Case Study

Stormwater Detention System Parameter Sensitivity and Uncertainty Analysis Using SWMM

James Knighton[1]; Edward Lennon[2]; Luis Bastidas[3]; and Eric White[4]

Abstract: A U.S. EPA (EPA) model was developed for the Cathedral Run stormwater wetland (Philadelphia, Pennsylvania). This research presents a formal sensitivity analysis of hydraulic and hydrologic model parameters contributing uncertainty with the multiobjective generalized sensitivity analysis (MOGSA) algorithm. The parameters identified as significant include: percent routed (P_R), subcatchment soils, subcatchment width, wetland soils, and the flood weir coefficient. These results suggest that this model is well parameterized for detailed simulations of stormwater control installations, and contests the existence of a globally sensitive set of parameters. This research demonstrates that detailed models of stormwater control installations are significantly affected by uncertainty related to parameters beyond traditional calibration (i.e., runoff generation) parameters. The authors present a monitoring design based on wetland water surface elevation. The simplified monitoring scheme obtained statistically significant calibration data as determined through MOGSA. The generalized likelihood uncertainty estimation (GLUE) algorithm was then applied to develop marginal posterior model parameter distributions and two-dimensional (2D) probability spaces using a formal Bayesian likelihood function. The GLUE results demonstrate the importance of uncertainty and equifinality within the context of stormwater wetland modeling. **DOI: 10.1061/(ASCE)HE.1943-5584.0001382.**

Author keywords: Storm water management model (SWMM); Stormwater wetland; Generalized likelihood uncertainty estimation (GLUE); Multiobjective generalized sensitivity analysis (MOGSA); Pennsylvania.

Introduction

Stormwater control devices such as green infrastructure, stormwater wetlands, detention basins, and bioswales are engineering designs which solve urban runoff issues by integrating construction practices with nature. These installations attempt to incorporate natural hydrology into designs to improve water quality. Such practices typically include engineered hydraulic control structures which regulate excess flows when natural hydrological process are overwhelmed. Ideally, these hydraulic control structures maximize water quality benefits while maintaining hydrologic conditions suitable for a potentially denser urban environment (EPA 2015). Therefore, it is critical that design and modeling of such installations should consider the uncertainty and interdependence of both the hydrologic and hydraulic parameters on the anticipated performance.

This research focuses on the Storm Water Management Model (SWMM) Version 5 Build 5.0.022, developed by the U.S. EPA (EPA), for simulation of a constructed wetland within an urban setting. SWMM has been applied to study thousands of stormwater systems and is widely used for the purpose of estimating the quantity and quality of runoff and for designing stormwater management practices (EPA 2015).

Recent improvements to SWMM have concentrated on the ability to simulate coupled hydraulic and hydrologic (H&H) processes for use in design and evaluation of stormwater management installations [for a list of improvements (EPA 2015)]. Combined H&H models may contain multiple processes occurring in series or parallel which directly affect model output. Despite these advancements, recent research on SWMM parameter uncertainty remains heavily focused on the hydrologic parameters defining runoff (Balascio et al. 1998; Khu and Werner 2003; Wan and James 2002; Barco et al. 2008; Sun et al. 2012; Gülbaz and Kazezyılmaz-Alhan 2013; Sun et al. 2014; Mancipe-Munoz et al. 2014; Zhang et al. 2015). This focus on hydrologic parameters is evident in many other studies conducted using an array of H&H models; as demonstrated by the model parameter estimation experiment (MOPEX) (Duan et al. 2006; Schaake et al. 2006). Further, various studies of SWMM hydrologic model parameter sensitivity have resulted in some disagreement over which parameters are the most sensitive (Khu and Werner 2003; Sun et al. 2012, 2014; Barco et al. 2008; Beling et al. 2011; Gülbaz and Kazezyılmaz-Alhan 2013; Zhang et al. 2015).

A case study of SWMM sensitivity and uncertainty analysis was performed for the Cathedral Run stormwater wetland. A nutrient and sediment total maximum daily load (TMDL) has been established for the Wissahickon Creek Watershed (EPA 2003) including the Cathedral Run tributary. The TMDL establishes an allowable limit of select pollutants to attain designated uses under the U.S. Clean Water Act (EPA 1991). To reduce siltation, the Philadelphia Water Department (PWD) is implementing several measures within the Wissahickon watershed including the creation of stormwater treatment wetlands (PWD 2011).

The purpose of this research is to demonstrate SWMM parameter sensitivity and uncertainty for H&H processes for a small-scale stormwater control wetland within Philadelphia, Pennsylvania. The

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authors demonstrate how uncertainty in wetland design components may be quantified and used to assess the uncertainty in predicted stormwater wetland performance. The authors evaluate model parameter sensitivity through a generalized sensitivity analysis on the feasible model parameter space. Through this research the authors illustrate the general sensitivity of the SWMM model in applications involving the simulation of natural H&H processes occurring in parallel with engineered components.

Methodology

Cathedral Stormwater Wetland Site Description

Cathedral Run within Northwest Philadelphia, Pennsylvania (latitude 40.07°, longitude 75.22°) is a first-order tributary to Wissahickon Creek (Fig. 1). The watershed experiences approximately 110 cm of precipitation annually (PWD 2011). Freezing temperatures typically occur from December through March (NOAA 2015). Native soils surrounding the Cathedral wetland are predominantly the Chester silt loam (CeB) and Manor loam (MaB) formations (USDA NRCS 2015); however, historical land use and development within the region has resulted in a spatially variable hydrologic response (Knighton et al. 2014).

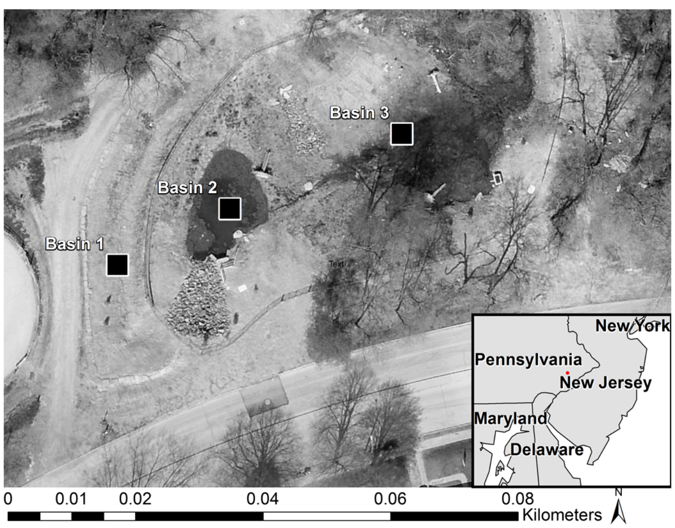

Fig. 1. Cathedral stormwater wetland plan view (image courtesy of Philadelphia Water Department)

The Cathedral stormwater wetland receives runoff from two separate drainage areas. The first is a 0.35 km^2 drainage area composed of single family detached houses at approximately 31% impervious cover. Runoff from this subcatchment is collected by street inlets and roof downspouts which connect directly to the storm sewer network. Before construction of the Cathedral Run stormwater wetland, the stormwater network discharged directly to Cathedral Run through a 1.22 m diameter stormwater gravity main (PWD 2007). A diversion chamber was constructed within the storm sewer network to divert stormwater into the Cathedral stormwater wetland Basin 2. Wet weather flows exceeding the capacity of the diversion chamber overflow a relief weir (W_1) and discharge downstream, directly to Cathedral Run through the original outfall.

A second drainage area of approximately 0.01 km^2 to the northwest of the wetland collects uncontrolled runoff from an area dominated by a horse stable and riding trails (Stable). Runoff from this drainage area enters the smaller upstream Basin 1, which acts as a sediment forebay. Fig. 2 demonstrates the complex flow paths within the Cathedral run wetland basins.

The Cathedral Run stormwater wetland was constructed with the design goal of reducing the volume and peak flow rate of runoff delivered to Cathedral Run (PWD 2007). The installation functions as a wetland as anaerobic conditions persist throughout the year. Urban runoff induced flows within Cathedral Run subsequently discharge to Wissahickon Creek and result in further bank destabilization and increased suspended sediments within the water column. By attenuating peak flows and infiltrating a portion of the runoff volume, the Cathedral stormwater wetland indirectly reduces suspended sediment within Cathedral Run, addressing requirements of the established Wissahickon sediment TMDL. A SWMM model of Cathedral stormwater wetland was developed to predict future performance of the stormwater wetland under various hypothetical precipitation scenarios. While the wetland naturally reduces the nutrient and suspended sediment loads to Cathedral Run, the authors focus on the peak flow attenuation as the engineering design of the wetland system had the goal of optimizing peak flow reduction to Cathedral Run (PWD 2011).

