ABSTRACT

Title of Document: STORMWATER RUNOFF AND WATER QUALITY MODELING IN URBAN MARYLAND

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Directed By: Dr. Barton A. Forman, Department of Civil and Environmental Engineering

Urbanization significantly affects storm water runoff through the creation of new impervious surfaces such as highways, parking lots, and rooftops. Such changes can adversely impact the downstream receiving water bodies in terms of physical, chemical, and biological conditions. In order to mitigate the effects of urbanization on downstream water bodies, stormwater control measures (SCMs) have been widely used (e.g., infiltration basins, bioswales). A suite of observations from an infiltration basin installed adjacent to a highway in urban Maryland was used to evaluate stormwater runoff attenuation and pollutant removal rates at the well-instrumented SCM study site. In this study, the Storm Water Management Model (SWMM) was used to simulate the performance of the SCM. An automatic, split-sample calibration framework was developed to improve SWMM performance efficiency. The results indicate SWMM can accurately reproduce the hydraulic response of the SCM (in terms of reproducing measured inflow) during spring, fall, and winter, but is less accurate in reproducing measured outflow during summer time. Similar results were found for the modeled (and observed) inflow water quality constituent, total suspended solids (TSS).

STORMWATER RUNOFF AND WATER QUALITY MODELING IN URBAN MARYLAND

By

Jing Wang

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Advisory Committee:
Assistant Professor Barton A. Forman, Chair
Associate Professor Kaye L. Brubaker
Professor Allen P. Davis

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CHAPTER 1: INTRODUCTION

1.1.Research Motivation

The rapid development of urban areas leads to an increase of impervious cover that results in higher peak runoff, increased runoff volumes, faster runoff velocities, shorter lag times, increased water contamination, and more frequent downstream flooding (Dunne and Leopold 1978; Kibler 1982; Burszta-Adamiak and Mrowiec 2013). These changes can affect the downstream receiving water bodies in terms of physical, chemical, and biological conditions (Paul and Meyer 2001; Wang et al. 2003; Konrad and Booth 2005).

In order to control the water quantity and pollution exacerbated by urbanization, stormwater control measures (SCMs) have been widely installed at the source, along the line, or at the end of the line of the drainage system (Kibler 1982). Infiltration basins and wetponds are examples of two common structural SCMs employed to control urban runoff flows and pollutant loadings near the source before the runoff reaches downstream water bodies (Kibler 1982).

Based on previous studies (Lindsey et al. 1992; Emerson and Traver 2008), the performance of infiltration basins could decline over time, especially during the first two years, when it would be defined as a 'failed' SCM (Natarajan 2012). From an engineering perspective, a 'failed' infiltration basin exhibits permanent ponding of water without active infiltration (Natarajan 2012). It can no longer capture, temporarily store, infiltrate, and percolate the stormwater as originally designed (Ferguson 1990; Birch et al. 2005; Barraud et al. 2005). On the other hand, a few research studies have monitored the long-term hydrologic performances of infiltration basins that did not find any function degradation (Dechesne et al. 2005; Emerson and Traver 2008).

However, relatively few research studies have focused on the environmental function of 'failed' infiltration facilities in mitigating stormwater runoff flows and reducing pollutant loads. Based on a recent research (Natarajan 2012), degraded infiltration basins can gradually transform into wetponds or wetland-like behavior that still possesses water quantity management, water quality control functionality, and suitability for wildlife habitat (Natarajan 2012). Rather than being removed or restored, the 'failed' infiltration facilities can remain on site and be considered as beneficial stormwater management practices that provide environmental and ecological benefits in urban and suburban areas (Natarajan 2012).

More research is needed to quantify the potential benefits of infiltration basins in urbanized and suburbanized area. However, measuring SCMs effectiveness is a challenge for researchers (Singh et al. 2011). Also, it is hard to predict the hydrologic and water quality behaviors of SCMs under future climate change scenarios, which is critical for designing an SCM (Pyke et al. 2011).

One means of better characterizing and predicting SCMs is with the use of performance computer models. Defined as a mathematical description of physical, chemical, and biological processes, a model can evaluate the function of infiltration basins or other SCMs in a more quantitative fashion and at a lower cost than extensive field studies (Kibler 1982; Bertrand-Krajewski et al. 2000).

This study employed the Storm Water Management Model (SWMM) to investigate its ability to reproduce hydrologic performance of a SCM installed adjacent to a major highway. SWMM is a publically-available dynamic hydrology-hydraulic water quality simulation model developed by United States Environmental Protection Agency (Gironas et al. 2009). It can model both urban and suburban hydrologic processes and track both the quantity and quality of runoff through a SCM (Gironas et al. 2009). The application of SWMM across a wide range of hydrologic regimes is well-documented and has been successfully employed to model the hydrologic improvement and non-point source pollution (NPS) reduction by implementing best management practices (BMPs) and SCMs in urban and suburban areas (Aad et al. 2009; Lee et al. 2010; Tobio et al. 2015; Rosa et al. 2015; Li et al. 2015).

1.2. Objectives and Research Benefits

The purpose of this study is to apply and calibrate SWMM using observed runoff flows and pollutant concentration measurements collected from an existing infiltration basin installed adjacent to Highway 175 in Columbia, Howard County, Maryland. The infiltration basin is designed to treat the runoff from a small portion of the highway (Natarajan 2012). The main objectives of the research are:

1. To setup the SWMM model for the study watershed.
2. To automatically calibrate (and validate) the SWMM model for the MD 175 infiltration basin. The ability of calibrated model to reproduce the past hydrological and water quality-related features of the study area will be evaluated.
3. To explore model sensitivities related to parameters, which can be used to improve model calibration via a reduction in the parameter dimensionality.

An automatic calibration routine will be developed for SWMM model calibration and validation, which can improve calibration efficiency and can eventually be used by the greater SWMM modeling community.

CHAPTER 2: BACKGROUND AND LITERATURE REVIEW

The following chapter describes background information related to urbanization and storm water management. It also introduces the Storm Water Management Model (SWMM).

2.1. Effects of Urbanization on Storm Water Management

Urbanization is the change in land use, e.g., from forested or agricultural land to urban and suburban areas, which can influence the downstream water bodies in terms of physical, chemical, and biological conditions.

