**International Journal of Scientific Engineering and Research (IJSER)**
www.ijser.in
**ISSN (Online): 2347-3878, Impact Factor (2014): 3.05**

# Urban Drainage Infrastructure Design Model Calibration and Output Uncertainty Minimization

## Are Model Users Pursuing Accuracy and Model Calibration?

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**Abstract:** ***Models are just simplifications of the real condition that is going to be simulated or analyzed. However, the series of entries and assumptions of input data reflect the most representative case of the practical conditions. Accurate and reliable modeling of storm water runoff (i.e. hydrologic, hydraulic, water quality…etc.), and associated phenomena have been and continue to be a challenge, despite the fact that models, model interfaces, and even model math engines have been improved. The designing and planning of major urban drainage infrastructures are significantly depends on the use of those complex, advanced models and their outputs. Therefore, to get the required degree of model output accuracy model calibrations are necessary. The calibration process minimizes the probabilities of inaccuracies that can be generated from different input parameters and model users. This paper aims to briefly discuss urban drainage infrastructure design models' calibration in order to minimize output value uncertainty. A case study, using SWMM-5, was performed in Astoria Heights, New York City, to assess and demonstrate model output uncertainties and the relative importance of calibration. The study involves adjustment of the primary model parameters until the model results are approximately close to the actual observed values as designed under similar conditions. After the model result and the observed values are in reasonable agreement the final model calibration was performed to recommend how to minimize model output uncertainties. In conclusion, the result analysis conformed that it is very crucial to establish model output calibration standards before proceeding to the final design stage of any urban drainage infrastructure. Furthermore, the author also recommends that model users to pursue accuracy and model calibration for reliable model output results.***

**Keywords:** Accuracy, Calibration, Input Parameter, Modeling, Urban Drainage, Uncertainty

## 1. Introduction

Modeling is a central element in urban drainage infrastructure design and planning. It requires extensive understanding of the hydrologic behavior of the drainage area and hydraulic principles of fluids. Hydrology, hydraulics, and water quality models are not exact simulations of the processes occurring in nature. Rather, they are approximate representations of natural processes based on a set of equations and parameters or measured data. Therefore, to get the required degree of model output accuracy model calibrations are necessary. The model output uncertainty depends on several factors (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) | $t_c = \frac{0.93L^{0.5}N^{0.6}}{i^{0.4}S^{0.3}}$ | 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 | $V = \frac{1.49(R^{2/3}S^{0.5})}{n}$ | 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 Modelling | | |
|---|---|---|
| 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, to ensure the highest possible accuracy for the output data. For some models, calibration is unnecessary due to the design of the model (Gaume et al. 1998, Giudice et al. 2013, H Madsen, 2003; Mailhot et al. 1997, Zarriello 1998). Calibration can be done manually or automatically. Manually by "trial-and-error" parameter adjustment, with the aim of improving the model simulations up to the desired level the 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).

## 4. Statistical Model Validation

The general simulation literature includes a large number of approaches for the statistical validation of simulation models. These approaches include goodness-of-fit measures, confidence intervals, and statistical tests of the underlying distributions and processes. The purpose is to verify that the calibrated model can perform well when it is used in conditions different than those used in calibration. Validation consists in generating model simulations for independent events and/or at independent locations and verifying that the model fit to the observations is comparable to that achieved in the calibration. The types of statistical approaches that are discussed include the Goodness-of-fit measures; Goodness-of-fit of a model describes how well the model fits a set of observations (it provides an objective assessment of the "closeness" of the simulated behavior to the observed measurements). A number of goodness-of-fit measures can be used to evaluate the overall performance of simulation models. Popular among them are the root-mean-square error (RMSE), the root-mean-square percent error (RMSPE), the mean error (ME), the mean percent error (MPE) statistics, The NSE (coefficient of efficiency), and Coefficient of Determination ($r^2$). The Hypothesis testing, confidence intervals, and Test of underlying structure are types of statistical approaches which can be used for the same purpose. In this paper the Goodness-of-fit measures approaches are discussed:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\lambda_n - y_n)^2} \tag{1}$$

$$RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{\lambda_n - y_n}{y_n}\right)^2} \tag{2}$$

