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Doing a Lot with a Little: A Diagnostic Analysis of SWMM to Simulate Hydrologic Behavior within LID Systems

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Abstract

Low Impact Development (LID) aims to mitigate the hydrological impacts of urbanization by promoting evapotranspiration, storing and slowing the flow of water in formerly impervious areas. Green roofs, a form of LID often utilized in highly urbanized watersheds, are widely simulated using the Storm Water Management Model (SWMM). However, methods to improve diagnostic analysis of SWMM have lagged compared to other environmental disciplines. In this study, I utilize frugal diagnostic analyses to investigate potential sources of non-linearity, uncertainty, and equifinality within SWMM applied to a particular case study, the OnCenter green roof in Syracuse, New York. My findings highlight the major sources of uncertainty in SWMM – model inputs, parameters, structural equations, and reconciling differences between simulated outputs versus observed variables – and demonstrate that more complex diagnostic analysis is necessary to fully understand the fundamental drivers of, and interactions amongst, uncertainty in the SWMM LID bioretention module. As SWMM contains many parameters and therefore multiple degrees of freedom, sensitivity analyses performed using one-at-a-time tests highlight that these analyses are only local estimates within a neighborhood of the selected parameter set. Though we could achieve strong agreements between simulated and observed runoff, SWMM was not able to replicate observed storage timeseries during simulation, suggesting that common approaches to calibrate only to periods of precipitation may misrepresent key hydrologic storages and fluxes within the model. While information gained from frugal analyses can aid in SWMM calibration, the approaches we’ve used oversimplify complex hydrological processes in an extremely non-linear model, limiting their effectiveness as diagnostic tools. The development of a more flexible model structure that allows for complex diagnostic analysis is necessary to fully understand the fundamental drivers of uncertainty in the SWMM LID bioretention module. Encouraging the co-production of knowledge through mutually beneficial dialog between researchers and practitioners presents an opportunity to accelerate SWMM model improvement.
Doing a Lot with a Little: A Diagnostic Analysis of SWMM to Simulate Hydrologic Behavior within LID Systems

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1 Introduction

Urbanization strongly modifies land cover, which subsequently alters various processes within the hydrological cycle (Arnold & Gibbons, 1996). In comparison to forested watersheds, urban watersheds typically exhibit larger surface runoff volumes, higher peak flows, reduced infiltration, decreased transpiration and more severe pollutant loads (Bannerman, Owens, Dodds, & Hornewer, 1993; Booth & Jackson, 1997; Haase, 2009; Jefferson et al., 2017; Lee & Heaney, 2003; Ruth, 2003). One alternative to mitigate the environmental impacts of urban land use is to utilize Low Impact Development (LID) systems. LIDS replicate predevelopment hydrological functions (Stovin, Vesuviano, & Kasmin, 2012; US EPA, 2000), and provide many additional ecosystem services, including removing air and runoff pollutants (Bianchini & Hewage, 2012; J. Li et al., 2010), mitigating urban heat islands (Blanusa et al., 2013; Susca, Gaffin, & Dell’Osso, 2011), and increasing urban biodiversity (Cook-Patton & Bauerle, 2012; Francis & Lorimer, 2011). Green roofs, a form of LID, manage stormwater directly at the source, by retaining (i.e., reducing volume) and detaining (i.e., shifting peak intensity) stormwater runoff (Y. Li & Babcock, 2014; Anna Palla et al., 2010; Stovin, Poë, De-Ville, & Berretta, 2015). Green roofs are a particularly attractive stormwater management option in dense urban areas, where rooftops in developed nations account for roughly 40 to 50% of urban impervious surfaces (Dunnett and Kingsbury 2008).

To date, numerous monitoring studies have been conducted to understand hydrologic processes within green roofs and to predict how much water they may retain under extreme scenarios (Y. Li & Babcock, 2014; Nawaz, McDonald, & Postoyko, 2015; Stovin et al., 2012). The latter can indicate the impact of green roofs on sewershed or city-wide stormwater management, and permits predictive extrapolation beyond observations and beyond a specific...
period of record (Cipolla, Maglioniico, & Stojkov, 2016). Modeling green roof behavior (i.e., fluxes and storages) and performance (i.e., runoff volume and peak intensity) is especially important given that green roof configuration and climate can lead to very different magnitudes of rainfall capture, and therefore may alter the timing and magnitude of green roof runoff (Carson, Marasco, Culligan, & Mcgillis, 2013; Mentens, Raes, & Hermy, 2006; Spolek, 2008).

Among commercial models, the Storm Water Management Model (SWMM) is the most commonly used hydrologic and hydraulic model by researchers and practitioners alike. SWMM has historically been applied to simulate the quality and quantity of runoff from urban subcatchments. As the need for understanding and predicting performance within individual LID systems has grown, SWMM has been modified to include more specific modular frameworks for different types of LID forced by both long-term and single-event simulations (Burszta-Adamiak & Mrowiec, 2013; Rossman, 2008). SWMM (version 5.1.012) (Rossman, 2017) currently contains a green roof module (Y. Li & Babcock, 2014) and a bioretention module (Burszta-Adamiak & Mrowiec, 2013) capable of simulating green roof hydrologic behavior, with validation studies across the literature (Cipolla et al., 2016; Krebs, Kuoppamäki, Kokkonen, & Koivusalo, 2016; Anna Palla & Gnecco, 2015; Peng & Stovin, 2017). Beyond SWMM, the simulation of hydrologic behavior within green roofs and other forms of LID has been performed with many different types of models, including characteristic runoff equations, HYDRUS-1D, PARFLOW, HELP, and others (Carson, Keeley, Marasco, McGillis, & Culligan, 2017; Fassman-Beck, Voyde, Simcock, & Hong, 2013; Hilten, Lawrence, & Tollner, 2008; Lim & Welty, 2017; A. Palla, Gnecco, & Lanza, 2012; She & Pang, 2010; Voter & Loheide, 2018). Though there are limitations to its use, SWMM remains one of the most popular tools for simulating green roofs among engineering practitioners, likely due to its historical legacy in urban hydraulic and
hydrologic applications. Though popular, SWMM LID modules are relatively new compared to the lifespan of the SWMM model, and have primarily been used in a ‘calibration-validation’ framework, with no formalized recommendations for best practices. Altogether, this has resulted in many studies that focus on demonstrating that SWMM LID modules can realistically simulate a green roof in a given place, but few critiques of the strengths and limitations of the SWMM model. This means that research related to SWMM LID modules does not move beyond this approach.

Like any model, SWMM is subject to numerous uncertainties, including uncertainty in model inputs, parameters, and structural equations, in addition to the uncertainty introduced by abstractions between observed and simulated variables. In this vein, studies that have applied SWMM to simulate green roof performance and behavior have recognized several important limitations. First, several studies have noted that SWMM parameters are conceptual rather than physically-based, meaning that field-based measurements of parameters may fail to depict observations when used as direct parameter values in the modeling framework (Alfredo, Montalto, & Goldstein, 2010; Burszta-Adamiak & Mrowiec, 2013). This is especially important, because as-built drawings with LID technical specifications and field measurements are often used as initial parameter inputs of SWMM models. If these parameters are not calibrated, the resulting simulations are likely to be unrepresentative of observations. Secondarily, because SWMM is often calibrated manually, researchers and practitioners rarely perform sensitivity and/or uncertainty analysis (Burszta-Adamiak & Mrowiec, 2013; Carson et al., 2017; Cipolla et al., 2016). We do note this is changing, but slowly. To our knowledge, only a few recent studies have attempted to explore the SWMM LID parameter space and model structure (Krebs et al., 2016; Peng & Stovin, 2017).
Diagnostic modeling approaches have long been applied to improve understanding of conceptual hydrologic and water quality models (Herman, Reed, & Wagener, 2013; Kelleher, Mcglynn, & Wagener, 2017; Tang, Reed, Wagener, & Van Werkhoven, 2007; Wagener, McIntyre, Lees, Wheater, & Gupta, 2003). Model diagnostic analyses are rooted in information theory and test theoretically relevant relationships among model performance, parameters, and initial conditions, including the testing of hypotheses about system structure (Gupta, Wagener, & Liu, 2008). These methods allow the modeler to explore the relations between different types of data and the processes simulated in the model, with the goal of improving the modeling process and representation of hydrologic behavior through computationally frugal methods (Foglia, Hill, Mehl, & Burlando, 2009; Hill et al., 2016). These approaches are critical to developing useful models of complex hydrologic systems for which important characteristics cannot be measured accurately or completely enough to define model input values prior to calibration (Gooseff, Bencala, Scott, Runkel, & McKnight, 2005; Scott, Gooseff, Bencala, & Runkel, 2003). We aim to bring diagnostic analyses to the SWMM LID literature with the goal of improving calibration-validation approaches. We also aim to show how sensitivity and uncertainty analysis can complement this approach, to provide a wealth of information that will facilitate more direct comparison of results across studies and contextualize the information obtained during calibration-validation.