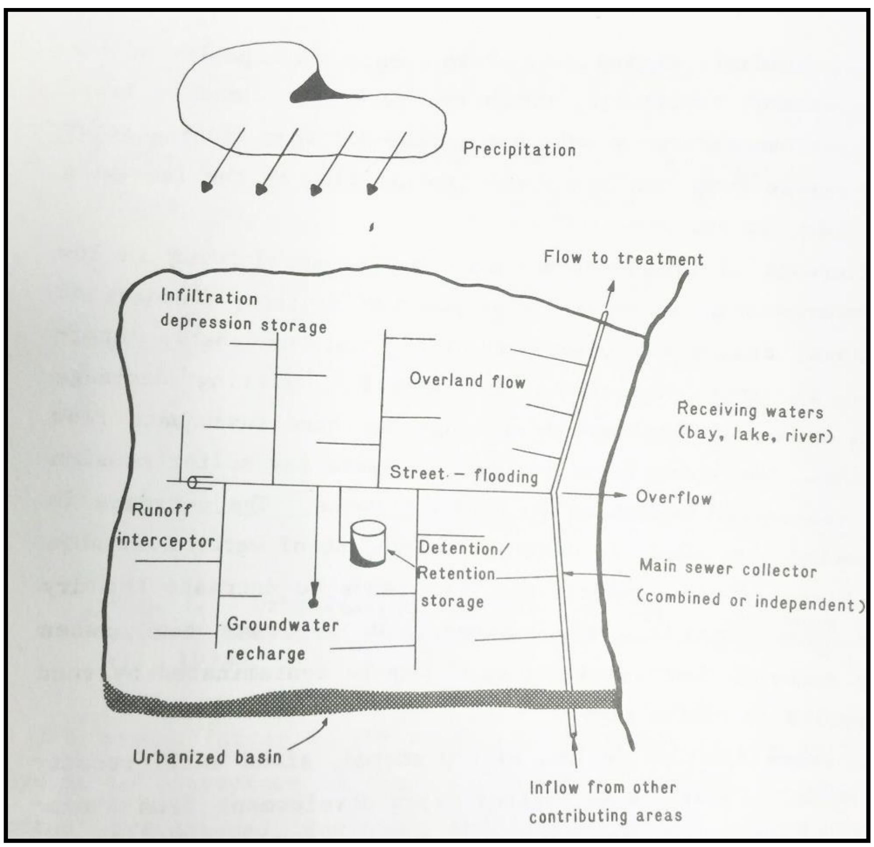

Figure 2.2.1-1. Urban storm-drainage system [Reproduced from (Kibler 1982)].

Figure 2.2.1-1 shows a schematic of an urban stormwater drainage system. A small portion of rainfall within the basin is first captured by the depression storage from where it is either intercepted by plants, infiltrates into the subsurface or evaporates from standing water, soil moisture, or plants (transpiration). Depending on the degree of development in the basin and the existence of a storm drainage system, all or a portion of the ensuing runoff is intercepted by storm drains or combined sewers and then conveyed to treatment facilities, detention or retention storage facilities, or spilled at an overflow point (Kibler 1982).

Urbanization significantly affects the rainfall-runoff process in a variety of ways. The replacement of vegetation with the creation of new impervious surfaces such as highways, parking lots, and rooftops, results in a large reduction of interception. Without vegetation, the amount of infiltration and evapotranspiration is reduced, which has a significant effect on the downstream water balance (Ng and Miller 1980; Simmons and Reynolds 1982; Rose and Peters 2001). In general, over 40 to 90 percent of the rainfall becomes surface runoff in urban areas (Roesner and Bledsoe 2003). In addition, the extensive network of pipes and channels that are designed into the urban environment intensifies the rate of stormwater runoff, which results in a reduction of the lag time (i.e., the time delay between peak rainfall and peak runoff as shown in Figure 2.2.1-2) to 10-25% of its natural basin value (Anderson and County 1970; Akan and Houghtalen 2003). Depending on the water balance, the surface stormwater runoff would have higher peaks, greater runoff volumes, and faster runoff rates that can produce flooding as well as watercourse and habitat destruction in low-lying areas when compared to natural areas (Zoppou 2001; Bengtsson et al. 2005).

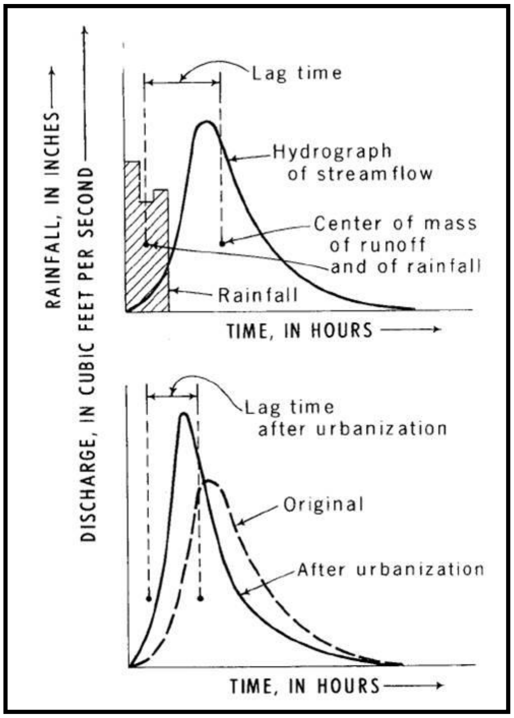

Figure 2.2.1-2. Urbanization impacts on basin response [Reproduced from (Leopold 1968)].

Stormwater quantity is not the only problem associated with urbanization. Stormwater quality is impaired as well (Akan and Houghtalen 2003). Typical stormwater pollutants include lead, chloride, and biochemical oxygen demand (BOD), which are generated from the vehicle exhaust emissions, the wear of tires and the roadway (Shaheen 1975). In addition, application of fertilizers and pesticides results in high concentration of dissolved nitrate, total nitrogen, phosphate, and total phosphorus loads in stormwater runoff (Groffman et al. 2004). Pollutants (e.g., dust, dirt, and sediments) generated by urban activities (or settled from the atmosphere) are generally accumulated on land surfaces between storm events, and eventually washed off during a rain event (Kibler 1982). The process of urbanization results in nonpoint source pollution, the primary source of water quality impairment in the United States (Akan and Houghtalen 2003). It has caused an increase of pollutant loads by at least one order of magnitude over natural catchment conditions (Kibler 1982).