ME and MPE indicate the existence of systematic under- or over prediction in the simulated measurements. These measures are given by

$$ME = \frac{1}{N}\sum_{n=1}^{N}(\lambda_n - y_n) \tag{3}$$

$$MPE = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{\lambda_n - y_n}{y_n}\right) \tag{4}$$

Where $\lambda_n$ and $y_n$ are the averages of observed and 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)

$$r^2 = \left(\frac{\sum_{i=1}^{n}(y_i - \bar{y})\left(\hat{y}_i - \bar{\hat{y}}\right)}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}\sqrt{\sum_{i=1}^{n}\left(\hat{y}_i - \bar{\hat{y}}\right)^2}}\right)^2 \tag{5}$$

Where $y$ and $\hat{y}$ are observed and predicted values respectively.

($r^2$) can also be expressed as the squared ratio between the covariance and the multiplied standard deviations of the observed and predicted values. Therefore it estimates the combined dispersion against the single dispersion of the observed and predicted series. The range of ($r^2$) lies between 0 and 1 which describes how much of the observed dispersion is explained by the prediction. A value of zero means no correlation at all whereas a value of 1 means that the dispersion of the prediction is equal to that of the observation.

The efficiency E proposed by Nash and Sutcliffe (1970) is defined as one minus the sum of the absolute squared differences between the predicted and observed values normalized by the variance of the observed values during the period under investigation.

$$E = 1 - \frac{\sum_{i-1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{6}$$

Where $y$ and $\hat{y}$ are observed and predicted values respectively.

E= Nash-Sutcliffe efficiency

The range of E lies between 1.0 (perfect fit) and. An 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

The accurate and reliable modeling of stormwater runoff (i.e. hydrology and hydraulics) and associated phenomena has been and continues to be a challenge, despite the fact that advances in models, model interfaces, and even model math engines have been improved (Freni et al. 2009, Gaume et al. 1998, Nix, 1994). Planning, design, maintenance and decision of billions of dollar worth major drainage infrastructure are being made on the basis of computer modeling output results and analysis (Giudice, et al. 2013, Urbonas, 2007). Even if most models have some degree of uncertainty the author and many of his peers agreed on some of the most important elements that contribute to the uncertainties of urban infrastructure drainage design model output, such as the modeler (user) professional's expertise; the challenge of selection of the appropriate model; the availability of credible and appropriate calibration data and so on (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). Moreover, limited research has been done about; how reliable and accurate the output results are? What are the sources and magnitude of uncertainty? How to reduce the model output uncertainties? Problems related to the accuracy of modeling from the perspective of less skilled professionals involved in modeling and output analysis. Are model users pursuing accuracy and model calibration? Accuracy of a model usually determined by comparing model outputs to the observations selected for calibration and validation.

## 6. 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).

## 7. 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: - 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.

## 8. 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.

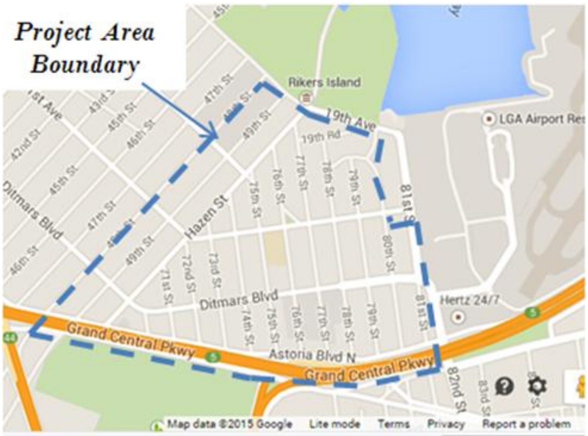



**Figure 1:** General Location of Study Area

## 9. 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-drainage areas 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.