Cathedral Stormwater Wetland SWMM Model

Because of the relatively small footprint of the Cathedral wetland (4,046 m^2), it is appropriate to employ a one-dimensional (1D) flow model as opposed to a two-dimensional (2D) flow model as recommended by Min and Wise (2010). The wetland model

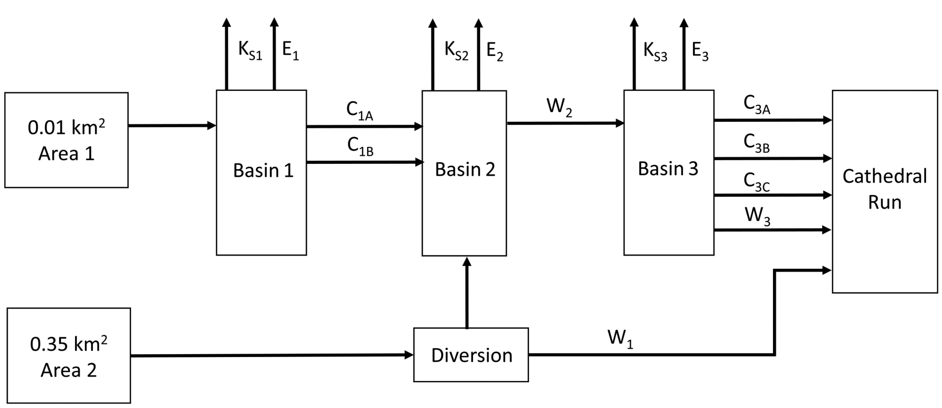

Fig. 2. Schematic of flow paths within the cathedral run stormwater wetland. k_s =infiltration, E = evapotranspiration, C = orifice flow, W = weir flow

structure in SWMM is composed of one rain gauge, two subcatchments, 18 links and 14 nodes. The wetland basins are represented as storage nodes supplied with the depth to surface area curves, which were derived from engineering designs and postconstruction survey data. Hydrologic calculations were performed at a 5-min time step supplied with 15 min precipitation forcing data. Hydraulic calculations were performed at a 5-s time step to meet Courant-Friedrichs-Lewey (CFL) stability criteria (Rossman 2010).

Subcatchment runoff is calculated using the *PERVIOUS* routing method whereby a percentage of the impervious area is routed (P_R) over the pervious subcatchment area. This method was chosen as the authors assumed it best represented potential overland runoff pathways within Philadelphia, Pennsylvania as in Knighton et al. (2014). Infiltration from subcatchments and within each wetland basin was solved with the Green-Ampt formulation. To maintain realistic soil textures the Green-Ampt parameters of saturated hydraulic conductivity (K_{SAT}), suction head (S) and initial moisture deficit (IMD) were reduced to one parameter. IMD values only represent initial conditions for each simulation and, therefore, have limited bearing on the model calibration. Values for K_{SAT} were randomly sampled. Values for S and IMD were selected from a lookup table of soil textures for each sampled value of K_{SAT} (Maidment 1993) (Fig. 3).

SWMM does not explicitly simulate evapotranspiration (ET) from storage nodes (Rossman 2010); however, SWMM does include an evaporation factor, E, which may be used to control the unique evaporation potential of each wetland basin (i.e., storage node). SWMM model documentation suggests this factor may be varied within (0, 1) to represent reduced evaporation (Rossman 2010). Model tests have shown that SWMM will in fact respond to factor values greater than 1. Wang-Erlandsson et al. (2014) estimate that global transpiration rates are 75% of total ET. Research by Bachland et al. (2013) suggests that traditional estimates of transpiration within wetlands at 55–74% of total ET may be underestimated because of overly simplified hydrologic model estimates. Coenders-Gerrits et al. (2014) demonstrate significant uncertainty in ET rates at the catchment scale. The authors, therefore, adopted the ad hoc assumption that the feasible domain for ET is (0, 3) of the average monthly evaporation rate. Monthly evaporation rates were estimated from meteorological observations at the Philadelphia International Airport.

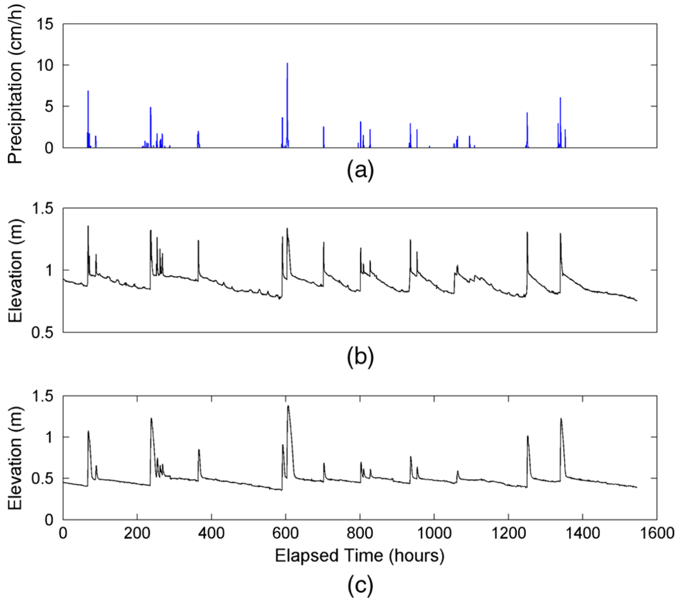

Fig. 3. Observed data: (a) precipitation; (b) water surface elevation in Basin 2; (c) water surface elevation in Basin 3

Uncertainty in hydraulic elements is defined as the uncertainty in the estimation of discharge coefficients for each orifice (C) and weir (W). The sensitivity analysis methodology presented in this paper could easily be applied to new wetland designs considering the geometry, orientation and elevation of hydraulic elements as random variables to optimize wetland performance.

Wetland Monitoring

Monitoring of the Cathedral stormwater wetland occurred over a 64-day period from August through October, 2013. Water surface elevations within wetland Basins 2 and 3 were monitored with 3 water level loggers (Onset, Bourse, Massachusetts): two recording absolute pressure within the storage ponds and one recording atmospheric pressure at 5 min time increments. Depth sensors used had a precision of approximately ±0.5 cm with a range of 0–9 m. Precipitation was from a Met-One Instruments (Grant Pass, Oregon) model 385 tipping bucket rain gauge recording at a 2.5 min increment. The precipitation gauge used had a precision of ±0.5% at 1.27 cm/h with a detection limit of 0.0254 cm.

The Cathedral wetland contains 17 flow paths (Fig. 2). Monitoring each wetland process individually would be resource intensive and largely infeasible in practice. The monitoring design records only the water surface elevation within the Cathedral wetland Basins 2 and 3. The authors propose that the water surface elevation represents a good composite measure of all H&H processes occurring within the wetland and, therefore, must contain information on important wetland processes. The instantaneous water surface elevation provides a measure of available storage capacity and the change in water surface elevation represents the rates of inflow versus outflow. This simplified monitoring scheme when applied to a valid H&H model should inform one on the stormwater reduction performance of the wetland.

Runoff from the residential area was monitored within the 1.22 m diameter stormwater main upstream of the diversion chamber with a Hach Sigma Model 910 Systems pressure transducer and acoustic Doppler velocity monitor (Hach, Loveland, Colorado) recording at a 15-min increment. Hach Sigma Model 910 Systems pressure transducer observations may *drift* from the correct water level if significant condensation accumulates within the atmospheric pressure tube of the sensor. Desiccant material is placed within the sensor to absorb accumulated condensation (Hach 2008).

Before the collection of any data, the authors determined that proper quality assurance of collected flow data required: (1) weekly maintenance of the desiccant, and (2) validation of the data through comparison to manual measurements of depth and velocity during sensor maintenance visits to ensure sensor drift was not occurring. During the monitoring period desiccant was replaced once a week; however dry weather validation readings by the flow monitor could not be obtained. The groundwater flow depth within the storm sewer was below the sensor detection limit (≤1 cm), which did not allow for dry weather flow measurement verifications.

As demonstrated in Dotto et al. (2014), unreliable or biased calibration data can have some effects on model parameter estimates. As the flow monitoring data could not be validated with the predetermined standards, the authors made the subjective decision to not refine model parameter value estimates based on this information. Reduced groundwater within storm sewers may be more common within urban areas with limited groundwater recharge potential (Maimone et al. 2011). As this monitoring limitation may apply frequently to urban stormwater studies, the authors evaluated the feasibility of utilizing a simplified monitoring scheme using only water surface elevation data within the wetland.

Multiobjective Generalized Sensitivity Analysis

Zheng and Keller (2006) suggest that a preliminary sensitivity analysis be performed before a formal model uncertainty analysis. This general proposed approach to model parameter sensitivity analysis is followed in this research.

Initial model sensitivity is determined using the multiobjective generalized sensitivity analysis (MOGSA) algorithm (Bastidas et al. 2006 ,1999). This algorithm allows the user to determine model sensitivity relative to multiple criteria, or objective functions. Through the Pareto-ranking concept (Clemen 1997), model responses are grouped in Pareto front and non-Pareto front sets. The Pareto front is the set of all nondominated parameter sets within the multiobjective function parameter space. The MOGSA algorithm then compares the parameter distributions within each set at the user-specified Pareto rank (*H0*: Distribution of Pareto front is same as nonfront distribution). The null hypothesis is evaluated through a two-sample Kolmogorov-Smirnov (KS) test. For this paper, the authors reviewed Pareto front ranks 1, 3, 5, and 10 and subjectively compared the consistency among results at different ranks. The authors ensured adequate sampling of the feasible model parameter space by assessing the parameter sensitivity at differing numbers of parameter evaluations (e.g., 2,000, 5,000, and 10,000 parameter evaluations considered). The authors ensured that sensitivity results reach a stable result within the evaluations considered with increasing numbers of parameter evaluations. The KS-test p-value presented is the median of the 50 bootstraps of MOGSA to further ensure stability of the result.