The changes that comes with urbanization have a profound effect in many ways. Impaired stormwater has negative impact on aquatic life in ways of polluted aquatic habitat, altered energy pathways in streams, and loss of riparian areas (Allan 2004). Although a formal risk analysis of the human health caused by stormwater runoff is not yet quantified, some studies have pointed out that the higher health risks are associated with swimming at storm-drain locations (Haile et al. 1999).

To mitigate environmental deterioration of increased urbanization, the concept of stormwater management was introduced for environmental protection, in terms of monitoring and analysis of constituents entering the system, implementation of preventive practices to control the quantity and quality of runoff and prevent the flooding of the downstream watersheds (Tsihrintzis and Hamid 1997). In fact, many innovative practices have been developed over the last two decades to mitigate the detrimental effects of urbanization on stormwater runoff. These practices are often referred to as stormwater control measures (Akan and Houghtalen 2003).

2.2. Stormwater Control Measure (SCM)

The term stormwater control measure (SCM) is, in general, synonymous with the term best management practice (BMP). A broadly stated goal of SCMs is to attenuate runoff and reduce pollutant loads to downstream waterbodies (Strassler et al. 1999).

There are two broad categories of SCMs, which include structural and non-structural practices. Structural SCMs are defined as any constructed facilities that treat the stormwater at the source of runoff or discharge point (Strassler et al. 1999). Non-structural SCMs are longer-term and lower-maintenance practices that are designed at the runoff source based on the local land use. This study will focus on two structural SCMs: infiltration basins and retention ponds.

2.2.1. Infiltration Basin

Infiltration basins are designed to control the water quantity and quality through capturing stormwater runoff and temporarily retaining it while allowing the stormwater to infiltrate (Ferguson 1990; Strassler et al. 1999; Winer 2000). As shown in Table 2.2.1-1, infiltration basins have high pollutant removal efficiencies, especially for heavy metals. Infiltration basins attenuate stormwater runoff via enhancing infiltration into the subsurface, thereby increasing baseflow and recharge to underlying aquifers (Strassler et al. 1999). The mechanisms for treating water in infiltration basins are filtration, adsorption, and biological conversion. As runoff infiltrates into the underlying soils, particulates and the attached contaminants such as metals and nutrients are filtered from the stormwater while some of the dissolved constitutes are adsorbed onto the surface of particles. Moreover, some organic pollutants can be metabolized by the micro-organisms in the soil (Strassler et al. 1999).

Table 2.2.1-1. Pollutant removal efficiency of infiltration basins [Adapted from (Winer 2000)].

PARAMETER	MEDIAN REMOVAL EFFICIENCY
TOTAL PHOSPHORUS ($\boldsymbol{TP}$)	*70%*
AMMONIA-NITROGEN ($\boldsymbol{NH_3-N}$)	*83%*
NITRATE ($\boldsymbol{NO_3}$)	*82%*
TOTAL NITROGEN ($\boldsymbol{TN}$)	*51%*
TOTAL SUSPENDED SOLIDS ($\boldsymbol{TSS}$)	*76%*
LEAD ($\boldsymbol{Pb}$)	*98%*
ZINC ($\boldsymbol{Zn}$)	*99%*

Although an infiltration basin has many benefits, it also has some disadvantages. First, infiltration basins usually can only intercept a certain volume of runoff. Any excess runoff will be bypassed through the system without control and treatment (Strassler et al. 1999). Moreover, frequent maintenance of the infiltration basin is required to maintain the capacity of the system and prevent clogging due to excessive sediment accumulation. Common maintenance activities include annual cleaning and removal of debris, removal of accumulated sediment from forebays every 3-5 years, and maintenance of upland vegetated areas (Livingston et al. 1997).

Figure 2.2.2.1-1 shows a typical design of an infiltration basin. The bottom of the infiltration basin is normally covered with 6 to 12 inches of thick sand, which traps and filters sediment from runoff (Pazwash 2011). The bottom elevation of the basin should be located above the high water table or the bedrock by 2 to 3 feet. Pazwash (2011) recommended the percolation rate of the soils should be at least 1 inch per hour since the infiltration rate diminishes with time due to silting. In order to prevent insect and odor problems, infiltration basins are typically designed to not retain a permanent pool volume. The volume of water in the infiltration basins should be drained within 72 hours to ensure the basin is operational by the arrival of the next rainfall-runoff event (Strassler et al. 1999).

Infiltration basins have relatively high failure rates compared to other SCMs (Hilding 1994). In this research, the infiltration basin is defined as a permanently ponded 'failed' facility by the Maryland State Highway Administration (SHA). The infiltration basin transitioned to a wet pond early in its operation (Natarajan 2012).