In this manuscript, we assess a SWMM LID bioretention model using the current SWMM model framework and diagnostic analysis that have been explored when using parsimonious watershed models to deliver conclusions around model uncertainty and sensitivity. We test three potential sources of sensitivity and uncertainty related to model calibration applied to a particular case study, the 1.5-acre OnCenter extensive green roof in Syracuse, New York.
First, we analyze the role of antecedent moisture in relation to calibration. Second, we utilize two sensitivity analyses with the goal to reduce overparameterization and improve understanding of controlling system characteristics (represented as parameters), as well as to assess how sensitivity may vary at different points in the SWMM parameter space. Third, we consider calibrating to complex hydrological processes (i.e. runoff vs soil moisture). From these analyses we provide recommendations to standardize current approaches to SWMM with an eye to frugal approaches to sensitivity and uncertainty analysis.

2 Case Study

2.1 Study Site

The study site is an extensive green roof located on the Nicholas J. Pirro Convention Center (OnCenter) in Syracuse, New York (43.04368N, 76.14824W). Syracuse climate, as relevant to this work, is detailed in Squier and Davidson (2016). The green roof was retrofit onto the existing structure in 2011. The roof is rectangular, with a geometry of 111 m North-South and 50 m East-West. As is typical, the roof has a peak running North-South midway between the East and West walls of the building, to help direct runoff. The roof is sloped at 1% in both directions from its peak. Vegetation, established by sprayed cuttings, includes species of *Sedum* and *Phedimus*.

The roof’s structure includes drain conduits and a drainage mat designed to convey excess water from the substrate. There are 12 roof drains along both the east and west sides of the building. Perforated triangular drain conduits, 5.1 cm tall, begin 5.1 meters from the centerline of the roof and run diagonally to each roof drain, as illustrated by Figure 1A. The mineral-based substrate was sprayed onto the roof with an average 7.6 cm depth. The substrate
and drainage layer are underlain by a geosynthetic fiber drainage mat, a single-ply waterproofing membrane, and traditional roofing structure. More detail on roof layers is given in Squier and Davidson (2016).

2.2 Experimental Data Collection

A CR1000 datalogger (Campbell Scientific, Logan, UT) and 2 AM 16/32B multiplexers were used to collect data from hydrologic, meteorological, and thermal instrumentation at 5-minute intervals. Rainfall was measured by a tipping bucket (TE 525, Campbell Scientific, Logan, UT) secured to a tripod approximately 29 meters from the southern end of the roof. Runoff from a 1708 m² region of the roof was collected from the eight drains in the southeastern portion of the roof and measured using an electromagnetic flowmeter (M2000, Badger Meter, Milwaukee, WI). Soil moisture sensors (CS616, Campbell Scientific, Logan, UT) were installed along a transect to measure the change in moisture content of the substrate. Meteorological instruments located on tripods south of the center of the roof, were sourced through Campbell Scientific. Data were collected between 4/1/15 and 10/31/18, but this study focuses on data from 4/1/17 and 10/31/17.

3 Methods

3.1 SWMM Model

The EPA Storm Water Management Model (SWMM version 5.1.012) is a dynamic hydrology, hydraulic, and water quality simulation model that can be used for both single-event or continuous simulation (Rossman, 2015). The LID controls in SWMM are designed to specifically model LIDs, such as green roofs. The LID framework tracks moisture balances in one-dimension between three different vertically-stacked layers (surface, substrate, and drainage layer), as illustrated by Figure 1B, that are defined by parameters in a graphical user interface.
(GUI). For green roofs with conduit drainage systems, it is recommended to use the SWMM LID bioretention module instead of the SWMM LID green roof module and restrict infiltration through the bottom of the storage layer, therefore creating an impermeable barrier like a green roof system. This approach was used in this study (Burszta-Adamiak & Mrowiec, 2013).

For SWMM LID bioretention modeling, six equations are used to describe the processes across the three model layers. Bottom exfiltration is not considered in this study. While input parameters and variables, and output variables are reported in SI metric units, within the model computer code all calculations are carried out using feet as the unit of length and seconds as the unit of time. Therefore, the units for model process equations are discussed according to model methods. A routing equation [Eq. (1)] is used to quantify surface runoff \( q_1 \) [ft/sec] according to

\[
q_1 = \max \left[ \frac{d_1 - D_1}{\Delta t}, 0 \right]
\]  

(1)

where it is assumed that any ponded surface water in excess of \( D_1 \) becomes immediate overflow, and \( d_1 \) represents depth of water stored on the surface [ft] all over a model timestep \( \Delta t \) [sec]. The Green-Ampt infiltration model [Eq. (2) and Eq. (3)] is adopted to calculate how much water infiltrates into the subsurface, following

\[
f = K_{sat} \left[ 1 + \frac{(\phi_2 - \theta)(d_1 + \psi)}{F} \right]
\]  

(2)

and

\[
F = K_{sat} + (\phi_2 - \theta)(d_1 + \psi) \ln \left[ 1 + \frac{F}{(\phi_2 - \theta)(d_1 + \psi)} \right]
\]  

(3)
where the infiltration rate \( f \), ft/sec) and the cumulative infiltration volume per unit area over a storm event \( F \), ft) only apply after a saturated condition develops at the top of the soil zone. Prior to this, all inflow from rainfall and runoff from impervious areas infiltrates. The initial value of moisture content \( \theta \), volume of water/total volume of soil) for a dry soil would be its residual moisture content or its wilting point \( \theta_{WP} \), volume of wilting point water/total volume of soil). \( K_{sat} \) represents the saturated hydraulic conductivity of the soil [ft/sec], \( \Psi \) represents the suction head at the infiltration wetting front formed in the soil [ft], and \( \phi_2 \) represents the porosity of the soil [void volume/total volume of soil] or the saturated moisture content. A variation of Darcy’s Law [Eq. (4)] is used to model the rate of percolation of water through the soil layer into the storage layer, according to

\[
f_p = \begin{cases} 
K_{sat} \exp[-(\phi_2 - \theta)S], & \theta > \theta_{FC} \\
0, & \theta \leq \theta_{FC} 
\end{cases}
\]  \tag{4}

where, when \( \theta \) drops below the field capacity \( \theta_{FC} \), volume of field capacity water/total volume of soil), percolation rate \( f_p \), ft/sec) becomes zero. \( S \) represents the conductivity slope [unitless] or decay constant derived from the moisture retention curve data that describes how conductivity decreases with decreasing moisture content. A simple empirical power law [Eq. (5)] is used to simulate storage layer underdrain flow \( q_3 \), ft/sec), following

\[
q_3 = C(h_3)^b
\]  \tag{5}

where the hydraulic head seen by the underdrain \( h_3 \), ft) varies with the height of water above the underdrain, the underdrain discharge exponent \( b \), unitless) is set to 0.5 to set the drain flow formula equivalent to the standard orifice equation, and the underdrain discharge coefficient \( C \), ft\(^{(b-1)}/\)sec) incorporates both the normal orifice discharge coefficient and available flow area.
There is no underdrain flow until the depth of water in the storage layer reaches the drain offset height ($H_d$, ft). Potential evapotranspiration ($PET_H$, ft/sec) is simulated following the Hargreaves equation [Eq. (6)] following

$$PET_H = 0.0023 \left( \frac{Ra}{A} \right) T_r^{\frac{1}{2}} (T_a + 17.8) \quad (6)$$

where $T_r$ represents the average daily temperature range for a period of five days [deg C], $T_a$ represents the average daily temperature for a period of five days [deg C], $Ra$ represents the water equivalent of incoming extraterrestrial radiation [MJm$^{-2}$d$^{-1}$], and $\lambda$ represents the latent heat of vaporization [MJkg$^{-1}$] or $2.50 - 0.002361 T_a$. The calculation of $PET_H$ proceeds from the surface layer downwards during dry periods. Any unused $PET_H$ is made available to the next lower layer.