The authors first evaluated the runoff module of SWMM to determine the hydrologic parameter sensitivity driving the rainfall-runoff response of the 0.35 km^2 Cathedral residential subcatchment. This research considers P_R, subcatchment soil parameters (K_{SAT}, S, and IMD), subcatchment width, mean subcatchment slope, surface roughness, and depression storage as random variables (Table 1). Total watershed area, gross percent impervious cover, and monthly evaporation rates are described deterministically. The objective measures used for evaluating SWMM runoff are total volume and peak flow rate as in Sun et al. (2014). The results of this sensitivity analysis were used to reduce the feasible parameter space of the SWMM runoff module in subsequent simulations.

The authors considered the geometric parameters of subcatchment slope and width to be parameters containing some uncertainty as in Khu and Werner (2003), Barco et al. (2008), James et al. (2011), Sun et al. (2014), and Zhang et al. (2015). The SWMM model idealizes subcatchments as rectangular planes with dimensions specified by the width inclined at the slope angle. While estimates of the slope and width can be made from aerial imagery (Jain et al. 2015), the authors consider these parameters to contain some uncertainty attributable to the simplified representation of the land surface within SWMM. The feasible domain of all runoff model parameter values was determined from references presented in Table 1.

As discussed in Hunt et al. (2012) and Mogavero et al. (2009), it is important to consider all design goals when evaluating wetland performance. The authors evaluated model parameter sensitivity within the Cathedral Wetland with respect to total volume delivered to the wetland, peak outflow to Cathedral Run, peak depth, and the volume of water lost through infiltration and ET. This analysis demonstrated which SWMM process is driving stormwater wetland performance. All model parameters were considered to be continuously and uniformly distributed within the feasible parameter domain presented in Table 2. As shown in the "Results and Discussion" section, the sensitive runoff parameters for this case study reduce to: K_{SAT}, P_R, and width.

Next, a sensitivity analysis was conducted with respect to the wetland monitoring data. The authors evaluated model performance with respect to observations made in the wetland through calculation of two objective function values root mean square error (RMSE) (Moussa and Chihinian 2009) and percent bias (P-bias) (Yu and Yang 2000). To better evaluate the wetland model calibration parameter sensitivity, both the P-bias and RMSE were considered as single objective functions and as a multicriteria objective function within MOGSA. At this point, researchers may determine which model parameters are sensitive to both wetland performance and calibration and which parameters may be removed from further consideration.

Generalized Likelihood Uncertainty Estimation Analysis

The authors performed a model parameter uncertainty analysis with respect to the period of observed data for the Cathedral Wetland. The generalized likelihood uncertainty estimation (GLUE) algorithm (Beven and Binley 1992) was applied to the Cathedral stormwater wetland. Parameter set vectors (Θ) are defined by sampling the prior distribution of each parameter, i, and running a simulation to produce a model output $F(\Theta)$. The likelihood of each $F(\Theta)$ was evaluated with respect to observed data. Posterior probability distributions for each Θ were derived from the calculated likelihood functions.

There are two primary considerations when applying the GLUE algorithm (Beven and Binley 2014). First is the selection of the prior model for each parameter. In this application, the authors selected continuous uniform prior distributions (Table 1). This choice of uniform parameter distributions will not affect the GLUE algorithm with any a priori distribution assumptions, and is in line with several previous SWMM analyses (Sun et al. 2012, 2014; Zhang et al. 2015).

Table 1. Feasible Parameter Space for Runoff Parameter Sensitivity Analysis

Dimension	Description	Domain	Units	Domain reference
K_S	K_{SAT}	(0.03, 2.5)	cm/h	Knighton et al. (2014)
P_R	Percent routed	(0, 100)	dimensionless	Rossman (2010)
Width	Shed width	(200, 1,066)[a]	m	James et al. (2011), Sun et al. (2014)
Slope	Mean slope	(0.1, 10)	degrees	PWD (2011)
S_I	Depression storage (impervious)	(0.02, 0.5)	cm	James et al. (2011), Sun et al. (2014)
S_P	Depression storage (pervious)	(0.02, 0.5)	cm	James et al. (2011), Sun et al. (2014)
N_I	Impervious roughness	(0.01, 0.04)	Manning's n	Maidment (1993)
N_P	Pervious roughness	(0.01, 0.04)	Manning's n	Maidment (1993)

[a]The subcatchment width domain was selected as 0.3 to 1.8 times the square root of the subcatchment drainage area.

Table 2. Feasible Parameter Space for the Cathedral Wetland SWMM Model

Location	Dimension	Description	Parameter domain	Units
Diversion	W_1	Overflow weir	(1, 5)	Dimensionless
Stable runoff	$K_{\mathrm{SR}1}$	K_{SAT}	(0.03, 2.5)	cm/h
	P_{R1}	Percent routed	(0, 100)	Dimensionless
	Width_1	Shed width	(30, 200)	m
Residential runoff	K_{SR2}	K_{SAT}	(0.03, 2.5)	cm/h
	P_{R2}	Percent routed	(0, 100)	Dimensionless
	Width_2	Shed width	(200, 1,066)	m
Basin 1	E_1	Evapotranspiration	(0, 3)	Dimensionless
	K_{S1}	K_{SAT}	(0.03, 2.5)	cm/h
	C_{1A}	Slow drain orifice	(0, 1)	Dimensionless
	C_{1B}	Slow drain orifice	(0, 1)	Dimensionless
Basin 2	E_2	Evapotranspiration	(0, 3)	Dimensionless
	K_{S2}	K_{SAT}	(0.03, 2.5)	cm/h
	W_2	Overflow berm	(1, 5)	Dimensionless
Basin 3	E_3	Evapotranspiration	(0, 3)	Dimensionless
	K_{S3}	K_{SAT}	(0.03, 2.5)	cm/h
	C_{3A}	Slow drain orifice	(0, 1)	Dimensionless
	C_{3B}	Slow drain orifice	(0, 1)	Dimensionless
	C_{3C}	Overflow grate	(0, 1)	Dimensionless
	W_3	Overflow berm	(1, 5)	Dimensionless

Second is the definition of the likelihood function with which the relative probabilities of proposed model parameter sets are weighted. It has been well demonstrated that the choice of likelihood function has a significant effect on uncertainty estimates (He et al. 2010; Vrugt and Sadegh 2013; Jung et al. 2014; Zhang et al. 2015). The correct choice of likelihood function has also been the subject of much debate (Mantovan and Todini 2006; Mantovan et al. 2007; Stedinger et al. 2008; Clark et al. 2011; Beven and Binley 2014). Therefore, a likelihood function as suggested by Stedinger et al. (2008) was used for this analysis.

The formal Bayesian likelihood function proposed by Stedinger et al. (2008) is derived under the assumption of normally independently distributed (NID) errors or residuals [Eq. (1)]

$$L(\Theta|D) = \exp\left[-\frac{n}{2}\frac{\sum_{t=1}^{n}(D_t - D_t)^2}{\sum_{t=1}^{n}(D_t - D_{t\mathrm{MLE}})^2}\right] \quad (1)$$

For this study the authors employed a uniform, noninformative prior distribution for each parameter set Θ. Wetland processes are simulated given Θ to develop estimates of the water surface elevation data from Basins 2 (d_2) and 3 (d_3). Researchers may then use the observed data to inform the likelihood of Θ [Eq. (1)]. The posterior distribution of each Θ is updated twice with the GLUE algorithm provided the water surface elevation data from Basins 2 (d_2) and 3 (d_2). Under this arrangement, the posterior probability of Θ may be expressed as

$$P(\Theta|d_2, d_3) = k \times L(\Theta|d_2) \times L(\Theta|d_3) \quad (2)$$

Mantovan and Todini (2006) and Mantovan et al. (2007) suggest that GLUE utilizing informal likelihood functions, such as Nash and Sutcliffe Model Efficiency, represents an incoherent and inconsistent methodology as the measure has no statistical basis. Adoption of a formal likelihood function [Eq. (1)] avoids two major shortcomings of the traditional GLUE approach. First, there is no need to subjectively separate parameter sets into behavioral and nonbehavioral sets; all parameter sets are assigned a posterior likelihood. Clark et al. (2011) discuss the need to incorporate a subjective threshold between behavioral and nonbehavioral itself introduces uncertainty as a poor choice returns invalid results. Second, the information content of the calibration data set is incorporated directly into the posterior probability distribution for parameter sets. As discussed in Stedinger et al. (2008) this allows one to objectively evaluate the information content of the calibration data. The authors agree that considering information content of calibration data is critical; however n does not directly represent the length of the observation data set.

Wetland processes are continuously occurring and, therefore, the calibration should not be separated into independent precipitation event statistics as in Sun et al. (2014). For this research the authors applied the likelihood measure proposed in Stedinger et al. (2008); in which the information content provided to the Cathedral wetland model is dependent on a subset of n independent observations within the calibration period. This methodology differs from Sun et al. (2014) as this research attempts to retain the full information provided by the temporal distribution of the water surface elevations throughout the period of observations.