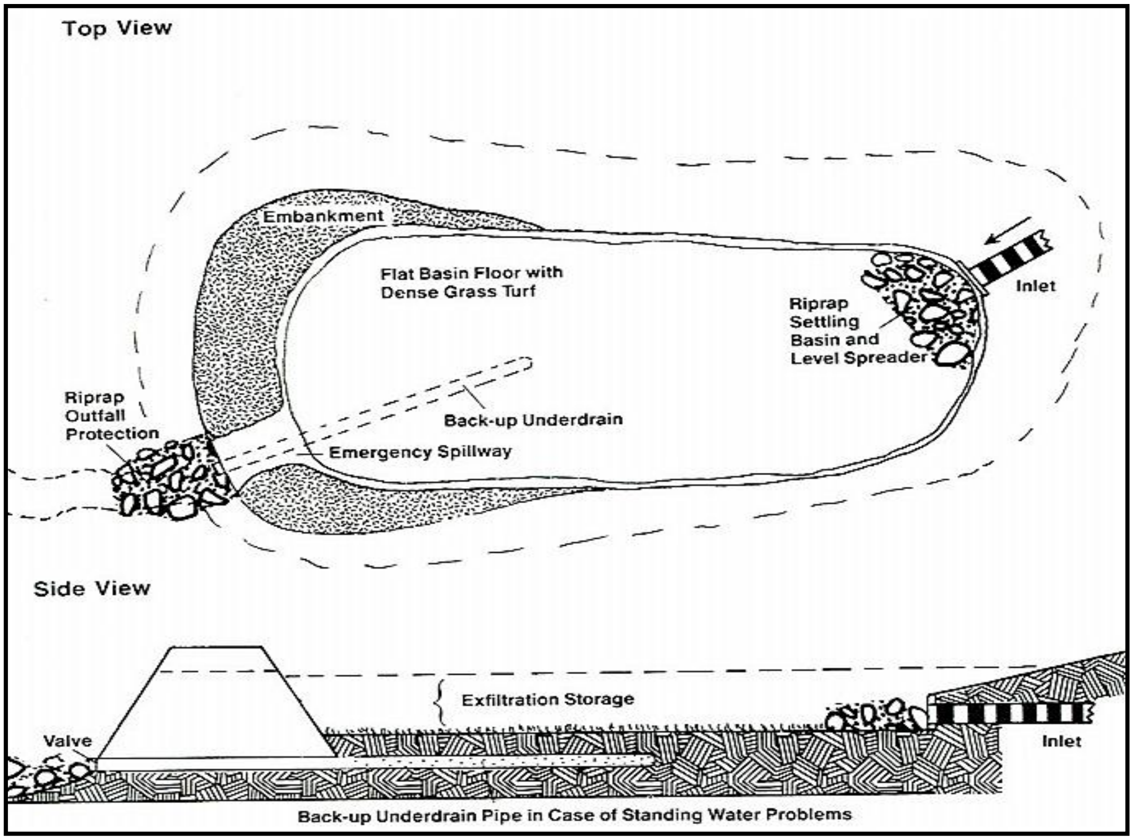

Figure 2.2.2.1-1. Infiltration basin [Reproduced from (Schueler et al. 1992)].

2.2.2. Wet Pond

Wet ponds (also known as retention ponds) have similar functions as infiltration basins. However, wet ponds are designed to capture stormwater volume, store, and improve the quality of the stormwater runoff. Unlike infiltration basins, wet ponds are intended to store water permanently. Figure 2.2.2.2-1 shows a typical design for a wet pond. The volume available for storage is defined as the permanent pool level of the system. The portion of water in the pond above the permanent pool level will be replaced by subsequent stormwater runoff (Strassler et al. 1999). Except for filtration, adsorption and biological conversion, the aquatic plants in wet ponds can provide pollutant control via uptake and transformation processes. As shown in Table 2.2.2-1, wet ponds are efficient at removing pollutants. Compared to infiltration basins, wet ponds can help mitigate a large variety of pollutants. Moreover, wet ponds have ecological value by providing habitat for a variety of aquatic plants and animals (Strassler et al. 1999). Common maintenance activities include annual repair of the embankments, side slopes and control structure, and removal of accumulated sediment and debris from the pond every 5 to 10 years (Livingston et al. 1997).

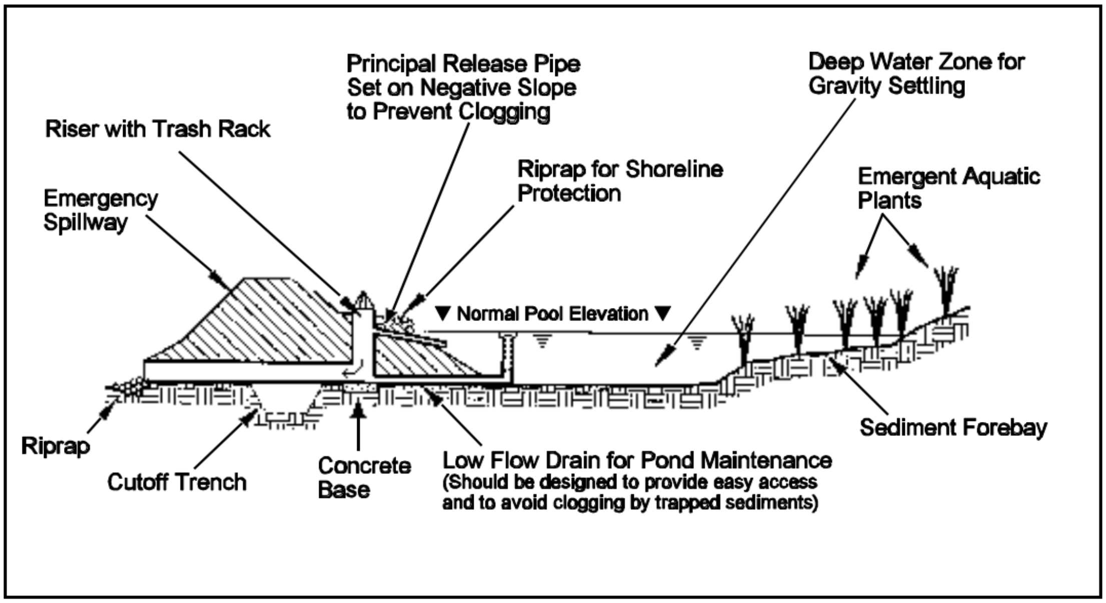

Figure 2.2.2.2-1. Design of a wet pond [Reproduced from (Michael Clar 2001)].

In the context of stormwater management, long-term effectiveness of SCMs is important. However, only short-year observational records are available. Therefore, the Storm Water Management Model is needed here to assess SCM performance over larger time periods beyond that which is observationally available.

Table 2.2.2.2-1. Typical pollutant removal efficiencies for wet ponds [Adopted from(Winer 2000)].

PARAMETER	MEDIAN REMOVAL EFFICIENCY
TOTAL PHOSPHORUS ($\boldsymbol{TP}$)	*46%*
AMMONIA-NITROGEN ($\boldsymbol{NH_3 - N}$)	*23%*
NITRATE ($\boldsymbol{NO_3}$)	*23%*
TOTAL NITROGEN ($\boldsymbol{TN}$)	*30%*
TOTAL SUSPENDED SOLIDS ($\boldsymbol{TSS}$)	*70%*
COOPER ($\boldsymbol{Cu}$)	*55%*
LEAD ($\boldsymbol{Pb}$)	*67%*
ZINC ($\boldsymbol{Zn}$)	*51%*

2.3. Storm Water Management Model (SWMM)

2.3.1. Introduction and Model Capabilities

The Environmental Protection Agency (EPA) developed the Storm Water Management Model (SWMM), which is used widely in urban and non-urban hydrologic modeling. As a physically-based, discrete-time simulation model, SWMM employs principles of conservation of mass, energy and momentum (Rossman 2010).