Daily minimum and maximum ambient air temperature gathered on the OnCenter green roof and the geospatial location of the roof were supplied as climate data to calculate daily $PET_H$.

### 3.2 Model Setup

The green roof was modeled in SWMM as a subcatchment that was 100% occupied by the green roof with a single outlet. The dimensions of the subcatchment were 111 m width by 50 m length; this matched the actual OnCenter green roof dimensions and flow path, as the modeled water flow path is perpendicular to the width. The SWMM bioretention module was used to generate runoff in response to three rainfall events. The internal simulation time step was set to 1 second with a reporting time step of 5 minutes to match observed data. This method followed standard green roof hydrology evaluation SWMM model setup (Carson et al., 2017; Cipolla et al., 2016; Peng & Stovin, 2017).
3.3 Model Calibration

The goal of calibration is to determine if SWMM can represent *in situ* observations. As is typical with SWMM simulations of green infrastructure, we set initial green roof parameters to realistic values representative of (or equal to) *in situ* estimates from this particular system. Many initial green roof parameter values were estimated from field measurements by Squier and Davidson (2016), Yang and Davidson (2017), and laboratory soil measurements from the Penn State Agricultural Analytical Services Lab (AASL). Additional parameters were based on initial modeling studies at this site performed by Jacobs Engineering, with inputs selected by Jacobs Engineering based on OnCenter green roof design specifications and as-built drawings. The values and sources for each parameter utilized in the SWMM LID bioretention module are presented in Table 2. As SWMM is often treated as a physically-based model, where real-world estimates can be translated into model estimates, our initial goal was to test whether these parameter estimates yielded accurate simulations of runoff, or whether calibration was required.

To identify storms for calibration, we identified 105 rain events from 4/1/17 to 10/31/18 and selected three events to incorporate in our model assessment. For each event, the percent initially saturated was determined from the average of the three soil moisture sensors and converted based on the SWMM definition of soil saturation. Characteristics of these events are summarized in Table 1. These three rainfall events selected intentionally varied in antecedent dry weather period, time of year occurrence, duration, intensity, and return period, to test the calibration under different scenarios. First, we calibrated the SWMM model to an event beginning on October 28, 2017, which has the greatest yearly return period. To assess whether the calibrated parameter set was capable of reproducing conditions for other storm events, we
also used this parameter set to simulate two events, one beginning on May 1 and one beginning on June 5, 2017.

Model performance was assessed between observed and simulated green roof runoff using the Nash-Sutcliffe model efficiency (NSE) coefficient (Nash & Sutcliffe, 1970). While NSE is a common error metric used in the hydrologic literature (Carson et al., 2017; Peng & Stovin, 2017; Razavi et al., 2010), it is biased towards identifying a best fit parameter set that fits peak flows due to its use of squared residuals (Legates & McCabe, 1999). Though use of NSE is debated for this reason (Foglia et al., 2009; Gupta, Kling, Yilmaz, Martinez, & Kling, 2009; Wagener et al., 2003), this analysis follows common SWMM calibration methods that use this error metric to assess model performance (Carson et al., 2017; Peng & Stovin, 2017). NSE for each event was calculated according to

\[
NSE = 1 - \left[ \frac{\sum_{i=1}^{N} (Q_{m,i} - Q_{p,i})^2}{\sum_{i=1}^{N} (Q_{m,i} - Q_{Am})^2} \right]^{1/2}
\]

where \( N \) represents the number of samples, \( Q_{m} \) is runoff observed, \( Q_{p} \) is modeled runoff, and \( Q_{Am} \) is the mean observed runoff. An NSE value equal to 1 indicates perfect agreement between simulated and observed values, while an NSE value greater than 0.5 is an indication of acceptable model performance (Peng & Stovin, 2017; Rosa, Clausen, & Dietz, 2015).

In most SWMM exercises, calibration from initial parameter estimates is necessary to match observed runoff. Standard SWMM calibration techniques follow a formulaic strategy (Carson et al., 2017; Cipolla et al., 2016; Peng & Stovin, 2017). Model predictions were refined through a manual calibration process, which is typical of SWMM applications. Manual calibration is performed through a trial-and-error procedure, often using a number of different measures of performance and visual inspection of the hydrograph (Gupta, Sorooshian, & Yapo,
In our exercise, parameters were adjusted one at a time until the difference between measured and simulated values was minimized. Parameters describing substrate depth, area, and width were held constant, given these properties describe static properties of the green roof. All other surface layer, soil layer, and storage layer parameters were allowed to vary, given these properties can change over time or are cannot be directly measured. The model was calibrated manually by first changing the (most sensitive) parameters, determined from an initial parameter set sensitivity analysis, to find good NSE model fit and then fine-tuning model fit with less sensitive model parameters. The resulting parameter set with the highest NSE across our manual search of the parameter space is hereafter referred to as the ‘best fit parameter set’.

3.4 Diagnostic Analysis of SWMM

Regardless of their structural equations and purpose, environmental models like SWMM are all simplified mathematical representations of physical systems (Kelleher et al., 2013; Wagener & Gupta, 2005). In this way, many SWMM parameters are either empirical, conceptual, or typically lumped in practice such that there is no singularly correct SWMM parametrization (or structure) for a given LID system. As many of the parameter values in SWMM are often conceptualized physical processes or system properties that cannot be directly measured, they must be estimated via calibration. When it comes to calibration, SWMM LID modules are still often treated and explored with simplistic methods (manual calibration and perhaps one assessment of parameter sensitivity). In this study we perform a diagnostic assessment to test three potential sources of sensitivity and uncertainty, with the goal of gaining insight to make recommendations about frugal approaches to sensitivity and uncertainty analysis within SWMM. Below, we outline different tests we have applied to assess sensitivity and uncertainty within
SWMM, with the goal of improving understanding of our system and making recommendations to other SWMM users.

3.4.1 Initial Conditions

Within SWMM, initial soil moisture represents a potential source of uncertainty, especially given that many green roofs may not be outfitted with sensors to observe this variable. As the soil water content in the beginning of a precipitation event depends on the antecedent conditions and varies from event to event, it represents a large source of uncertainty in the simulation of green roof runoff (Burszta-Adamiak & Mrowiec, 2013; Palla & Gnecco, 2015). To demonstrate the impact of this initial condition on simulations, we tested the impact of setting initial soil moisture at zero and at an average observed soil moisture for the best fit parameter set for the October 28, 2017 and June 5, 2017 events. We report NSE for both events and scenarios.