## 10. 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 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.

## 11. 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.

## 12. 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).

## 13. 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% |

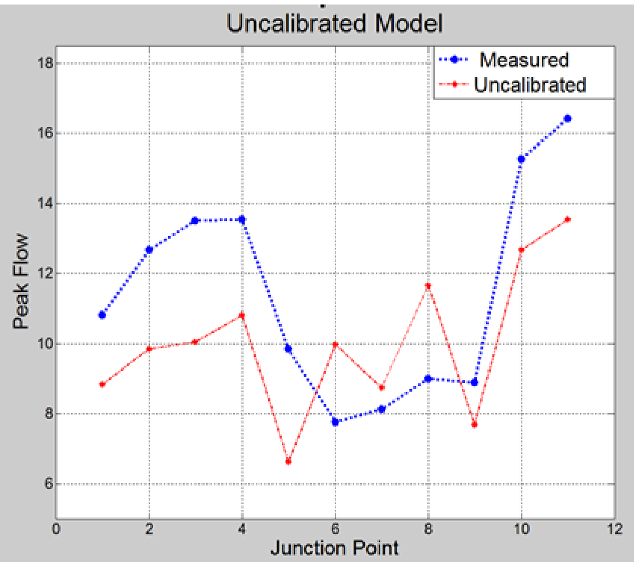



**Figure 2:** Un calibrated Model Result of Measured vs Modeled Output Value of Peak Flow (cfs)

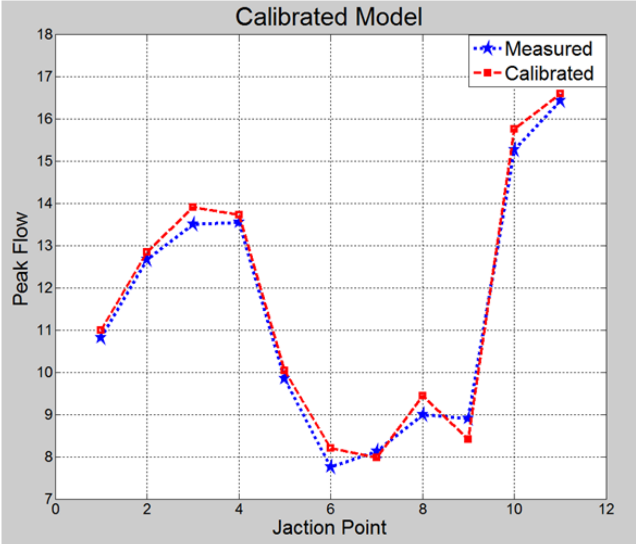


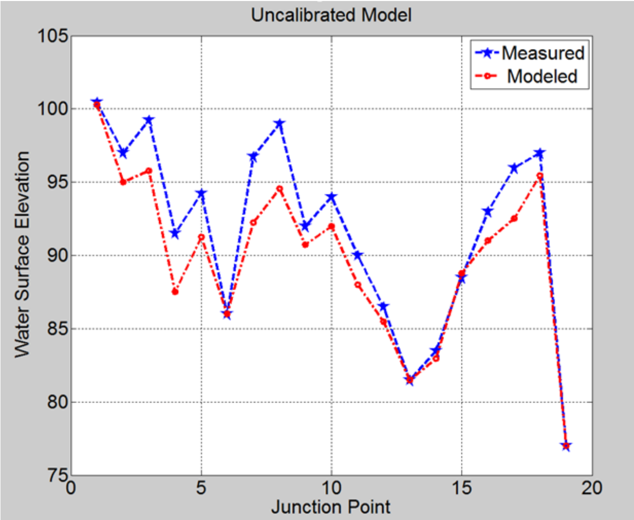

**Figure 3:** Celebrated Model Result of Measured Vs Modeled Output Value of Peak Flow (cfs)

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, Califbrated 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.)