SWMM is typically used for planning, analysis, and design related to stormwater runoff, combined and sanitary sewers, and other drainage systems. Typical applications of SWMM in stormwater and sewer studies include flood control, water quality protection, design of control strategies, controlling site runoff using LID practices, and evaluating the effectiveness of SCMs in reducing pollutant loading (USEPA 2015).

There are four compartments in SWMM: (1) the atmospheric compartment (via rain gages), (2) the land surface compartment (via subcatchments), (3) the groundwater compartment (via aquifers), and (4) the transport compartment (via links and junction nodes).

As shown in Figure 2.3.1.-1., SWMM accounts for various hydrologic processes that produce runoff from urban and suburban areas. These include time-varying rainfall, rainfall interception from depression storages, evaporation from standing water, snow accumulation, infiltration of rainfall into unsaturated soil layers, percolation of infiltrated water into underlying soils, interflow between groundwater and the drainage system, nonlinear reservoir routing of overland flow, and runoff reduction via low impact development controls (Rossman 2010).

SWMM also tracks the quantity of runoff flow rate, flow depth, and quality of the water in the routing network (Gironas et al. 2009). It mimics the function of SCMs during the routing of water through treatment storage units or by natural processes in pipes and channels (USEPA 2015).

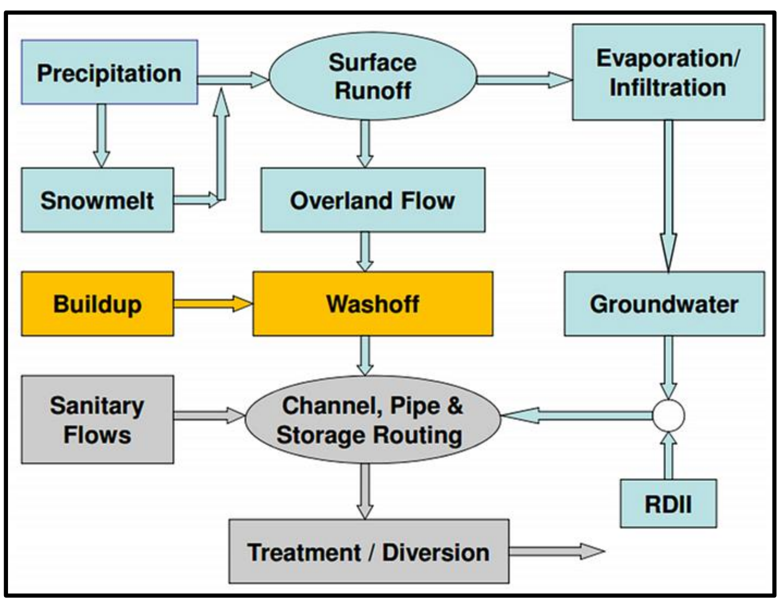

Figure 2.3.1.-1. Simple schematic of SWMM process representations [Reproduced from (USEPA 2012)].

2.3.2. SWMM Applications

The application of SWMM in hydrologic and water quality assessments in urban areas is well documented (Huber et al. 1988; Rossman 2010). SWMM has been successfully applied to all types of storm water management, including urban drainage, natural watersheds, and flood routing (Hsu et al. 2000; Zaghloul 1998). It is capable of simulating small, medium, and large urban and suburban catchments (Tsihrintzis and Hamid 1998; Jang et al. 2007; Khader and Montalto 2008; Barco et al. 2008; Shinma and Reis 2014). SWMM also shows some skill at modeling first flush phenomenon, which is defined as the discharge of a larger mass of a contaminant in the early part of a storm relative to the later part (Stenstrom and Kayhanian 2005; Modugno et al. 2015). Moreover, SWMM can help investigate the optimal design of SCMs and predict the optimal physical characteristics and rainfall design criteria for an existing LID (Li et al. 2015; Tobio et al. 2015)

SWMM provides two ways to model SCMs. One is to model SCMs with the 'LID' block. A variety of SCMs, such as rain barrels or gardens, detention ponds, infiltration trenches and green roofs, can be modeled by SWMM (Bengtsson et al. 2005; Khader and Montalto 2008; Li et al. 2015; Tobio et al. 2015). However, SWMM has limited capabilities at simulating pollutant loads on pervious surfaces such as permeable pavements (Rosa et al. 2015).

Many studies have investigated the effects of spatial resolution on SWMM model output. There are two basic approaches to model the urban hydrologic processes based on the scale and level of investigation: the micro-approach and macro-approach (also known as lumped parameter model approach) (Kibler 1982). The results indicate that peak runoff is more sensitive to spatial scale than runoff volumes, especially for small storm events (Warwick and Tadepalli 1991; Ghosh and Hellweger 2011). However, the spatial resolution of SWMM did not significantly affect the modeled flows in combined sewer systems (Zaghloul 1998; Khader and Montalto 2008)

Multiple studies investigated the calibration of SWMM. Barco (2008) proposed an automatic calibration approach for a large urban catchment. The approach can be applied to any objective functions. When coupled with GIS, this research provides a new procedure to model extremely large watersheds (Barco et al. 2008). In order to deal with increasing data availability, Shinema et al. (2014) proposed the use of multi-site approaches and multi-events during calibration. In the multi-site approach, the objective functions were calculated by weighting each site's objective function by it respective drainage area. In the multi-events approach, calibration was conducted simultaneously for upstream and downstream watersheds for all rainfall events at once. It produced better objective function values, reduced uncertainties, and improved computing efficiency (Shinma and Reis 2014). Gaume and Desbordes (1998) also presented a global approach to identify the best set of parameters and reduce the uncertainties with SWMM (Gaume et al. 1998). A genetic algorithm (GA) was applied to search for the optimal values of catchment calibration parameters. The results show that GA can improve the calibrating efficiency and yields relatively high prediction accuracy (Liong et al. 1995).

CHAPTER 3: METHODS

In this study, Storm Water Management Model (SWMM) was utilized as the modeling environment. The development of a SWMM model for the study area was performed in two major steps: model setup and model calibration (with validation). An automatic calibration procedure was developed in MATLAB©. To improve calibration efficiency, the sensitivity of SWMM parameters was analyzed. The research methods are described in detail in this chapter.