3.4.2 Parameter Equifinality

Ideally, the best fit parameter set can be treated as a unique combination of parameter values that best reproduce the observed data (Cobelli & DiStefano, 1980; Sorooshian & Gupta, 1983). However, it is also possible that many parameter combinations will reproduce the observations equally well with respect to a single error metric (Cobelli & Distefano, 1980; Wagener et al., 2003). This condition is often referred to as equifinality (Beven, 1989; Beven & Binley, 1992; Kelleher et al., 2013; Wagener et al., 2003). Parameter equifinality is especially problematic for complex models with many parameters (Beven & Binley, 1992; Wagener et al., 2003), and is generated by either insensitive parameters (e.g., parameters that can be varied but have little effect on simulated runoff) or interactive parameters (e.g., parameters values that effect simulated runoff based on dependence to other parameter values).
To test equifinality as it relates to SWMM, we explored the parameter space to identify combinations of parameter values that generated hydrographs yielding similar error metric values. This was, in part, an exploratory exercise, to assess whether equifinality is a concern within SWMM. Though there are recommended ranges for SWMM LID parameters (Rossman, 2015), our assessment included values that exceeded these reasonable ranges. Analyzing how far the model could be “pushed” with respect to parameter equifinality was critical to demonstrate potential uncertainty in model calibration.

3.4.3 Parameter Sensitivity

Sensitivity and uncertainty analysis encourages greater understanding of system dynamics. It may help to identify parameters that interact and therefore produce equifinal simulations, and assists in obtaining a model that reproduces observed quantities with a minimum amount of effort during the calibration process (Beck, 1987; Beven, 2008; Kelleher et al., 2013; Sorooshian & Gupta, 1983). In SWMM, sensitivity analyses are often used to determine the parameters that would most effectively minimize the difference between observed and simulated results, with the goal of improving model fit (Krebs et al., 2016; Peng & Stovin, 2017). However, sensitivity analyses can also provide information about the potential sources of equifinality in a model, as equifinality can be the result of parameters that are insensitive (Johnston & Pilgrim, 1976) and/or interactive (Ibbitt and O’Donnell 1971). Due to the current SWMM setup, most SWMM users perform what is termed one-at-a-time (OAT) sensitivity analysis. This is a simplistic analysis in which a single parameter value is increased or decreased by some equal amount holding all other values constant; it may be performed from an initial parameter set, or from a calibrated parameter set, though which sensitivity analysis is reported varies throughout the literature.
Assessing whether a parameter is insensitive, influences model output through interactions, or has a direct impact on model output can be performed through a variance-based sensitivity analysis (Kelleher et al., 2013; Pianosi et al., 2016; Song et al., 2015), though this requires running a given model thousands of times. In the case of graphical user interface (GUI)-based models like SWMM where there is no flexibility to directly implement variance-based sensitivity analysis without additional programming, parameter influence on model output can be assessed through two tests which can be seen in Figure 2. If a parameter is important by itself or through interactions, with an equal increase or decrease of the parameter value by some fraction of the parameter range, the error metric (i.e. NSE) between observed and simulated runoff increases or decreases (Figure 2, Test 1). From this result, no distinction can be made between individual or interactive importance. However, if the error metric does not increase or decrease, then a second test needs to be performed (Figure 2, Test 2). If a parameter is sensitive but interactive, the error metric should vary if this parameter value is set to zero. In contrast, if the error metric improves, this suggests this parameter is sensitive because the conceptual property or process it represents is not critical to reproducing the system behavior of interest (e.g., green roof runoff). However, if the error metric still does not change when the parameter value is set to zero then the parameter is insensitive.

The portion of the parameter space being sampled can also influence the interpretation of identifiability and sensitivity (Saltelli, Ratto, Tarantola, & Campolongo, 2006). Therefore, parameter sensitivity also may depend on “location” in the parameter space. To assess this, we performed a sensitivity analysis with respect to initial parameter values (Table 2) as well as calibrated values (October 28, 2017 event) and reported changes in NSE per parameter.
4 Results

4.1 Calibration and Assessment of Model Performance

The results of individual event simulations using initial parameter values (Table 2) showed relatively poor agreement between measured and simulated runoff from the OnCenter green roof, with NSE values below 0.5 for all three events (May 1, 2017; June 5, 2017; October 28, 2017). All simulated runoff peak runoffs were underestimated. Simulated runoff also failed to capture the steepness of the falling limb. All these phenomena indicate that the green roof detention processes were not well represented within the initial parameter set SWMM model.

With manual calibration, model performance improved substantially. NSE increased to 0.9 for the calibration period (October 28, 2017 event; Figure 3A) and exceeded 0.9 for two additional storms not included in calibration (May 1, 2017, Figure 3B; June 5, 2017; Figure 3C). Table 2 lists parameter values corresponding to the manually obtained best fit parameter set. All parameter values fell within literature ranges.

4.2 Diagnostic Analysis of SWMM

4.2.1 Equifinality

To explore the potential for equifinality in SWMM, we were capable of identifying several parameter sets spanning both reasonable and unreasonable ranges that yielded nearly equivalent values of NSE. These parameter combinations, visualized in Figure 4A, all resulted in NSE values above 0.9 and nearly equivalent simulations of runoff that closely match observations (Figure 4B). Table 3 further illustrates how parameter interactions between saturated hydraulic conductivity ($K_{sat}$) and soil porosity ($\Phi_2$) can yield equifinality across multiple storm events.
Even unreasonable values of $K_{\text{sat}}$ were capable of producing acceptable error metric values when varied in tandem with $\Phi_2$.

### 4.2.2 Initial and Best Fit Parameter Set Sensitivity Analyses

Results of the initial parameter set OAT sensitivity analysis are presented in Figure 5A. The OAT sensitivity analysis indicated that NSE was most sensitive to one ($\Phi_2$) of the thirteen defined parameters (change in NSE $> 0.100$), moderate for four ($\Theta_{\text{FC}}, \Theta_{\text{WP}}, C, b$) parameters ($0.099 > \text{NSE} > 0.001$), and insensitive for eight ($n, S_1, S, \Psi, H_d, K_{\text{sat}}, D_3, \Phi_3$) parameters (change in NSE $= 0$). In contrast, the best fit parameter set sensitivity analysis indicated that model performance was most sensitive to four ($\Phi_2, \Theta_{\text{FC}}, H_d, D_3$) of the thirteen defined parameters, moderate for five ($\Theta_{\text{WP}}, C, b, K_{\text{sat}}, S$) parameters, and insensitive for four ($n, S_1, \Psi, \Phi_3$) parameters (Figure 5B).

As an additional test on parameter insensitivity, we determined NSE when all insensitive parameters were set to zero. It was not possible to set $K_{\text{sat}}, D_3$, and $\Phi_3$ to zero, so these parameters were excluded from this analysis. For both the initial and best fit parameters, we observed no difference in NSE when setting each of these values to zero, confirming these parameters were insensitive local to initial and best fit parameter sets.

### 4.2.3 Initial Soil Moisture Analysis

Soil moisture can be critical to predicting runoff peaks for events with short antecedent dry weather periods, such as successive storms, and storm events with high intensity precipitation peaks in the beginning half of an event. To test the impact of having no information (set to a value of zero) versus observed information (set to average of observed) to inform initial soil moisture conditions on event simulations, we compared NSE for two events (June 5, 2017;
October 28, 2017) in Figure 6. Figure 6A shows the event beginning on October 28, 2017 which had an antecedent dry weather period of 42.17 hours and reached both peak precipitation intensity of 1.7 mm 5-min⁻¹ and peak runoff at 30.25 hours into the storm event. Increasing the initial soil moisture from zero to the observed initial measured soil moisture value of 0.11 only slightly decreased the model error metric from an NSE of 0.939 to 0.973. Figure 6B shows the event beginning on June 5, 2017 which had an antecedent dry weather period of 13.5 hours and reached both peak runoff and peak precipitation intensity of 3.8 mm 5-min⁻¹ at 10 hours into the storm event. Increasing the soil moisture from zero to the initial measured soil moisture value of 0.35 improved NSE from 0.304 to 0.942.