To determine the information content of the data set, the inherent correlation within the collected monitoring data is evaluated. As discussed in Weijs et al. (2013a, b), periods of inundation will show significantly less temporal persistence than dry weather. Therefore, the observation data set is divided into two subsets based on water surface elevation (>0.6 m and <0.6 m). The temporal autocorrelation of each data set is estimated by calculating the sample Pearson's correlation coefficient (ρ) as a function of the lag as in Schoups and Vrugt (2010)

$$\rho(\mathrm{lag}) = \frac{\sum_{i=\mathrm{lag}}^{n}(x_i - x_{\mathrm{avg}})(x_{i-\mathrm{lag}} - x_{\mathrm{avg}})}{\sqrt{\sum_{i=\mathrm{lag}}^{n}(x_i - x_{\mathrm{avg}})^2}\sqrt{\sum_{i=1}^{n}(x_{i-\mathrm{lag}} - x_{\mathrm{avg}})^2}} \quad (3)$$

The thinned data set is accepted at the data set lag which shows no significant temporal persistence ($|\rho| \leq 0.2$ at the 95% confidence level). The resulting distributions of independent residuals for each simulation are tested for normality and homoscedasticity. Similar to methods in Romanowicz et al. (1994) the issues of heteroscedasticity and non-normality of residuals are resolved through a log transformation. Schoups and Vrugt (2010) present an alternate method for dealing with non-NID residuals in which the issues of non-normality, temporal autocorrelation and heteroscedasticity are formally incorporated into the likelihood function. The following transformation is applied to create an NID residual data set

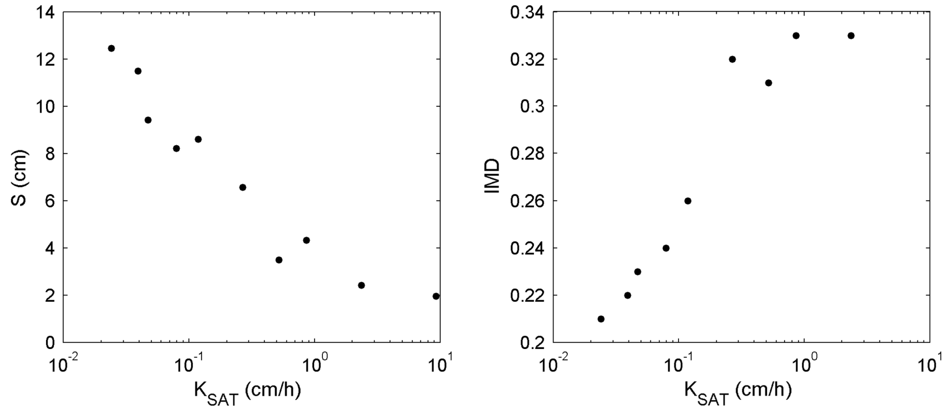

Fig. 4. Soil texture relationships for K_{SAT}, S, and IMD (data from Maidment 1993)

$$\text{NID Res}_i = \log(|\text{Sim}_i - \text{Obs}_i| + 1) \quad (4)$$

To adequately cover the entire feasible parameter space (Table 1) the authors evaluate a total of 50,000 model parameter sets sampled randomly from the uniform prior distributions.

Results and Discussion

Monitoring Results

Monitoring of the Cathedral stormwater wetland was conducted over a 64-day period from August to October 2013. The time series

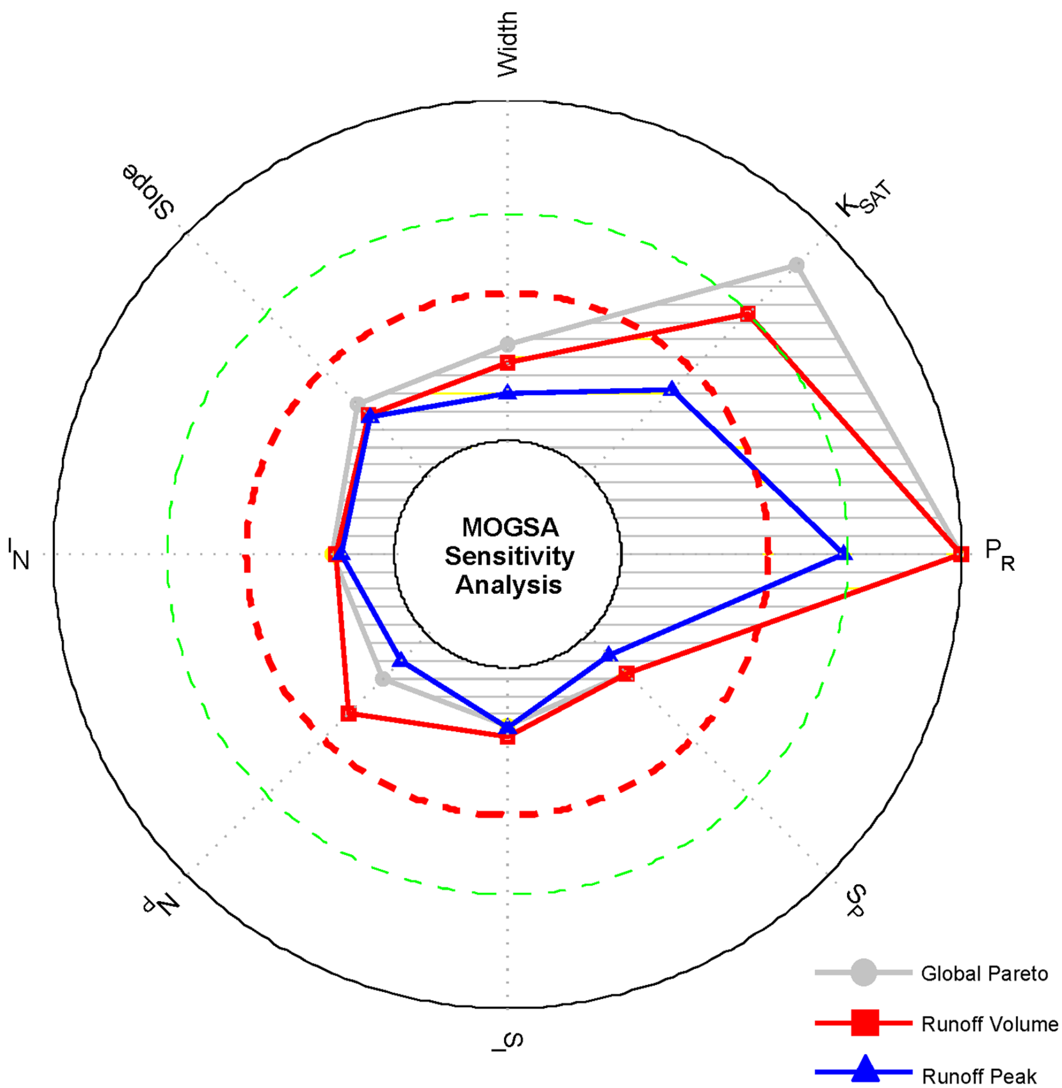

Fig. 5. MOGSA results for SWMM subcatchment runoff parameters; the concentric circles correspond to KS p-values or significance levels of $\alpha \leq 0.001$, $\alpha = 0.01$, and $\alpha = 0.05$, respectively, moving inward

of the Cathedral wetland water surface elevation data is presented in Fig. 4. A total of 19 unique precipitation events were recorded assuming a precipitation interevent time of 6 h.

SWMM Generalized Parameter Sensitivity

SWMM Runoff Module Parameter Sensitivity

The first 10,000 simulation sensitivity analysis considered SWMM runoff module parameters defining the rainfall-runoff relationship of a subcatchment. The results (Fig. 5) demonstrate that the runoff volume and peak flow as calculated by SWMM is primarily sensitive to K_{SAT} and P_R. Runoff volume and peak flow rate were identified as being insensitive to subcatchment surface roughness (N_I, N_P), surface depression storage (S_I, S_P), and mean slope.

Several previous studies have demonstrated that runoff peak flow is sensitive to subcatchment width (Barco et al. 2008; Beling et al. 2011; Zhang et al. 2015), therefore, this parameter was carried forward as well. The differences in runoff parameter sensitivity between this study and among various published SWMM studies indicated that runoff parameter sensitivity is largely site specific (Barco et al. 2008; Beling et al. 2011; Gülbaz and Kazezyılmaz-Alhan 2013; Sun et al. 2014; Zhang et al. 2015). These results suggest that SWMM is a well parameterized model for simulating runoff from a variety of landscapes. The authors' findings refute the idea that a set of globally significant parameters exist for runoff simulations.

Wetland Performance Sensitivity

The second 50,000 simulation sensitivity analysis was carried out on all Cathedral wetland parameters (Fig. 2 and Table 2). The runoff parameters identified demonstrate significant sensitivity as they determine the total volume of water to be treated by the wetland. The Stable subcatchment showed no significant sensitivity with respect to P_R or width primarily because the contributing drainage area was 0.01 km^2 out of a total 0.36 km^2.

Total Cathedral wetland overflow volume showed significant sensitivity to the Cathedral runoff parameters (P_R, soils, width), Stable runoff soils, Basin 3 soils, and the W_3 weir coefficient (Fig. 6). These results are intuitive as the runoff parameters determine the total volume of runoff, Basin 3 K_{SAT} results in infiltration which reduces overflow volume, and the weir W_2 determines the overflow rate when the wetland is filled beyond its storage capacity.