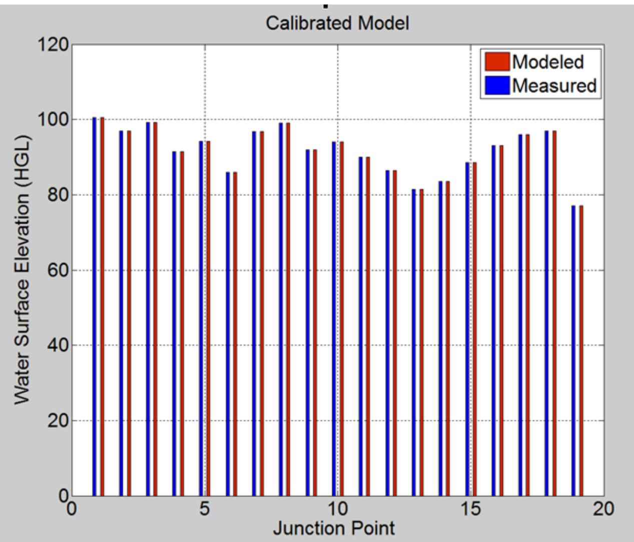




**Figure 5:** Celebrated Model Result of Measured vs Modeled Output Value of water surface Elevation (HGL in ft.)

## 14. 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] Abraham W. 1943 Test of statistical hypotheses concerning several parameters when the number of observations is large, Transactions of the American Mathematical Society, Vol.54, pp. 426-482

[2] Arnbjerg-Nielsen, K., Harremoës, P., 1996. The importance of inherent uncertainties in state-of-the-art urban storm drainage modelling for ungauged small catchments. Journal of Hydrology 179 (1-4), 305 – 319. 5, 53

[3] Ball, JE, (2009), Discussion on “Automatic calibration of the US EPA SWMM Model for a Large Urban Catchment” by Barco, J, Wong, KM, and Stenstrom, MK, ASCE, Journal of Hydraulic Engineering, 135(12):1108-1110.

[4] Beck MB. Water quality modeling: a review of the analysis of uncertainty. Water Resource 1987; 23:1393–442.

[5] Bertrand-Krajewski, J. L. and Bardin, J. P. (2002) Evaluation of uncertainties in urban hy¬ drology: application to volumes and pollutant loads in a storage and settling tank. Wa¬ ter Sei. Technol, 45(4-5), 437-444.

[6] Bertrand-Krajewski, J. L., Bardin, J.-P., Mourad, M., Beranger, Y., 2003. Accounting for sensor calibration, data validation, measurement and sampling uncertainties in monitoring urban drainage systems. Water Science & Technology 47 (2), 95 – 102. 4

[7] Bertrand-Krajewski, J. L., Barraud, S., Bardin, J.-P., 2002. Uncertainties, performance indicators and decision aid applied to stormwater facilities. Urban Water 4, 163–179. 4H.H. Crokell, “Specialization and International Competitiveness,” in Managing the Multinational Subsidiary, H. Etemad and L. S, Sulude (eds.), Croom-Helm, London, 1986. (book chapter style)

[8] K. Deb, S. Agrawal, A. Pratab, T. Meyarivan, “A Fast Elitist Non-dominated Sorting Genetic Algorithms for Multiobjective Optimization: NSGA II,” KanGAL report 200001, Indian Institute of Technology, Kanpur, India, 2000. (technical report style)

[9] J. Geralds, "Sega Ends Production of Dreamcast," vnunet.com, para. 2, Jan. 31, 2001. [Online]. Available: http://nl1.vnunet.com/news/1116995. [Accessed: Sept. 12, 2004]. (General Internet site)

[10] Beven, K., 2007. Towards integrated environmental models of everywhere: uncertainty, data and modelling as a learning process. Hydrology and Earth System Sciences 11 (1), 460–467. 4, 58

[11] Beven, K., Binley, A., 1992. The future of distributed models: Model calibration and uncertainty prediction. Hydrological Processes 6 (3), 279–298. 4, 56

[12] Beven, K., Freer, J., August 2001. Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. Journal of Hydrology 249 (1-4), 11–29. 4

[13] Carpenter, T. M., Georgakakos, K. P., 2004. Impacts of parametric and radar rainfall uncertainty on the ensemble streamflow simulations of a distributed hydrological model. Journal of Hydrology 298, 202 – 221. 4, 43

[14] Choi, KS and Ball, JE, (2002), Investigation of Influence of Model Complexity and Structure on Calibration Process, Proc. 9th International Conference on Urban Drainage, Portland, Oregon, USA, published as a CD.