4.2.4 Considering Multiple Error Metrics

In stormwater management, the most common output to calibrate to is runoff. Reduction in peak runoff intensity and shift in peak are two of the foremost desired outcomes from low impact development systems. However, other observations beyond runoff may provide unique information to constrain parameter uncertainty. Figure 7 shows the range of soil moisture values that were gathered from three soil moisture sensors on the OnCenter green roof compared to soil moisture content simulated based on a best fit porosity and a measured porosity. These two simulated time-series were quite different, and produced NSE values of 0.476 (best fit) and -0.356 (measured) when compared to the observed soil moisture averaged across these three sensors. This exercise illustrates that it can be difficult to use physically measured values as inputs to, or constraints on, the SWMM model. The modeler exhausted all efforts, even letting parameters vary widely, and could not achieve any strong agreement between modeled soil moisture and an envelope of observed soil moisture, illustrating that while SWMM simulations
are capable of replicating the observed hydrograph, representative simulations of soil moisture were more difficult to attain.

5 Discussion

5.1 Assessment of SWMM Bioretention Module

As shown in Figure 3, model simulations approximated observed OnCenter green roof runoff for three events. Notably, our error metrics for all storms were comparable to or exceeded error metrics documented in other literature (Krebs et al., 2016; Palla & Gnecco, 2015; Peng & Stovin, 2017). Like many SWMM studies, we used a ‘calibration-validation’ approach to demonstrate that the parameter set yielding high NSE for several storms was capable of simulating observed runoff for additional events. We used a total of three events (Table 1), with the goal of incorporating multiple return periods, event sizes, and initial conditions (e.g., wet vs. dry soil substrate). Still, we caution that parameter estimates (Table 2) were biased by the period and conditions for which they were assessed (Peng & Stovin, 2017), meaning that extrapolation to larger events or for periods beyond spring, summer, and fall may not be possible. We therefore recommend that any modeling analysis of SWMM LID behavior incorporate events from all seasons, multiple events exceeding a 1-year return period, and events that display varying sizes and initial conditions.

Earlier studies of modelling green roof runoff have produced results with varying success. Alfredo et al. (2010) achieved reasonable results using SWMM after significant calibration efforts with both the ‘storage node’ and ‘curve number’ approaches, two alternative methods to model green roofs in SWMM prior to the creation of SWMM LID modules. Burszta-Adamiak and Mrowiec (2013) applied the SWMM LID bioretention module to simulate runoff
monitored from different green roof test beds and concluded that the model had limited capabilities in simulating green roof runoff. They reported mostly negative model efficiencies resulting from excessive simulated runoff peaks, while the model achieved a good replication of the monitored event runoff volume. More recently, Cipolla et al. (2016), Krebs et al. (2016), and Peng and Stovin (2017) reported reasonable results using the SWMM LID green roof module to model full-scale green roofs and green roof test beds but thorough comparison to their study is difficult since their roof systems did not include drainage conduit systems (Figure 1), only drainage mats. These studies underscore the importance that further testing with SWMM applied to LID systems such as green roofs is needed.

5.2 How can and why should we aim to prove model realism within applications of SWMM?

All models are assumed to be imperfect representations of the system they are designed to simulate. In this sense, deviations between simulations and observations are the result of uncertainty introduced throughout the modeling process. Within SWMM, model realism, ensuring the model is a reasonably accurate representation of reality, is tied to two different aspects of the model: initial conditions and model structural equations. The source of uncertainty that SWMM modelers have the least control over is uncertainty in model structure, introduced when translating real-world processes into SWMM structural equations. There are several model assumptions incorporated into the SWMM LID bioretention module that may differ from real-world green roof structure and function. In particular, substrate water detention is modeled by Eq. (4) assuming the matric potential varies linearly with water content and porosity, and the wetting front advances at the same rate with depth. However, as experimental tests have shown, the soil moisture curve (i.e., water content vs. matric potential) of green roof
substrate may deviate from this model assumption (Berretta, Poë, & Stovin, 2014; Cipolla et al., 2016). While the SWMM LID bioretention module assumes a drainage system within a gravel drainage layer, many green roofs are not designed in this manner. The OnCenter green roof has a waterproof membrane, thin drainage mat, and drain conduits in the soil substrate layer on top of the drainage mat. To account for this, the gravel drainage layer was minimized, and the drain offset height was set to allow the drain system to be within the soil layer, though we caution that this configuration has the potential to introduce errors in the estimation of the overall bioretention water balance. The best fit parameters for the underdrain should therefore not be assumed representative of other green roofs, and should be treated as specific to the OnCenter green roof used in this study. Values such as porosity and saturated hydraulic conductivity are assumed to be constant over time. However, it is known that porosity changes during the aging of media and saturated hydraulic conductivity varies based on depth and saturation of substrate. Broadly, this demonstrates that flexible model structures within SWMM, a concept widely adopted when it comes to rainfall-runoff modeling (Clark et al., 2008, 2015), may be needed so that users can ensure that model structure closely approximates green roof design.

Opportunistically, SWMM modelers do have control over setting initial subsurface saturation conditions. As we and others have shown (Burszta-Adamiak & Mrowiec, 2013; Palla & Gnecco, 2015), initial conditions shape the agreement between simulations and observations of runoff intensity and volume, depending on the time of peak and the intensity of the event (Figure 6). Collecting data on antecedent substrate moisture can be used as a simple and strategic method to reduce model uncertainty. This underscores the importance of instrumenting green roofs to gain soil moisture observations, which can be used to inform this key model input.
5.3 What can we learn from and how can we improve SWMM sensitivity analyses?

Sensitivity analysis can assist a modeler in the process of identifying a parameter set that reproduces an observed variable of interest. In this way, sensitive parameters can be treated as those pieces of the model that contain the most “information” for ensuring that model simulations match observations. In this work, we incorporated sensitivity analysis within our calibration framework, with the goal to shorten what can be a lengthy calibration process. Currently, OAT sensitivity analysis is the only possible approach for assessing parameter sensitivity in SWMM. Moreover, most studies only report an initial parameter set sensitivity analysis (Krebs et al., 2016; Peng & Stovin, 2017) to aid in determining which parameters to estimate, those that will have the most influence on minimizing a chosen error metric. As we show, OAT sensitivity results vary based on which baseline parameter set is used (Figure 5). In our analysis, we assessed sensitivity with respect to an initial parameter set, informed by physical measurements and expert information (e.g., Jacobs Engineering), and with respect to a manually calibrated, best fit parameter set that achieved very high NSE across three storms. We found that parameter sensitivity varied widely across these two analyses, with several parameters \((S, H_d, K_{sat}, D_3)\) that were insensitive with respect to the initial parameter set (e.g., no change in NSE) found to be sensitive for the ‘best fit’ parameter set. The differences shown between initial and best fit parameter set sensitivity analyses occur due to non-linear relationships between parameters and simulated runoff.

As we show, executing additional sensitivity analyses may identify new sensitive parameters, as sensitivity varies with “location” in the parameter space. As manual calibration requires awareness and information on the sensitivity of parameters, running initial and best fit parameter set sensitivity analyses can reveal information that can improve the calibration
process. Since most studies report sensitivity analysis results to highlight the most important “controlling” model parameters, it is vital to report the sensitivity analysis around the best parameter set estimate. Sensitive parameters, as identified from the initial parameter set, are often sensitive because their estimated value does not approximate observations (e.g., negative NSE). In contrast, sensitive parameters identified from the ‘best fit’ parameter set can be treated as containing more information about the system being simulated. In this sense, it is especially important that SWMM modelers incorporate both of these analyses into their own diagnostic analyses.