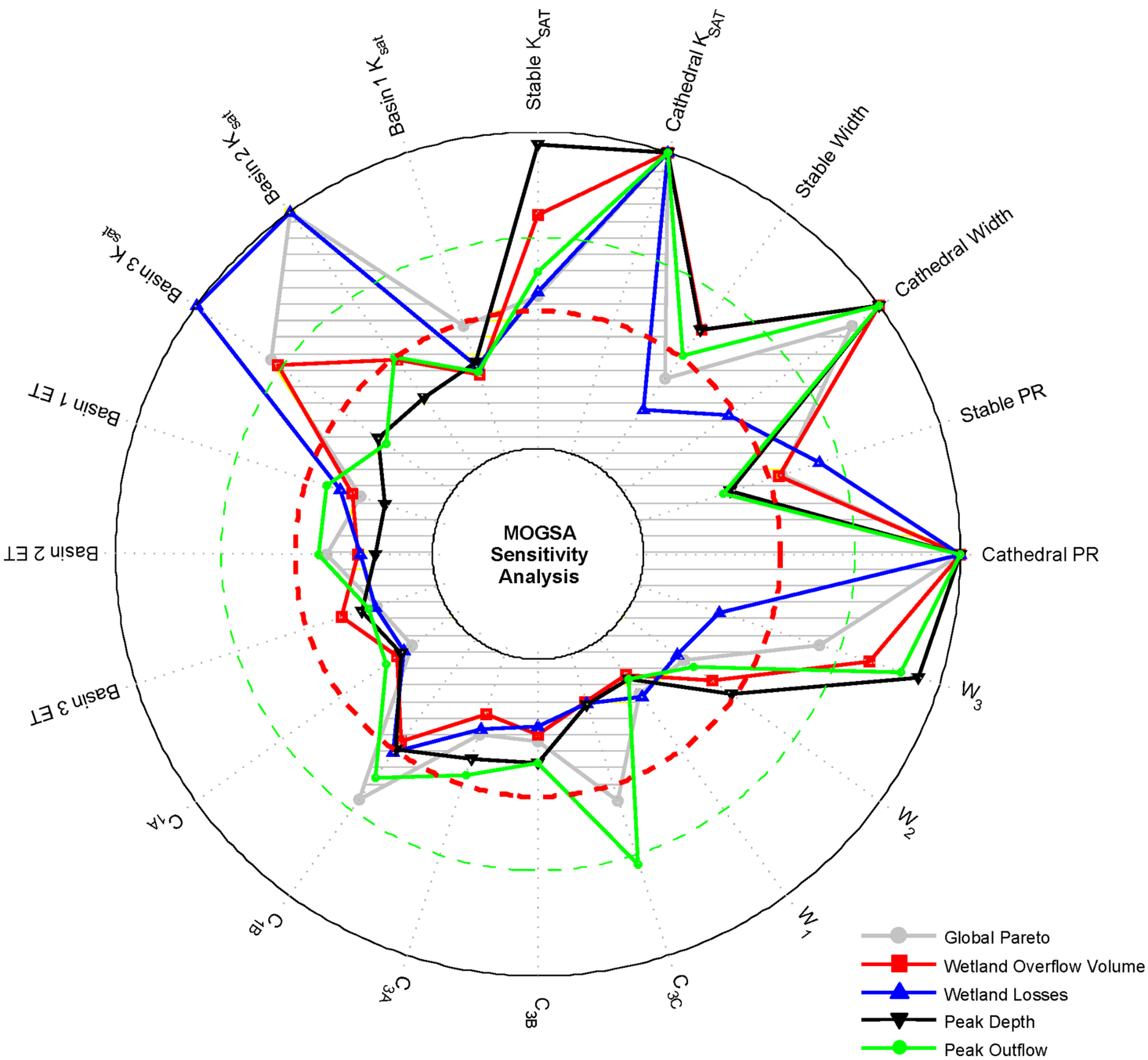

Fig. 6. MOGSA results for cathedral wetland; the concentric circles correspond to KS p-values or significance levels of $\alpha \leq 0.001$, $\alpha = 0.01$, and $\alpha = 0.05$, respectively, moving inward

The greater sensitivity to Cathedral runoff parameters as opposed to Stable runoff parameters is the result of the significantly greater contributing drainage area of the Cathedral catchment.

Wetland losses (infiltration and ET) are primarily sensitive to the Cathedral runoff parameters (P_R, soils, width) and Basins 2 and 3 soils (Fig. 6). ET is occurring in parallel with wetland infiltration however, the rate is several orders of magnitude less than the infiltration capacity of the wetland. While ET is an important hydrologic pathway, the uncertainty in the understanding of ET may be overwhelmed by the greater uncertainty in other model processes. Unless ET could be measured through other methods as in Drexler et al. (2004) and Clulow et al. (2012), the additional complexity of ET processes may not be justified for inclusion. Wetland infiltration rates show significant sensitivity to wetland losses, but significantly less sensitivity to overflow volume. The reason for this contrast is the relatively small storage volume of the Cathedral wetland.

Peak depth within the wetland and peak overflow to Cathedral Run demonstrates sensitivity to similar parameters (Fig. 6). Cathedral runoff parameters (P_R, soils, width), Stable runoff soils, overflow weir W_3, and slow drain orifice C_{3C}. Orifice C_{3C} represents an overflow grate above the slow drain orifices C_{3A} and C_{3B}, as such it has some effect on controlling flooding within the wetland and the downstream peak flow rate. This result suggests that wetland flooding and peak overflow reduction are controlled primarily by the wetland relief berm (W_3). The author's hereby demonstrate that parameter sensitivity for urban stormwater control (e.g., wetlands, detention basins, green stormwater infrastructure) simulation should be expanded beyond the parameters defining runoff to include uncertainty in all relevant processes and flow paths.

Wetland Calibration Parameter Sensitivity

The generalized sensitivity analysis of the Cathedral wetland parameters was performed with respect to the ability of the model to reproduce water surface elevation data within Basins 2 and 3 with precipitation forcing data (Figs. 7 and 8). The purpose of this analysis was to determine if the calibration design collected statistically significant information pertaining to parameters driving wetland performance.

The RMSE and P-bias objective functions calculated for Basin 2 show sensitivity to Cathedral soils, P_R, Basin 2 soils, overflow weir W_2, and orifice coefficients C_{3A} and C_{3C} (Fig. 7). The W_3 weir coefficient shows near significant sensitivity ($\alpha \leq 0.1$). The sensitivity analysis for Basin 3 demonstrates that the calibration data contains information on the Basin 2 and 3 soils, Cathedral P_R, and the C_{3A} and C_{3C} orifice coefficients (Fig. 8).

The wetland monitoring design based on water surface elevations was sufficient to obtain statistically significant information

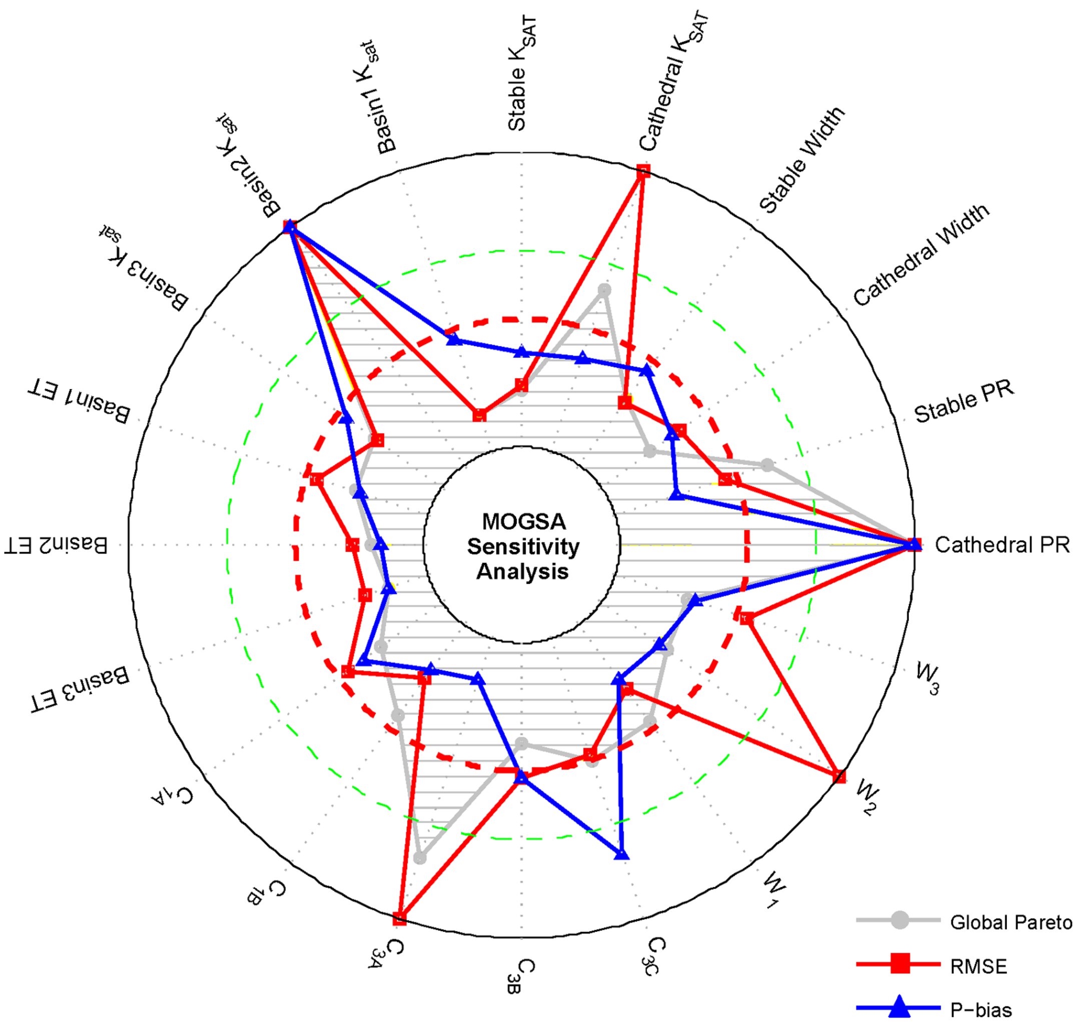

Fig. 7. Cathedral wetland parameter sensitivity to Basin 2 water elevation data; the concentric circles correspond to KS p-values or significance levels of $\alpha \leq 0.001$, $\alpha = 0.01$, and $\alpha = 0.05$, respectively, moving inward