[15] Deletic, A., Dotto, C. B. S., Fletcher, T. D., McCarthy, D. T., Bertrand-Krajewski, J. L., Rauch, W., Kleidorfer, M., Freni, G., Mannina, G., Tait, S., 2009. Defining uncertainties in modelling of urban drainage systems. In: Proceedings of the 8th International Conference on Urban Drainage Modelling, Tokyo. 5, 42, 46, 53, 118

[16] Dotto, C. B. S., Deletic, A., Fletcher, T. D., 2009. Analysis of parameter uncertainty of a flow and quality stormwater model. Water Science & Technology 60 (3), 717 – 725. 4, 67
[17] Engeland, K., Xu, C.-Y., Gottschalk, L., 2005. Assessing uncertainties in a conceptual water balance model using Bayesian methodology. Hydrological Sciences Journal 50(1), 45 – 63. 4, 64
[18] Fang, T and Ball, JE, (2007), Evaluation of Spatially Variable Control Parameters in A Complex Catchment Modelling System: A Genetic Algorithm Application, Journal of Hydro-informatics, 9(3):163-173 (doi:10.2166/hydro.2007.026)
[19] Freni, G., Mannina, G., & Viviani, G. (2009). Uncertainty in urban stormwater quality modeling: The influence of likelihood measure formulation in the GLUE methodology. Science of the total environment, 408(1), 138-145.
[20] Freni, G., Mannina, G., Viviani, G., 2009a. Uncertainty assessment of an integrated urban drainage model. Journal of Hydrology 373 (3-4), 392 – 404. 5, 58
[21] Frey, H. C. and Rhodes, D. S. (1998) Characterization and simulation of uncertain frequency distributions: Effects of distribution choice, variability, uncertainty, and parameter dependence. Hum. Ecol. Risk Assess., 4(2), 423-468.
[22] Gaume E., Villeneuve J. P. and Desbordes M. (1998). Uncertainty assessment and analysis of the calibrated parameter values of an urban storm water quality model. Journal of Hydrology, 210 35-50.
[23] Gironás, J., Roesner, L. A., Rossman, L. A., & Davis, J. (2010). A new applications manual for the Storm Water Management Model (SWMM). Environmental Modeling & Software, 25(6), 813-814.
[24] Giudice, D. D., Honti, M., Scheidegger, A., Albert, C., Reichert, P., & Rieckermann, J. (2013). Improving uncertainty estimation in urban hydrological modeling by statistically describing bias. Hydrology and Earth System Sciences, 17(10), 4209-4225.
[25] H Madsen, (2003), Parameter estimation in distributed hydrological catchment modelling using automatic calibration with multiple objectives, Advances in Water Resources, 26:205-216
[26] Harremoës, P., 2003. The role of uncertainty in application of integrated urban water modelling. In: IMUG Conference. Tilburg, Netherlands. 5
[27] Haydon, S., Deletic, A., 2009. Model output uncertainty of a coupled pathogen indicator-hydrologic catchment model due to input data uncertainty. Environmental Modelling & Software 24 (3), 322 – 328. 4
[28] Helge, D. (2006). “Parameter uncertainties in modeling urban wastewater systems”, PhD thesis. Zürich.
[29] Hoppe, H., Gruening, H., 2007. Significance of uncertainties in the input data used in the integrated design of wastewater systems. In: 6th International Conference on Sustainable Techniques and Strategies in Urban Water Management - Novatech. Vol. 3. Lyon, France, pp. 1607 –1614. 4, 5
[30] Kanso, A., Tassin, B., Chebbo, G., 2005. A benchmark methodology for managing uncertainties in urban runoff quality models. Water Science & Technology 51 (2), 163–170. 4, 67
[31] Kavetski, D., Kuczera, G., Franks, S. W., 2006a. Bayesian analysis of input uncertainty in hydrological modeling: 1. Theory. Water Resources Reseach 42 W03407. 4, 70, 72
[32] Kleidorfer, M., Deletic, A., Fletcher, T. D., Rauch, W., 2009a. Impact of input data uncertainties on urban stormwater model parameters. Water Science & Technology. 4, 5, 7
[33] Kleidorfer, M., Möderl, M., Fach, S., Rauch, W., 2009b. Optimization of measurement campaigns for calibration of a conceptual sewer model. Water Science & Technology 58 (8), 1523–1530. 4, 7