When equifinality occurs (Table 3; Figure 4), it is usually the result of parameters that are insensitive (Johnston & Pilgrim, 1976) and/or interactive (Ibbitt and O’Donnell 1971). The power in identifying insensitive parameters is that they have no effect on the model output. These identified insensitive parameters tell what make the system distinct, and that their processes or components are insignificant. This information can provide a “check” on model realism, to ensure the model is providing a realistic representation of the system being simulated. For instance, $\phi_3$ was insensitive, signifying that this property of our storage layer did not impact model fit; given our green roof system does not have a storage layer, this analysis suggests that our simplification to set this value to zero (Table 2) was realistic, and would not impact our simulations. At the same time, insensitivity may also be a reflection of certain limitations. For instance, insensitivity for parameters $S_1$ and $n$ signified that ponding was not an important control on runoff in our system. However, we simulated events where surface ponding is not expected to occur; we would expect that these parameters would be more sensitive when simulating larger magnitude or high intensity events.
Though local OAT sensitivity analyses have limitations, a local sensitivity analyses should be the first step in evaluating if computationally demanding analysis is necessary (Beven & Binley, 1992; Hill et al., 2016). Regardless, determining sensitive parameters, a key step to improving calibration as well as our fundamental understanding of the SWMM model, requires more computationally demanding methods (Kelleher et al., 2013; Pianosi et al., 2016; Song et al., 2015). To date, few studies have applied global sensitivity analysis to SWMM, though the use of these computationally demanding methods is increasing (Krebs et al., 2016). The use of these more complex methods is necessary to improve the application of SWMM LID modules to LID systems.

5.4 How can we and why do we need to improve SWMM calibration?

As shown by other researchers, parameters within SWMM may be conceptual and cannot always be taken as physically-based, ultimately meaning that adjustment through calibration is needed. In this vein, we unsurprisingly found differences between a best model estimate of porosity (\(\Phi_2 = 0.47\)) and a single field validation of porosity (0.57) (Figure 7). Importantly, increasing \(\Phi_2\) to the measured porosity while maintaining a high NSE required adjustment of field capacity (\(\Theta_{FC}\)) and wilting point (\(\Theta_{WP}\)) beyond realistic values outside of literature ranges. This highlighted the important role of \(\Phi_2\), which is consistent with the results of the OAT sensitivity analyses. Given that porosity is a heterogeneous and dynamic property, changing through time due to the aging of media and shifts in ratio of macropores and micropores, modeling may help document changes to this dynamic property that are difficult to obtain via field validation.

Many analyses of SWMM LID modules rely on manual calibration to search the model parameter space for a combination of model parameters that achieves an optimal error metric value (Carson et al., 2017; Cipolla et al., 2016; Peng & Stovin, 2017). However, as SWMM is
highly nonlinear, manual calibration is not an adequate solution for searching the parameter space. Currently, to manually calibrate SWMM, modelers perform numerous model iterations to explore the parameter space “by hand”. The time required to manually search the parameter space therefore requires that model run times be short. This often limits SWMM calibration to a shorter period that incorporates fewer events (Broekhuizen, Leonhardt, Marsalek, & Viklander, 2019), though this is balanced by demonstrating that the ‘best fit’ parameter set can reliably simulate additional storms. Furthermore, SWMM simulations are prone to equifinality (Figure 4). The fact that there are multiple disparate model structures and parameterizations which may be equally good at simulating a particular period of monitored record is the concept of equifinality (Beven, 2006), which has shaped a considerable body of environmental modeling research in recent decades. Current methods of manual calibration are time consuming, monetarily expensive, and require in-depth knowledge of the model system.

The alternative to manual calibration is auto-calibration, where an algorithm is used to search the parameter space for a parameter set that minimizes single or multiple error metrics. The pros and cons of manual versus auto-calibration techniques have been discussed in the hydrological literature for decades (e.g. Boyle, Gupta, & Sorooshian, 2000; Gupta et al., 2009). Due to the complexity and skill required, there are few papers that analyze SWMM LID modules through external software packages (Krebs et al., 2016). Auto-calibration certainly has many advantages over manual techniques, but may also incorporate subjective elements, such as the selection of parameter ranges and the choice of an auto-calibration algorithm (Jackson-Blake & Starrfelt, 2015; Vrugt, Braak, Gupta, & Robinson, 2009). At the same time, manual calibration can be as expensive and time consuming as some analysis methods, requiring 1000s of trial and error model runs to provide a thorough explanation for calibration results. This can be
impractical, where forward SWMM model runs sometimes take hours or days to complete, even based on computational costs alone (Hill et al., 2013, 2016; Razavi et al., 2010).

One path forward may be to combine auto-calibration and manual techniques. As shown by Boyle et al. (2000), the time and effort required to estimate the parameter range representing the trade-offs in the performance of the model can be dramatically reduced by use of a computerized global search procedure algorithm. Then, the attention of the hydrologist can be redirected from the tedious effort of manually searching for the “good” regions. While SWMM LID literature already provides expected parameter ranges, automatic calibration can certainly further aid the search process. The inclusion of an automatic calibration technique would decrease calibration time and allow for a potential starting location for further manual calibration. While we argue that the wide use of SWMM necessitates the incorporation of auto-calibration strategies, this addition should ultimately consider the wide literature that exists on this topic, to best balance flexibility and user consideration.

5.5 How do we best incorporate new sources of information into the model evaluation process?

Typical evaluations of SWMM calibration select runoff for error metric evaluation and have concluded that SWMM LID modules are able to simulate measured runoff (Carson et al., 2017; Cipolla et al., 2016; Krebs et al., 2016; Peng & Stovin, 2017). While matching to runoff is key, there are multiple signals in a green infrastructure system that can be considered in model evaluation. Calibrating to more complex hydrological variables can elucidate potential error or misrepresentation within the model. In our own diagnostic analysis, capturing the falling and rising limb of the soil moisture graph was not achievable (Figure 7). This suggested that soil moisture is potentially sensitive to different parameters than runoff. Ultimately, this highlights
that SWMM structural equations may not accurately represent hydrological processes as a green roof wets up and dries down.

Evapotranspiration (ET) between precipitation events is ultimately going to determine and be determined by available soil moisture. In SWMM LID modules, ET is represented by the Hargreaves equation on a daily timestep, which is temperature based and disaggregated to the model timestep. Though there are many who argue that ET is poorly represented in SWMM (Carson et al., 2017; Cipolla et al., 2016; Peng & Stovin, 2017), model calibration nearly always only considers fitting to runoff. The key to understanding model representation of processes such as changes in soil moisture could be the periods in between these events. To have the processes within green roofs represented more accurately, it may be critical to consider dry periods during parameter estimation and model evaluation. Our soil moisture simulations (Figure 7) highlight that there is room for improvement.

Overall, the types of observations included in both calibration/validation and diagnostic analyses exert important influence over what can be learned from model simulations. While we focused on fitting SWMM with respect to a single error metric, other researchers have shown that multi-response error metrics offer the potential for improved simulation of model outputs (e.g., runoff) as well as other state variables, such as ET and soil moisture (Kuczera & Mroczkowski, 1998). Including observations of internal processes, such as concentrations and fluxes, in diagnostic analysis can help to ensure that the right results are being obtained for the right reasons. Incorporating such additional ‘soft’ data into auto-calibration is not common practice at present, but it is feasible and indeed highly desirable (e.g. Rankinen, Karvonen, & Butterfield, 2006; Seibert & McDonnell, 2002).
6 Conclusions

While there are existing studies demonstrating that SWMM is capable of simulating green roof behavior, we are currently missing an understanding of the fundamental drivers of uncertainty within SWMM and how these can best be addressed in the current generation of SWMM models. In this study, we performed diagnostic analyses of the SWMM LID bioretention module through a modeling study of the OnCenter green roof in Syracuse, New York. Utilizing frugal sensitivity and analysis methods, we evaluated calibration processes to examine potential sources of parameter and model structure uncertainty. As discussed here and by others, many of the parameters are either empirical, conceptual, or typically lumped in practice such that there is no singularly correct SWMM parametrization (or structure) for a given LID system. Thus, while EPA SWMM is inherently a deterministic model predicting a single set of model outputs from a single set of parameters and inputs, there are typically many different parametrizations and structures which could be used to represent a system of interest, potentially yielding 10s of 100s of different “good” simulations. In the case of SWMM LID modules, simply relying on modeler’s best judgement point estimates for uncertain parameters where the feasible parameter space can generate a large range of outputs (i.e., ignoring equifinality) can limit the use and acceptability of SWMM LID module results for management purposes.