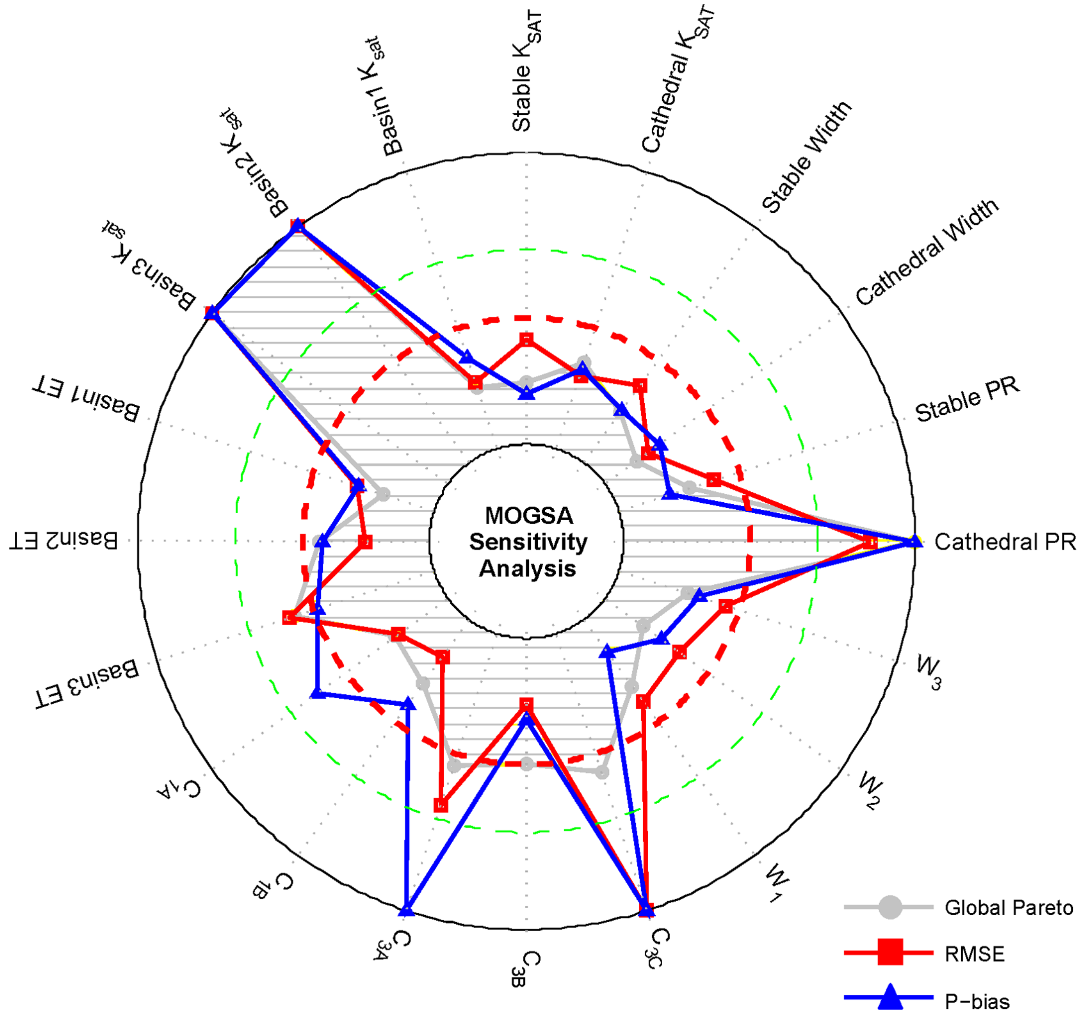

Fig. 8. Cathedral wetland parameter sensitivity to basin 3 water elevation data; the concentric circles correspond to KS p-values or significance levels of $\alpha \leq 0.001$, $\alpha = 0.01$, and $\alpha = 0.05$, respectively, moving inward

on most Cathedral wetland calibration parameters as defined by each single objective sensitivity measure.

The KS-test significance values for the global sensitivity analysis based on Pareto rank 10 utilizing 50,000 simulations is presented in Table 3. The globally sensitive model parameters for wetland performance includes a mix of H&H parameters (subcatchment P_R and soils, Basin 2 soils, and orifice C_{3C}).

The calibration period globally sensitive calibration parameters demonstrate at least $\alpha \leq 0.1$ level sensitivity for all performance parameters except orifice C_{3C} (Table 3). As demonstrated in Fig. 8, the single objective functions for Basin 3 showed significant sensitivity to orifice C_{3C} therefore the calibration data contain some information on this parameter. It is, therefore, feasible that the water surface elevation data could provide a statistically significant refinement of the feasible parameter space through GLUE analysis. This finding supports the concept of simplified monitoring programs for urban stormwater control installations where direct runoff measurement may be infeasible.

GLUE Analysis

Determining Observed Data Information Content

The first step towards applying GLUE, as in Sun et al. (2014), is to distill the monitoring data down to a record of independent observations that still express the information content of the monitoring

Table 3. Cathedral Wetland Performance and Calibration Parameter Global Pareto KS-Test Significance Values

Parameter	Wetland performance	Basin 2 calibration	Basin 3 calibration
Cathedral P_R	0.00[a]	0.00[a]	0.02[a]
Cathedral K_{SAT}	0.00[a]	0.07[b]	0.16
Basin 2 K_{SAT}	0.01[a]	0.00[a]	0.00[a]
C_{3C}	0.02[a]	0.14	0.11
Stable K_{SAT}	0.05[b]	0.34	0.29
Basin 3 K_{SAT}	0.07[b]	0.21	0.00[a]
W_3	0.1	0.26	0.24
Cathedral width	0.13	0.3	0.42
Stable width	0.13	0.2	0.3
Basin 1 K_{SAT}	0.15	0.39	0.3
C_{3A}	0.17	0.02[a]	0.08
C_{1B}	0.19	0.1	0.23
Stable P_R	0.2	0.16	0.25
C_{3B}	0.2	0.13	0.1
Basin 2 ET	0.21	0.3	0.17
Basin 3 ET	0.26	0.39	0.08[b]
Basin 1 ET	0.3	0.26	0.32
W_2	0.32	0.27	0.38
C_{1A}	0.35	0.21	0.26
W_1	0.37	0.07[b]	0.2

[a]Sensitivity at the $\alpha \leq 0.05$ level.
[b]indicates parameter sensitivity at the $0.05 \leq \alpha \leq 0.1$ level.

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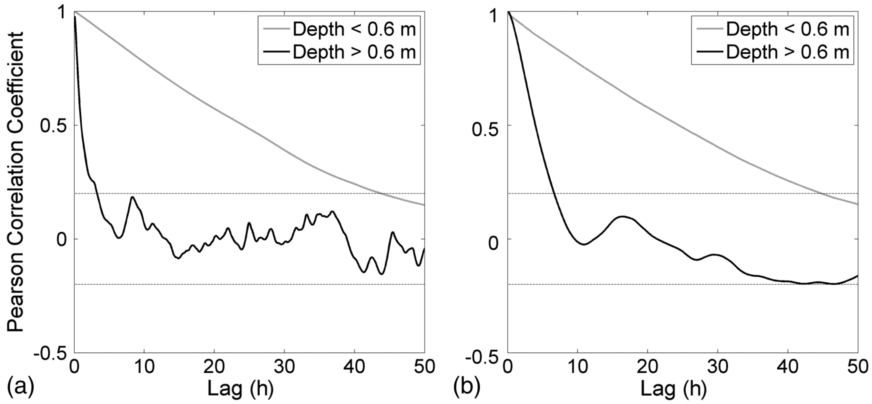

Fig. 9. Pearson's correlation coefficient for time lags of (a) Basin 2; (b) Basin 3 observed water surface elevations

data. The Pearson's correlation coefficient (ρ) for the observed water surface elevation data in Basins 2 and 3 is calculated against varying time lags to determine the temporal persistence of the data sets (Fig. 9). Applying progressively increasing lags to the time series indicates that water surface observations separated by greater times are generally less correlated

The analysis demonstrates that data points at higher water elevations (>0.6 m) are much less autocorrelated than during periods of low water surface elevation (<0.6 m). Similar to findings in Weijs et al. (2013a, b) data points during wet weather periods are significantly more informative than dry weather periods.

Correlation coefficients within the $|\rho| \leq 0.2$ threshold demonstrate no statistically significant correlation (at the 95% confidence level). Resampling the observed data at this time step constitutes removal of the temporal persistence within the data set. This research, therefore, considers a data set composed of 2- and 6-h data in Basins 2 and 3, respectively, during wet weather and 48-h data during dry weather conditions within the wetland (Fig. 10) for calculation of the GLUE likelihood function.