3.1. Storm Water Management Model (SWMM)

As discussed in Section 2.3, SWMM is a physically based, discrete-time simulation model, which employs principles of conservation of mass, energy and momentum (Rossman 2010). There are four compartments in SWMM: (1) the atmospheric compartment (via rain gages), (2) the land surface compartment (via subcatchments), (3) the groundwater compartment (via aquifers), and (4) the transport compartment (via links and junction nodes). The following sections will discuss the properties of these compartments related to the study area for this study.

3.1.1. Land Properties

Land surface is represented as "subcatchments" in SWMM, which can receive precipitation and consequently can generate runoff and pollutant loads. Subcatchment areas are hydrologic units of land containing both pervious and impervious surfaces whose runoff drains to a common outlet (Rossman 2010).

3.1.1.1. Water Quantity

Subcatchment surfaces are treated as nonlinear reservoirs in SWMM. Inflow to the reservoir originates from precipitation and any designated upstream subcatchments. Outflows leave the reservoir in the form of infiltration, evaporation, and surface runoff. The capacity of this reservoir is the maximum depression storage, or the maximum surface storage provided by surface ponding (Rossman 2010). Water stored as depression storage on pervious areas is subject to infiltration (and evaporation), while water stored in depression storage on impervious areas is depleted only by evaporation (Huber et al. 1988). The conceptual view of surface runoff is illustrated in Figure 3.1.1.1.-1.

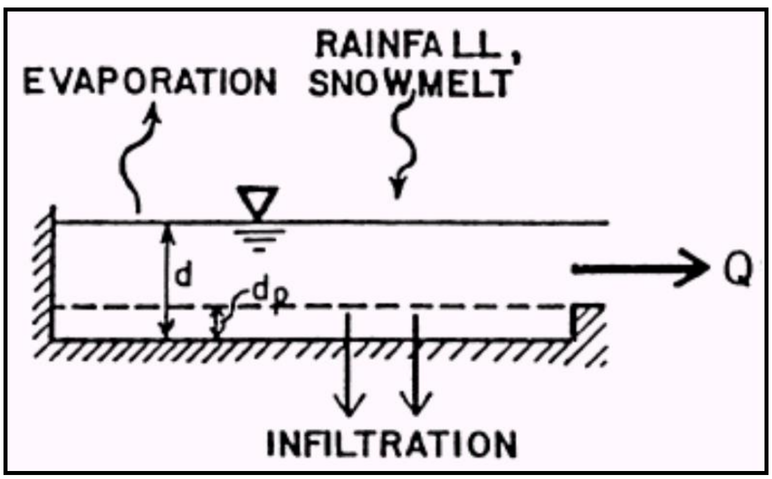

Figure 3.1.1.1.-1. Nonlinear reservoir representation of subcatchment [Reproduced from (Rossman 2010)].

Surface runoff (Q) occurs only when the water depth in the reservoir exceeds the maximum depression storage (d_p). Surface runoff is given by Manning's equation,

$$Q = W \frac{1.49}{n} (d - d_p)^{5/3} S^{1/2} \qquad (3.1.1.1 - 1)$$

where Q is the subcatchment surface runoff (cfs); W is the subcatchment width (ft); n is the

Manning's roughness coefficient; d is the water depth (ft); d_p is the depth of depression storage (ft); and S is the surface slope (ft/ft).

The infiltration method used in this study is the Curve Number method, which has the least number of parameters in SWMM. It assumes the total infiltration capacity of a soil can be found from the soil's tabulated Curve Number. During a rain event, this capacity is depleted as a function of cumulative rainfall and remaining capacity (Rossman 2010).

The Curve Number method is derived from the Soil Conservation Service (SCS) Curve Number method used in the runoff model (Gironas et al. 2009), which can be written as,

$$R = \frac{(P - I_a)^2}{(P - I_a) + S_D} \qquad (3.1.1.1 - 2)$$

where R is the runoff (inch); P is the precipitation (inch); I_a is initial abstraction, includes the water intercepted by vegetation, the water retained in surface depressions, evaporation, and infiltration before runoff begins (inch); and S_D is soil moisture storage deficit (inch) at the time runoff begins (Akan and Houghtalen 2003), which can be written as,

$$S_D = \frac{1000 - 100CN}{CN} \qquad (3.1.1.1 - 3)$$

where CN is runoff curve number. With a reasonable assumption about the relationship between I_a and S_D, runoff (R) can be written as a function of soil moisture storage (total infiltration capacity).

3.1.1.2. Water Quality

Pollutants build up in an urban watershed between storm events (dry weather) at different rates (Kibler 1982). The rate of this accumulation is most rapid during the first 2 to 3 days after a significant rainstorm and subsequently decreases over time (Sartor et al. 1974). Therefore, an exponential buildup function in SWMM was selected. Pollutants build up can be computed as,

$$Buildup\ Mass = C_{max}(1 - e^{-C_2 t}) \qquad (3.1.1.2 - 1)$$

where Buildup Mass is the amount of buildup pollutant (kg/ha); C_{max} is maximum possible buildup (kg/ha); C_2 is buildup rate constant (1/days); and t is the number of antecedent dry days (days).

Pollutants wash off from a land during storm events (wet weather). To maintain model consistency, an exponential washoff function in SWMM was selected. Pollutants wash off can be computed as,

$$Washoff\ Mass = C_1 q^{C_2} B \qquad (3.1.1.2 - 2)$$

where Washoff Mass is the amount of washoff load (kg/hr); C_1 is washoff coefficient (dimensionless); C_2 is washoff exponent (dimensionless); B is pollutant buildup in mass units (kg); and q is the runoff rate per unit area (mm/hr).

3.1.2. Channel Properties

Channels and culverts in urban watersheds are represented via “conduits” in SWMM, which apply Manning’s equation to calculate flow rate as,

$$Q = \frac{1.49}{n} A R^{2/3} S^{1/2} \qquad (3.1.2 - 1)$$

where Q is the runoff discharge (cfs); n is the Manning’s roughness coefficient; A is the cross sectional area of the conduit (ft^2); R is the hydraulic radius (ft); and S is the surface slope (ft/ft).