SWMM, even for what may be considered a simple case – simulating green roof runoff – is prone to nonlinearity, uncertainty, and equifinality. Frugal diagnostic analyses elucidated multiple feedbacks between the model and observations, including that runoff simulations for SWMM were highly sensitive to initial soil moisture conditions. As shown with initial and best fit parameter set sensitivity analyses, any OAT sensitivity analyses are only local estimates within a neighborhood of the selected parameter set. SWMM, while successful at simulating
runoff, was not capable of simulating other hydrological processes (i.e. substrate moisture). These results indicate that the prediction of SWMM LID runoff is likely due to complex interactions between the numerous model parameters used to describe LID characteristics, further highlighting the extreme nonlinearity of SWMM LID modules.

While we show there is still information that can be gleaned from these frugal analyses to test and improve understanding of responses, they fundamentally oversimplify hydrological behavior within green roofs and limit the research that can be done with this tool. Partially influenced by structural analysis limitations, many SWMM applications focus on single events and wet periods. However, our research highlights that this strategy may miss important information and misrepresent other hydrological processes. Utilizing different sources of information to “calibrate” SWMM (i.e. measurements of ET, soil moisture, etc.) can identify these misrepresentations. We also found that calibration strategies are often not explicitly stated or consistent, making comparisons between reporting for model uncertainty problematic. We recommend that applications of SWMM be elevated to a level of consistency that moves beyond frugal analysis methods if the research goal is to improve representation of processes beyond runoff simulation. Model structure flexibility combined with more robust diagnostic analyses are necessary to fully understand the fundamental drivers of uncertainty in SWMM, allowing for better predictions.

At the same time, SWMM represents a real opportunity through its popularity amongst researchers and frequent application by practitioners. Encouraging interactions between these groups can create symbiotic conversations that will only improve SWMM LID modules. The strategy builds off the co-production of knowledge theory, which aims to build dialog between parties that possess mutually beneficial knowledge. In the case of SWMM, practitioners convey
the practical applications of the model, which provides information to researchers around how to formalize diagnostic analyses to be most informative. As the end users in many cases, practitioners likely have developed key insights with respect to challenges applying SWMM and suggestions for improvement; researchers possess the opportunity to explore these suggestions and produce helpful tools, ultimately refining the model. Utilizing this co-production of knowledge can supply more necessary data for SWMM LID module flexibility and complex diagnostic analyses improvements.
### 7 Tables

**Table 1. Characteristics of rainfall events.**

<table>
<thead>
<tr>
<th>Event Number</th>
<th>Start of Event</th>
<th>Rainfall Duration [h]</th>
<th>Rainfall Depth [mm]</th>
<th>Peak Intensity [mm 5min⁻¹]</th>
<th>Antecedent Dry Weather Period [h]</th>
<th>Return Period [yrs]</th>
<th>Initially Saturated [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>37</td>
<td></td>
<td>33.0</td>
<td>31.3</td>
<td>3.8</td>
<td>13.5</td>
<td>&lt;1</td>
<td>34.9</td>
</tr>
<tr>
<td>105</td>
<td></td>
<td>38.0</td>
<td>90.0</td>
<td>1.7</td>
<td>42.2</td>
<td>&gt;5</td>
<td>11.1</td>
</tr>
</tbody>
</table>

**Table 2. SWMM Parameters: Initial and best fit values for simulations.**

<table>
<thead>
<tr>
<th>Description</th>
<th>Initial Value</th>
<th>Units</th>
<th>Symbol</th>
<th>Data Source</th>
<th>Best Fit Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Subcatchment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Area</td>
<td>5600.00</td>
<td>m²</td>
<td>A</td>
<td>Squier and Davidson (2016)</td>
<td>5600.00</td>
</tr>
<tr>
<td>Width</td>
<td>111.00</td>
<td>m</td>
<td>W</td>
<td>Squier and Davidson (2016)</td>
<td>111.00</td>
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<tr>
<td><strong>Surface layer</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Berm height</td>
<td>0.00</td>
<td>mm</td>
<td>D₁</td>
<td>Jacobs Estimate</td>
<td>0.00</td>
</tr>
<tr>
<td>Vegetation volume</td>
<td>0.00</td>
<td>fraction</td>
<td>1-φ₁</td>
<td>Jacobs Estimate</td>
<td>0.00</td>
</tr>
<tr>
<td>Surface roughness</td>
<td>0.40</td>
<td>manning’s n</td>
<td>n</td>
<td>Jacobs Estimate</td>
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</tr>
<tr>
<td>Surface slope</td>
<td>1.00</td>
<td>%</td>
<td>S₁</td>
<td>Squier and Davidson (2016)</td>
<td>0.00</td>
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<tr>
<td><strong>Soil (substrate)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Thickness</td>
<td>7.60</td>
<td>cm</td>
<td>D₂</td>
<td>Squier and Davidson (2016)</td>
<td>7.60</td>
</tr>
<tr>
<td>Porosity</td>
<td>0.57</td>
<td>volume fraction</td>
<td>Φ₂</td>
<td>Penn State AASL</td>
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<td>Field capacity</td>
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<td>Wilting point</td>
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<tr>
<td>Conductivity</td>
<td>32,400.00</td>
<td>mm/hr</td>
<td>Kₑsat</td>
<td>Yang and Davidson (2017)</td>
<td>2032.00</td>
</tr>
<tr>
<td>Conductivity slope</td>
<td>10.00</td>
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<td>S</td>
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<tr>
<td>Suction head</td>
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<td>Ψ</td>
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<td><strong>Storage</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Thickness</td>
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<td>mm</td>
<td>D₃</td>
<td>Jacobs Estimate</td>
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<tr>
<td>Void ratio</td>
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<td>Φ₃</td>
<td>Jacobs Estimate</td>
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<tr>
<td>Seepage rate</td>
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<td>mm/hr</td>
<td>f₃</td>
<td>Jacobs Estimate</td>
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<tr>
<td>Clogging factor</td>
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<td>[unitless]</td>
<td>CF</td>
<td>Jacobs Estimate</td>
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<tr>
<td><strong>Underdrain</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drain coefficient</td>
<td>0.08</td>
<td>mm/hr</td>
<td>C</td>
<td>Jacobs Estimate</td>
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<tr>
<td>Drain exponent</td>
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<td>[unitless]</td>
<td>b</td>
<td>Jacobs Estimate</td>
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<tr>
<td>Drain offset height</td>
<td>0.00</td>
<td>mm</td>
<td>Hₘ</td>
<td>Jacobs Estimate</td>
<td>0.25</td>
</tr>
</tbody>
</table>
Parameter interactions between saturated hydraulic conductivity ($K_{sat}$) and porosity ($\Phi_2$) generate equifinal results (e.g., similar but high objective function values) when varied in tandem.

<table>
<thead>
<tr>
<th>$\Phi_2$ [volume fraction]</th>
<th>$K_{sat}$ [mm/hr]</th>
<th>1-May</th>
<th>5-Jun</th>
<th>28-Oct</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.38</td>
<td>2032</td>
<td>0.930</td>
<td>0.942</td>
<td>0.968</td>
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<tr>
<td>0.40</td>
<td>2540</td>
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<td>50,800</td>
<td>0.938</td>
<td>0.935</td>
<td>0.962</td>
</tr>
<tr>
<td>0.50</td>
<td>1,778,000</td>
<td>0.956</td>
<td>0.939</td>
<td>0.959</td>
</tr>
<tr>
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8 Figures

Figure 1. Conceptual diagrams of (a) the OnCenter green roof layers, drainage system, and monitoring equipment locations and (b) conceptualization of green roof processes in the SWMM LID bioretention module including model parameters, storage zones, and fluxes.