Vrugt et al. (2002) discuss a shortcoming of classic GLUE likelihood functions in that they do not weigh the usefulness of calibration data points to refine specific model parameters. Care must be taken to apply only NID data to a formal statistical likelihood function as in Stedinger et al. (2008) and Sun et al. (2014) to properly discern between information content and record length.

Similar to findings presented in Schaefli et al. (2007), the Cathedral wetland residuals of simulated versus observed water surface elevations are both non-normal [Fig. 11(a)] and highly heteroscedastic [Fig. 11(b)]. Eq. (4) is applied to the model residuals and a test for normality to ensure NID residuals.

Model Parameter Probability Distributions

Prior and marginal posterior probability distributions for each model parameter are presented in Fig. 12 as determined by the GLUE algorithm incorporating a formal Bayesian likelihood function [Eq. (1)]. Subcatchment P_R determines the portion of impervious runoff which is diverted onto pervious areas. This parameter directly affects the runoff volume of all events and, therefore, was able to be significantly refined (Fig. 12). Subcatchment soils (K_{SAT}, S, and IMD) and width were minimally refined based on water surface elevations within Basins 2 and 3 (Fig. 12). The reason for this result is that the flow into the wetland is regulated by the diversion chamber (Fig. 2). The MOGSA algorithm demonstrated some sensitivity of the calibration to runoff subcatchment soils (Fig. 7), however, the potential refinement that could be provided through application of this monitoring data to the GLUE algorithm is modest (Fig. 12).

This methodology focuses on the model as a complete system in contrast to the piece-wise parameter calibration presented in Sangal and Bonema (1994). The author's methodology has several advantages for SWMM. First, model parameter refinements are generated only for parameters that are supported by the data set. Second, one can consider second-order interactions among all model parameters, which is somewhat lost in the methodology proposed by Sangal and Bonema (1994). Finally, this methodology generates probability distributions for model parameters, which gives the user an objective measure of parameter uncertainty as opposed to a best-fit parameter value.

Flow through Basins 2 and 3 is dominated by wetland infiltration (Basins 2 and 3 K_{SAT}), orifice C_{3C}, and weir W_2. Weir W_2 is the only direct hydraulic connection between Basins 2 and 3 and, therefore, controls the higher water surface elevations within Basin 2. Orifice C_{3C} is the lowest elevation orifice within Basin 3 and is the most frequently activated orifice. Orifices C_{3A}, C_{3B}, and weir W_3 control flood level water surface elevations. While these structures are important to overall wetland design, periods of flooding

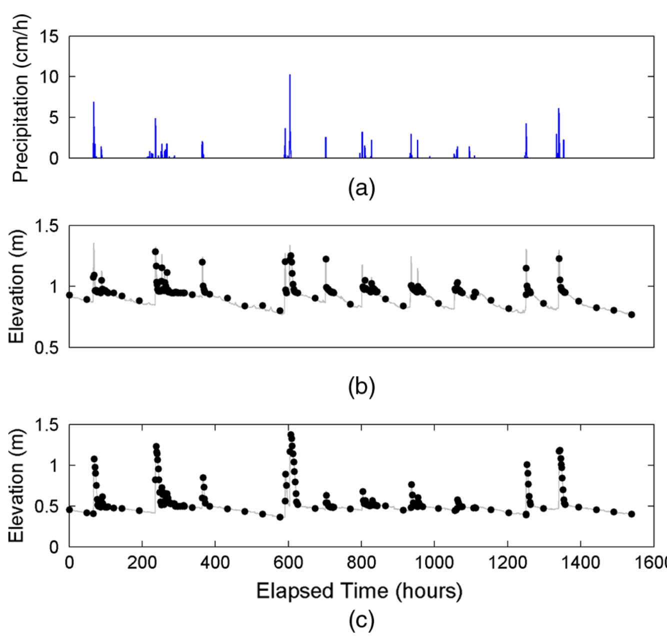

Fig. 10. Independent wetland observations (solid circles) considered for GLUE uncertainty analysis: (a) precipitation; (b) water surface elevation in Basin 2; (c) water surface elevation in Basin 3

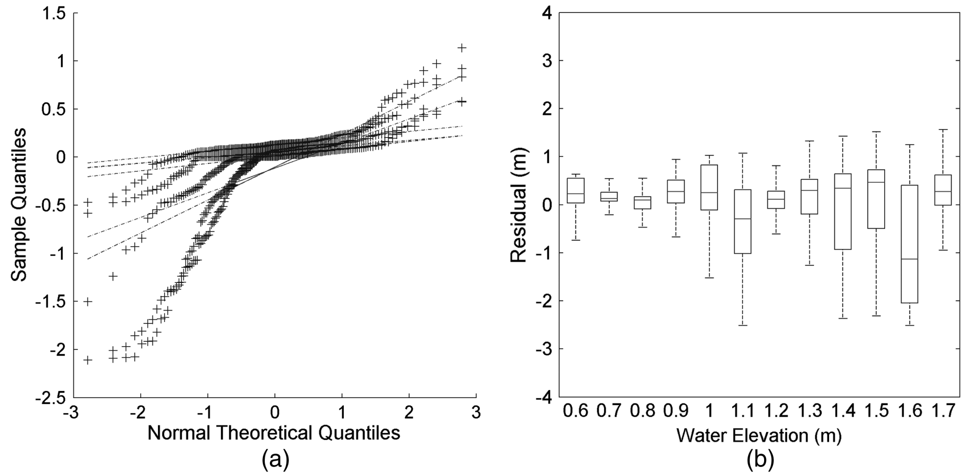

Fig. 11. (a) Q-Q plots for five randomly selected simulation set residuals; (b) boxplots of residuals within Basin 3 for 50,000 simulations demonstrating heteroscedasticity

are very brief and had a limited effect on reproduction of the observed data set. The Cathedral Wetland posterior parameter sets demonstrate that significant uncertainty in H&H model predictions comes from the hydraulic model parameters. The wetland soils infiltration estimates of 0.4 to 0.8 cm/h are similar to infiltration rates estimated from available soil maps (USDA NRCS 2015).

The simplified monitoring scheme using only water surface elevations is capable of providing information on four of six model parameters. All significant processes (Fig. 5), with the exception of the subcatchment soils and the emergency flood overflow weir (W_3), are refined through the GLUE algorithm incorporating a formal Bayesian likelihood function (Stedinger et al. 2008; Sun et al. 2014).

Next, this research examined the 2D parameter space to consider second-order parameter sensitivity and a qualitative review of parameter dependencies for parameters showing a refinement of the feasible parameter space. Fig. 13 demonstrates that the posterior probability distributions of several parameters are dependent on other parameters.

The 2D parameter space of Basins 2 and 3, in particular, demonstrated a strong dependence between wetland infiltration rates. This result highlights equifinality within the GLUE analysis results.

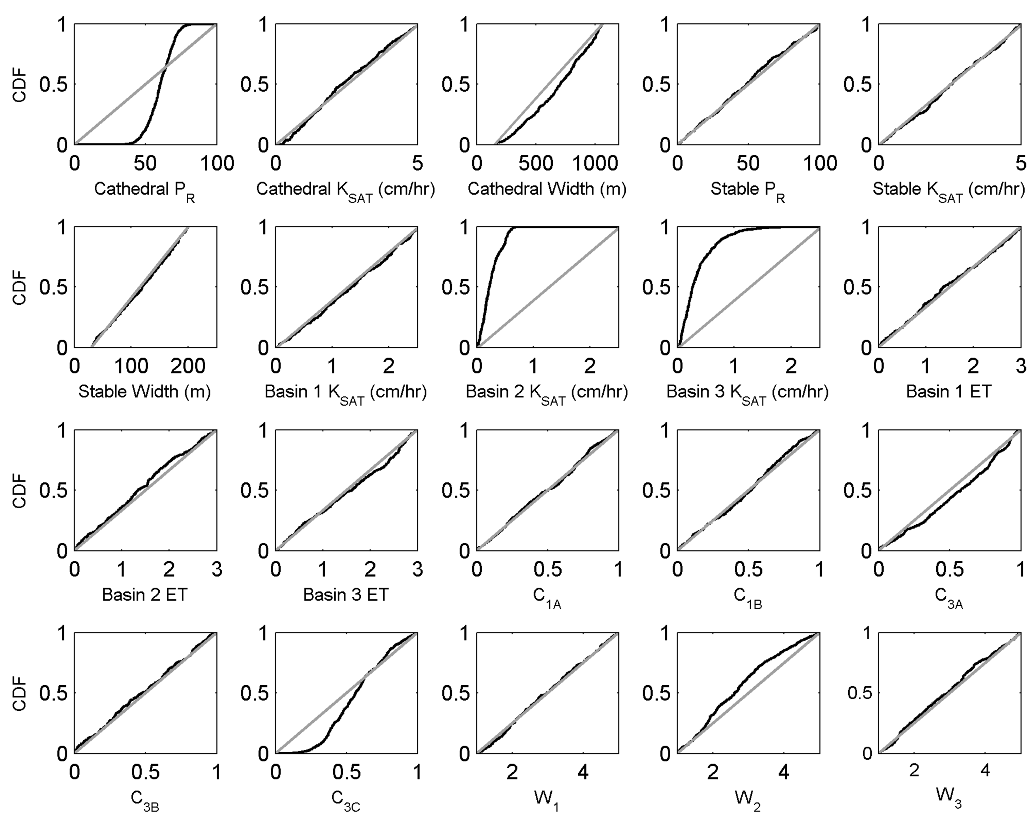

Fig. 12. Prior (gray) and marginal posterior (black) parameter distributions incorporating water surface elevation information