3.1.3. Stormwater Control Management (SCM) Properties

SCMs can be represented as “LID controls” or “storage units” in SWMM. LID controls, including infiltration trenches, bio-retention cells, continuous porous pavement, rain barrels, and vegetative swales are designed to capture surface runoff and reduce runoff through some combination of detention, infiltration, and evapotranspiration (Rossman 2010). Storage units can model the reduction of stormwater runoff and removal of pollutants from the flow streams. In fact, storage units could represent “storage facilities as small as a catch basin or as large as a lake”, which provide storage volume. With a user-defined mathematical function, storage units can model the change of runoff quality through SCMs (Gironas et al. 2009).

3.2. SWMM Model Calibration

SWMM is a mathematical simulation model that mimics the performance of a storm under various conditions (Rossman 2010). The correct use of the SWMM is based on the premise that it reproduces the real-life hydraulic and hydrologic behaviors with acceptable accuracy (Kibler 1982). However, there are many difficulties due to the scarcity of data, uncertainty of parameters and inherent model assumptions (Huber et al. 1979). Manual calibration is not a feasible option. Therefore, an auto-calibration strategy was developed with MATLAB© for this study.

3.2.1. Auto-Calibration Procedure

The auto-calibration procedure is based on Monte Carlo simulation techniques. To perform a Monte Carlo simulation, the first step is to define the critical parameters with their boundaries (feasible ranges) and statistical characteristics (Ayyub and McCuen 2011).

In this study, the boundaries (feasible ranges) of input parameters were defined based on peer-reviewed literature. The distribution of the input parameters was assumed to be uniform (non-informative) and no serial correlation between these characteristic. Therefore, the parameters can be calculated within feasible boundaries as follows:

$$X_{i,j} = L_i + r_{i,j}(U_i - L_i) \qquad (3.2.1 - 1)$$

where $X_{i,j}$ is the value of the ith parameter in the jth replicate; U_i is upper bound of the ith parameter; L_i is lower bound of the i th parameter; $r_{i,j}$ is random variable that has a uniform distribution on the continuous range [0, 1]; i is ith parameter; and j is j th replicate for a set of size J (Barco et al. 2008).

3.2.2. Objective Functions

The objective function, which is defined as an optimization procedure used to select better solutions over poorer solutions (King and Wallace 2012), is critical for model calibration and validation. Several objective functions were applied for hydrology and water quality analyses in this study.

3.2.2.1. Nash-Sutcliffe Model Efficiency Coefficient

The Nash-Sutcliffe efficiency (NSE) is a normalized statistic estimator that determines the magnitude of the modeled runoff discharge, relative to the measured runoff discharge (Nash and Sutcliffe 1970),

$$NSE = 1 - \frac{\sum_{t_1}^{t_2}(Q_0^t - Q_m^t)^2}{\sum_{t_1}^{t_2}(Q_0^t - \overline{Q_0})^2} \qquad (3.2.2.1 - 1)$$

where NSE is the Nash-Sutcliffe model efficiency coefficient; $\overline{Q_0}$ is the time-averaged mean of observed discharge (LPS); Q_m^t is the SWMM modeled discharge (LPS) at time t; Q_0^t is observed discharge at time t (LPS); t_1 is start time of simulation; and t_2 is end time of simulation.

3.2.2.2. Bias

As a systematic error, bias results from systematic distorting of the data (Ayyub and McCuen 2011), such that bias can be computed as

$$B = \frac{\sum_1^n (\hat{y_i} - y_i)}{n} \qquad (3.2.2.2-1)$$

where B is the bias; $\hat{y_i}$ is the model predicted data; y_i is the measured data; and n is the number of values. Relative bias provides a measure of the magnitude of the bias and is computed as

$$Rel.B = \frac{B}{\bar{y}} \qquad (3.2.2.2-2)$$

where $Rel.B$ is the relative bias; and $\bar{y}$ is the mean of the measured data.

3.2.2.3. Root Mean Squared Error

As a measure of model accuracy, root mean squared error (RMSE), can help estimate the closeness of measured and modeled data as

$$RMSE = \sqrt{\frac{\sum_1^n (\hat{y_i} - y_i)^2}{n}} \qquad (3.2.2.3-1)$$

where RMSE is the root mean squared error; $\hat{y_i}$ is the model predicted data; y_i is the measured data; and n is the number of data.

3.2.2.4. Correlation Coefficient

As an index of the degree of association as a function of time, correlation coefficients quantify the degree of association between the elements of two samples of data (McCuen 1989),

$$R = \frac{\sum_1^n x_i y_i - (\sum_1^n x_i)(\sum_1^n y_i)/n}{(\sum_1^n {x_i}^2 - (\sum_1^n x_i)^2/n)^{0.5} \cdot (\sum_1^n {y_i}^2 - (\sum_1^n y_i)^2/n)^{0.5}} \qquad (3.2.2.4-1)$$

where R is the correlation coefficient; x_i is the ith variable of x; and y_i is the ith variable of y.

3.2.3. Sensitivity analysis for SWMM parameters

There are roughly 100 parameters that need to be calibrated in the study. Based on literature (Tsihrintzis and Hamid 1997; Barco et al. 2008), SWMM parameters exhibit different sensitivity when modeling different watersheds. Therefore, a sensitivity analysis was conducted to improve calibration efficiency and reduce the overall parameter dimensionality in this study.

Defined as the rate of change of one factor with respect to change in another factor, sensitivity analysis is important in model simulation (McCuen 2002). There are three types of sensitivity indicators: (1) deviation sensitivity, (2) absolute sensitivity, and (3) relative sensitivity (McCuen 2002). In this study, relative sensitivity was used to quantify the relative importance of each parameter.

The normalized sensitivity coefficient (or sensitivity index) is calculated through the following formula,

$$NSC = \frac{(\emptyset - \emptyset_0)/\emptyset_0}{(P - P_0)/P_0} \qquad (3.2.3-1)$$

where NSC is the normalized sensitivity coefficient; P_0 is the nominal (initial) parameter value; P is the perturbed parameter value (perturbation size is $\pm 10\%$); $\emptyset_0$ is the nominal (initial) model output; and $\emptyset$ is the perturbed model output associated with P.