Figure 2. Flowchart showing a *frugal* sensitivity analysis approach for assessing whether model parameters are sensitive or insensitive with parameter value changes.
Figure 3. Timeseries of rainfall, observed runoff, and modeled runoff from the best fit parameter set for (a) October 28, 2017 (calibration) and (b) May 1, 2017 (validation) and (c) June 5, 2017 (validation).
Figure 4. To demonstrate that SWMM is prone to parameter interactions, we have documented seventeen parameter sets, visualized as a parallel coordinate plot (top), and corresponding runoff simulations (bottom) all with similar, high values of model fit (NSE > 0.94). Within the parallel coordinate plot, each parameter set corresponds to a line that spans the suite of 14 model parameters. These results show that equifinal parameter values largely span each parameter range, which suggests that SWMM parameters are highly interactive.
Figure 5. OAT sensitivity analysis results documenting change in NSE with respect to (a) the initial (pre-calibrated) parameter set and (b) best fit (post-calibrated) parameter set for increasing and decreasing each parameter by 50%, and for setting each parameter value to zero. (c) We qualitatively summarized these results with respect to the initial (left) and best fit (right) parameter sets, with color indicating storage or flux each parameter is most closely associated with and shading documenting most sensitive, highly sensitive, and insensitive parameters. Comparing results reveals fundamentally different process dominance based on location within the parameter space, indicating model non-linearity.
Figure 6. To assess how limited soil moisture information can impact runoff simulations, we compared simulated runoff for two storms using uninformed (e.g., no observed soil moisture; initial soil moisture set to zero) versus informed (e.g., observed soil moisture available; initial soil moisture set to observed value coincident with model start) estimates of soil moisture. While informed versus uninformed estimates yielded similar model fits for (a) an event on October 28, 2017, model fits were severely degraded for (b) June 5, 2017 in the absence of information on initial soil moisture.
Figure 7. While simulations from a calibrated (orange) versus a laboratory-based (gold) estimate of porosity ($\phi_2$) were similar for runoff (top), these two porosity estimates produced very different simulations of soil moisture content (bottom) that poorly approximated the range of observed soil moisture from the OnCenter green roof.


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EDUCATION

Jun 2017-Present Syracuse University | College of Engineering & Computer Science | Syracuse, NY
M.S. Environmental Engineering | Expected May 2019
Advisors: Cliff I. Davidson, Ph.D. & Christa Kelleher, Ph.D.
GPA: 4.0

Aug 2009-May 2013 University of New Hampshire | College of Engineering & Physical Science | Durham, NH
B.S. Environmental Engineering, Summa Cum Laude
Study Abroad: Budapest University of Technology and Economics, Hungary
Senior Capstone: The Dominican Republic Clean Water Project in Cumayasa, DR
GPA: 3.79

RESEARCH EXPERIENCE

May 2017-Present Syracuse University | Department of Civil & Environmental Engineering | Syracuse, NY
Graduate Research Fellow
Advisor: Professor Cliff I. Davidson, Ph.D.
Project | Doing a Lot with a Little: A Diagnostic Analysis of SWMM to Simulate Hydrologic Behavior within LID Systems

Jun 2012-May 2013 University of New Hampshire | Department of Natural Resources & The Environment | Durham, NH
Undergraduate Research Assistant
Advisor: Professor Rich Smith, Ph.D.
Project 1 | Cultivar diversity as a means of ecologically intensifying dry matter production in a perennial forage stand
Project 2 | Increased productivity of a cover crop mixture is not associated with enhanced agroecosystem services
Project 3 | Cover crop species as distinct biotic filters in weed community assembly
Project 4 | Effects of living mulch and fertilizer on the performance of broccoli in plasticulture

Jun 2011-Aug 2011 University of New Hampshire | Department of Environmental Engineering | Durham, NH
REU Grant Researcher
Advisor: Professor Nancy Kinner, Ph.D.
Project | Evaluate microbe reactions under varying concentrations of chlorinated solvents during groundwater remediation practices

PUBLICATIONS & PRESENTATIONS

Conference Papers

Conference Posters

Sep 2018

Sep 2018

Aug 2018

May 2013
Im J., **Worthen L.**, Anderson M., Miller B., “Dominican Republic Clean Water Project”. Presented at the University of New Hampshire Senior Capstone Presentation. Durham, NH.

HONORS & AWARDS

**Syracuse University**

Sep 2018
First Place – SyracuseCoE Graduate Student Poster Competition | Syracuse, NY

May 2018
Graduate Student Organization (GSO) Travel Grant

Apr 2018-Apr 2019
CHI University Grant

Oct 2017-May 2019
Women in Science & Engineering Future Professional Program (WiSE-FPP) Associate

Aug 2017-Aug 2019
National Science Foundation (NSF) NRT EMPOWER Fellowship

**University of New Hampshire**

Aug 2011-May 2013
Marie L. Langelier Scholarship

Aug 2010-May 2011
Kenneth J Higson Scholarship

Aug 2009-May 2013
University of New Hampshire Presidential Scholarship

Aug 2009-May 2013
Dean’s List

Aug 2009
Bristol United Church of Christ University Scholarship

TEACHING EXPERIENCE

Aug 2017-May 2018
**Syracuse University, College of Engineering & Computer Science** | Syracuse, NY
Graduate Teaching Assistant
Treatment Processes in Environmental Engineering | Fall 2017
Sustainability in Civil & Environmental Systems | Spring 2018

May 2015-Apr 2016
**Denver Permaculture Design Course** | Denver, CO
Coordinator
Taught sustainable urban design utilizing systems within nature as a design framework

Sep 2013-May 2014
**HETIC College** | Paris, France
Professor of English
Curated curriculum and taught lecture to graduate students
WORK EXPERIENCE

May 2018-Present  Jacobs  |  Syracuse, NY
Water Engineer Intern
Provided program management support, design support, and construction inspection support for the Onondaga County green infrastructure program “Save the Rain” through project cost analyses, AutoCAD and GIS construction design and standard drawings, PCSWMM GI analysis, attendance at client and stakeholder meetings, and technical memorandum, grant application, and report writing

Feb 2015-Apr 2016  CBDRx  |  Longmont, CO
Indoor Research & Development Farm Manager
Managed breeding research for optimum hemp genetics cultivars, provided data driven analysis of cultivar breeding program through the implementation of standard protocols and documentation, curated and maintained critical growing environment based on sustainable practices and USDA organic certification

PROFESSIONAL AFFILIATIONS & HONORARY SOCIETIES

Sep 2018-Present  International Association of Building Physics
Oct 2017-Present  Women in Science & Engineering Program | Syracuse University
Aug 2017-Present  NSF NRT EMPOWER Program | Syracuse University
Sep 2011- Present  American Society of Civil Engineers (ASCE)
May 2011-Present  Tau Beta Pi Engineering Honors Society
May 2011-Present  Golden Key International Honour Society
Sep 2011-May 2013  Engineers Without Borders | University of New Hampshire
Sep 2009-May 2013  Society of Women Engineers | University of New Hampshire

VOLUNTEER & COMMUNITY SERVICE

May 2015-Oct 2015  U urbiculture Community Garden  |  Denver, CO
Weekend farmers market coordinator, harvester, and food bank delivery driver

SOFTWARE SKILLS

Sep 2018  HydroCAD
Jan 2018  ArcGIS
Sep 2017  PCSWMM
Sep 2017  R Studio
Sep 2017  Hydrus 1-D
Jan 2013  HEC RAS
Jan 2012  AutoCAD
Jan 2012  USGS PHABSIM
Jan 2012  EPA NET