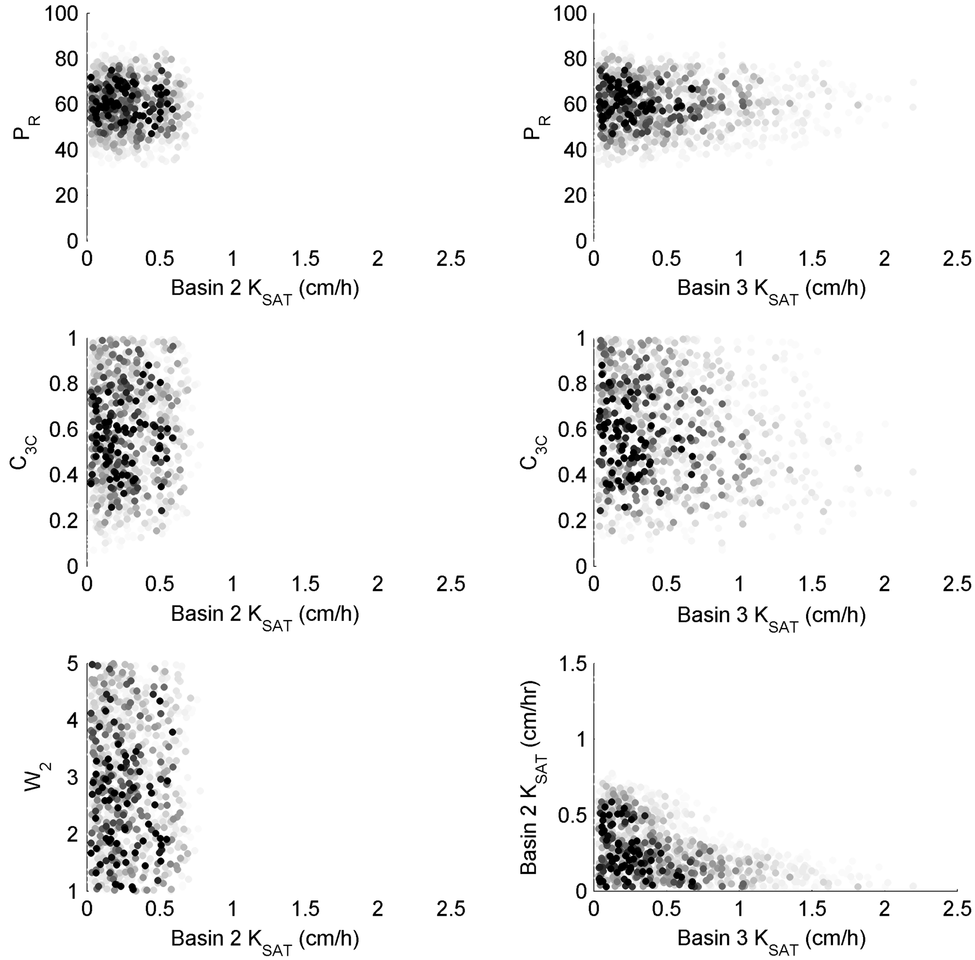

Fig. 13. Two-dimensional probability density ("dotty plot") of select parameters; darker shades indicate greater likelihood

The probability space shows that higher estimates of infiltration capacity of each basin may have a high likelihood, but only when the hydraulic conductivity of the opposite basin is lower. In this paper, the authors demonstrated the importance of considering the posterior parameter set, $P(\Theta|d_1, d_2)$, in its entirety. Resampling each parameter according to Fig. 12 would not reproduce the appropriate model output. The results show the importance of equifinality (e.g., a system may demonstrate a similarly strong calibration under differing model parameterizations) (Beven 2006) and the need to consider higher order parameter spaces in resampling.

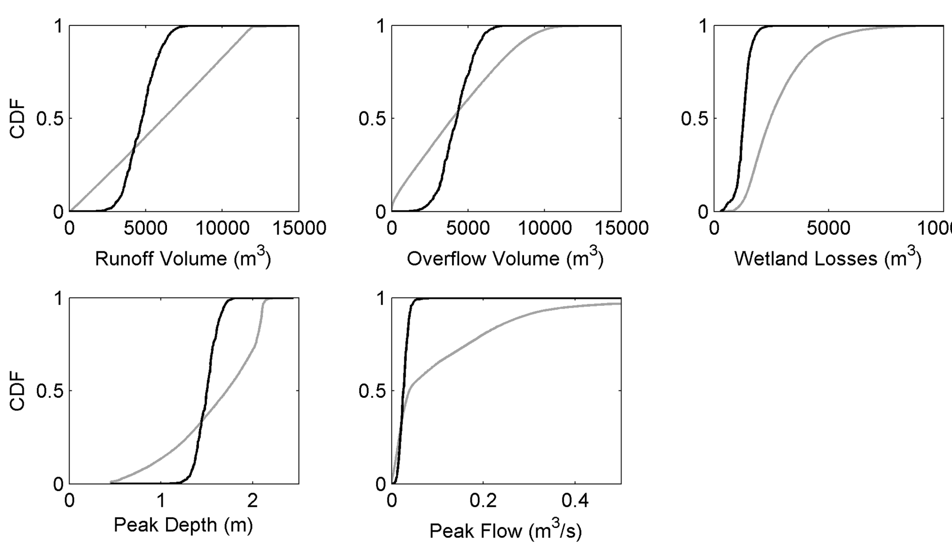

Fig. 14. Wetland model performance metric prior (gray) and posterior (black) distributions

Wetland Performance Uncertainty

The authors present the prior and marginal posterior distributions for the wetland performance indices of total runoff volume, total overflow volume to Cathedral Run, the volume of water lost through infiltration, ET, peak depth, and the peak flow rate to Cathedral Run (Fig. 14) over the duration of the monitoring period. Of particular interest is the refinement in the understanding of in the peak flow delivered to Cathedral Run as this most directly affects the Cathedral Stormwater Wetland ability to address the requirements of the sediment TMDL for Wissahickon Creek (USEPA 2003; PWD 2007).

As discussed in Stedinger et al. (2008), data provides information, and more data provides more information. This research demonstrates how a simplified monitoring program design allows one to collect hydrologic data with an information content that allows for significant refinement of model parameters and predictions.

Conclusions

This research presents a SWMM parameter sensitivity analysis for an urban stormwater wetland installation. The authors present a methodology for identifying sensitive model parameters and the information content of calibration data. Through a simplified monitoring program, the authors demonstrated refinements to model parameters and predictions of wetland performance where direct monitoring of runoff was largely infeasible.

- The differences between this study and among other published research on SWMM runoff parameter sensitivity indicate that runoff sensitivity is site specific (Barco et al. 2008; Beling et al. 2011; Sun et al. 2014; Zhang et al. 2015). This result suggests that SWMM is well parameterized to estimate runoff from varying land uses, but care must be taken to properly identify the sensitive parameters. This research presents evidence that there is no globally sensitive set of SWMM parameters. Parameter sensitivity depends on the case study and the effects of second-order interactions among model parameters. This research demonstrates that detailed models of stormwater control installations are significantly affected by uncertainty related to parameters beyond traditional calibration (i.e., runoff generation) parameters. This is particularly important for stormwater control structure models which feature parallel flow pathways. The authors demonstrated a methodology that objectively identifies sensitive model parameters and evaluates the information content of calibration data to make meaningful estimates of SWMM parameters.
- ET from each wetland basin was included as a SWMM model process; however, this hydrologic pathway showed minimal sensitivity to objective wetland performance and calibration measures. This result demonstrates that increasing model complexity to incorporate ET processes may not be statistically justified in all cases because of the potentially greater uncertainty in other wetland processes. In stating this conclusion, the authors note that a monthly constant evaporation parameter multiplied by a factor was used to account for transpiration. This simplification does not account for vegetation-dependent transpiration or longer dry periods in which ET may become significant.
- The wetland monitoring program design, based on only water surface elevation and precipitation observations, was sufficient to obtain statistically significant ($\alpha \leq 0.1$) calibration data as measured by RMSE and P-bias single objective functions. The authors demonstrated that significant parameter refinements can be obtained without direct measurements of runoff, which are often difficult to obtain for urban stormwater control structures.

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Notation

The following symbols are used in this paper:

D_t = observed depth at time t;
$\dot{D}_t$ = simulated depth at time t, using parameter set Θ;
$\dot{D}_{t\mathrm{MLE}}$ = simulated depth using the maximum likelihood estimator of the parameter set Θ;
d_2 = observed water surface elevations from Basin 2;
d_3 = observed water surface elevations from Basin 3;
i = time step;
k = normalizing constant ensuring distribution sums to 1;
$L(\Theta|Q)$ = likelihood of parameter vector Θ, given depth observations, D;
$L(\Theta, d)$ = likelihood of parameter vector Θ given observation vector d;
lag = lag step;
NID Res_i = normally independently distributed residual at time step i;
n = information content of calibration data;
Obs_i = observed value at time step i;
$P(\Theta|d_2, d_3)$ = posterior probability of parameter set Θ, given depth observation vectors d_2 and d_3;
Sim_i = simulated value at time step i;
x_{avg} = average of depth observations;
x_i = depth observation at time step i;
Θ = parameter vector; and
ρ = Pearson's correlation coefficient.

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