[34] Korving, H., Clemens, F., 2005. Impact of dimension uncertainty and model calibration on sewer system assessment. Water Science & Technology 52 (5), 35–42. 5
[35] Krause, P. and Flugel, W.-A.: Integrated research on the hydrological process dynamics from the Wilde Gera catchment in Germany; Headwater Control VI: Hydrology, Ecology and Water Resources in Headwaters, IAHS Conference, and Bergen 2005.
[36] Kuczera G. and Parent E. (1998). Monte Carlo assessment of parameter uncertainty in conceptual catchment models: the Metropolis algorithm. Journal of Hydrology, 211 69 - 85.
[37] Lei, J. H., 1996. Uncertainty analysis of urban rainfall - runoff modelling. Dissertation, Norwegian University of Science and Technology. 4
[38] Lei, J. H., Schilling, W., 1996. Preliminary uncertainty analysis - a prerequisite for assessing the predictive uncertainty of hydrologic models. Water Science & Technology 33, 79–90. 4
[39] Lindblom, E., Madsen, H., Mikkelsen, P., 2007. Comparative uncertainty analysis of copper loads in stormwater systems using GLUE and grey-box modelling. Water Science & Technology 56(6), 11 – 18. 4, 58
[40] Looper, J. P., Vieux, B. E., & Moreno, M. A. (2012). Assessing the impacts of precipitation bias on distributed hydrologic model calibration and prediction accuracy. Journal of Hydrology, 418, 110-122.
[41] Mailhot, A., Gaume, E., & Villeneuve, J. P. (1997). Uncertainty analysis of calibrated parameter values of an urban storm water quality model using Metropolis Monte Carlo algorithm. Water science and technology, 36(5), 141-148.
[42] Mannina, G., & Viviani, G. (2010). An urban drainage stormwater quality model: model development and uncertainty quantification. Journal of hydrology, 381(3), 248-265.
[43] McColl, C., & Aggett, G. (2007). Land-use forecasting and hydrologic model integration for improved land-use decision support. Journal of environmental management, 84(4), 494-512.
[44] McCuen RH. 2005. Accuracy assessment of peak discharge models. Journal of Hydrologic Engineering 10(1): 16–22.
[45] Melching, C. S., Yen, B. C., & Wenzel, H. G. (1990). Reliability estimation in modeling watershed runoff with uncertainties. Water Resources Research, 26(10), 2275-2286.
[46] Nix, S. J. (1994). Urban stormwater modeling and simulation. CRC Press.

[47] Omlin, M. (2000). "Uncertainty analysis of model predictions for environmental systems concepts and application to lake modelling", PhD thesis. Zürich.
[48] Overeem, A., Buishand, A., Holleman, I., 2008. Rainfall depth-duration-frequency curves and their uncertainties. Journal of Hydrology 348 (1-2), 124 – 134. 4
[49] 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.
[50] Reichert, P. and Borsuk, M. E. (2005) Does high forecast uncertainty preclude effective decision support? Environmental Modelling & Software 20, 991-1001.
[51] 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.
[52] 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.
[53] 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.
[54] Thorndahl, S., 2008. Uncertainty assessment in long term urban drainage modelling. Phd thesis, Aalborg University. 5, 39, 56, 94
[55] 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.
[56] 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
[57] 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.
[58] Umakhanthan, K and Ball, JE, (2005), Rainfall Models for Catchment Simulation, Australian Journal of Water Resources, 9(1):55-67.
[59] 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).
[60] 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),
[61] Vaze, J., & Chiew, F. H. (2003). Comparative evaluation of urban storm water quality models. Water Resources Research, 39(10).
[62] 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.
[63] Willmott, C. J. 1981. On the validation of models. Physical Geography, 2, 184–194
[64] 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