity analysis of model output; performance of the iterated fractional design method. Computational Statistics and Data Analysis 20, 387–407.

[6] Savic, D.A., and G.A.Walters, Genetic Algorithm Techniques for Calibrating Network Models, report No. 95/12, Center for Systems and Control, University of Exeter, UK, 1995.

[7] Sun, N., Hong, B., & Hall, M. (2014). Assessment of the SWMM model uncertainties within the generalized likelihood uncertainty estimation (GLUE) framework for a high-resolution urban sewer shade Hydrological Processes, 28(6), 3018-3034.

[8] Thorndahl, S., 2008. Uncertainty assessment in long term urban drainage modelling. Phd thesis, Aalborg University. 5, 39, 56, 94

[9] Thorndahl, S., Beven, K. J., Jensen, J. B., & Schaarup- Jensen, K. (2008). Event based uncertainty assessment in urban drainage Modeling, applying the GLUE methodology. Journal of Hydrology, 357(3), 421-437.

[10] Thorndahl, S., Beven, K., Jensen, J., Schaarup-Jensen, K., 2008. Event based uncertainty assessment in urban drainage modelling, applying the GLUE methodology. Journal of Hydrology 357 (3-4), 421 – 437. 5, 53, 58

[11] Umakhanthan, K and Ball, JE, (2002), Importance of Rainfall Models in Catchment Simulation, Proc. 13th Congress of Asia Pacific Division of IAHR, IAHR, Singapore (Advances in Hydraulics and Water Engineering, World Scientific Publications, Ed. JJ Guo), Volume 1, pp 551-556, ISBN 981-238-108-2.

[12] Umakhanthan, K and Ball, JE, (2005), Rainfall Models for Catchment Simulation, Australian Journal of Water Resources, 9(1):55-67.

ISSN: 1934 -9955www.ijise.net

Vol-07 Issue-01 Feb 2012

[13] Urbonas, B. (2007, July). Stormwater runoff modeling; Is it accurate as we think. In International conference on Urban Runoff Modeling: Intelligent Modeling to Improve Stormwater Management, Arcata USA (pp. 1- 12).

[14] Van Griensven, A., Meixner, T., Grunwald, S., Bishop, T., Diluzio, M., & Srinivasan, R. (2006). A global sensitivity analysis tool for the parameters of multi- variable catchment models. Journal of hydrology, 324(1),

[15] Vaze, J., & Chiew, F. H. (2003). Comparative evaluation of urban storm water quality models. Water Resources Research, 39(10).

[16] Willmot, C. J. On the evaluation of model performance in physical geography, in Spatial Statistics and Models, edited by: Gaile, G. L. and Willmot, C. J., D. Reidel, Dordrecht, 443–460, 1984.Willmott, C. J. 1981. On the validation of models.
Physical Geography, 2, 184–194

[17] Zarriello, P. J. (1998). “Comparison of Nine Un- calibrated Runoff Models to Observed Flows in Two Small Urban Catchments,” Proceedings First Federal Interagency Hydrology Model Conference, Las Vegas, NV, April, 1998: Subcommittee on Hydrology of Interagency Advisory Committee on Water Data, p. 7– 163 to 7–170