In this study, the parameters related to subcatchment (width, surface slope, Manning's N for impervious/pervious area, depression depth on impervious/pervious area, percent of impervious area with no depression storage, runoff curve number, and drying day) were calculated by weighting proportionally to their drainage areas.

3.3. Study Domain

The study site is located along MD 175 East in Columbia, Howard County, Maryland (Figure 3.3.-1.). It is a small drainage area (2.9 ha) that includes an existing infiltration basin.

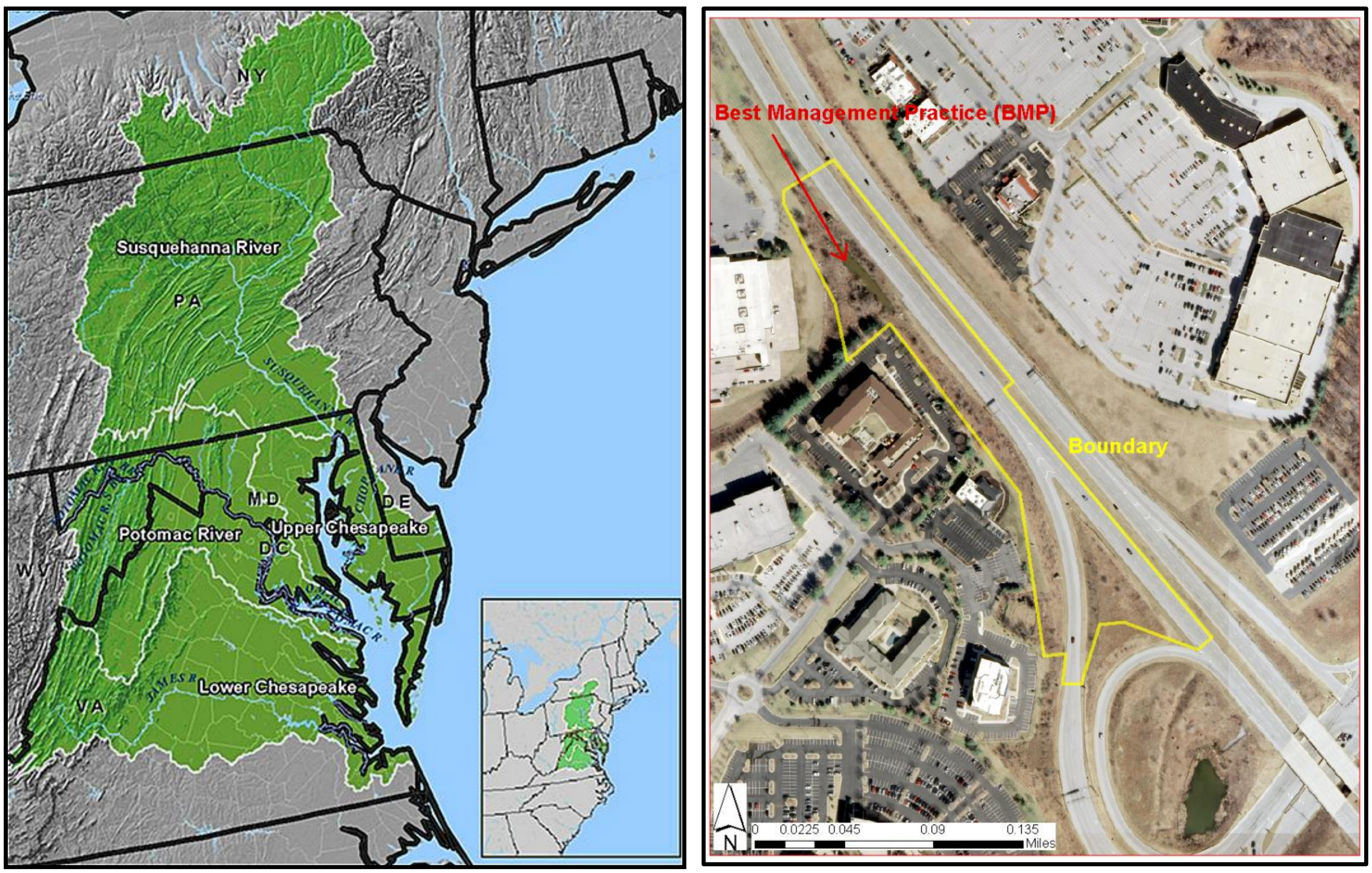

Figure 3.3.-1. Area map of the study site location along MD 175 East.

Based on SHA investigation report, the total area of the study site is 2.9 ha of which 33% is impervious. The weighted curve number for infiltration is 75. The drainage area consists of impervious highway surfaces and grassy areas directly connected to the infiltration basin. Runoff from the entire drainage area is concentrated into the grassy area and then flows into the infiltration basin.

The infiltration basin has one inflow and one outflow point via installation of calibrated weirs. The source of inflow is sheet flow from the highway, along with culvert and swale flow. All of these flows lead into a vegetated swale as inflow to the infiltration basin through wooden V-notch weirs (Natarajan 2012). The water quantity and quality data from the infiltration basin were collected from August 2009 to August 2012 by Dr. Allen Davis' research group. The basic characteristics of the SCM are listed in Table 3.3.-1.

Table 3.3.-1. Basic characteristic of the MD 175 infiltration basin site [Adopted from (Natarajan 2012)].

CHARACTERISTIC	VALUE
STORAGE CAPACITY	$650\ m^3$
SIDE SLOPE	$4:1$
DEPTH	$0.91\ m$
LENGTH	$71\ m$
BOTTOM WIDTH	$3.7 \sim 7.6\ m$
SOIL TYPE AROUND THE BASIN	*USDA Loam*

3.3.1. Model Setup

In this study, both water quantity and water quality variables were of interest. Therefore, the study area was modeled in SWMM for both runoff and pollutant loads.

3.3.1.1. Land Properties

At the land surface, a portion of the precipitation is intercepted by vegetation, a portion will infiltrate into soil, and a portion may evaporate from the soil (Akan and Houghtalen 2003). What remains consequently can generate runoff and pollutant discharges.

The delineation of the study area was performed in SWMM. Based on the hydrologic behavior of the study area, four “subcatchments” were established in SWMM model that included two highways and two grassy areas (Figure 3.3.1.1.-1.). The area of each subcatchments was estimated using the dot grid method, which is a simple method to calculate areas on a map.

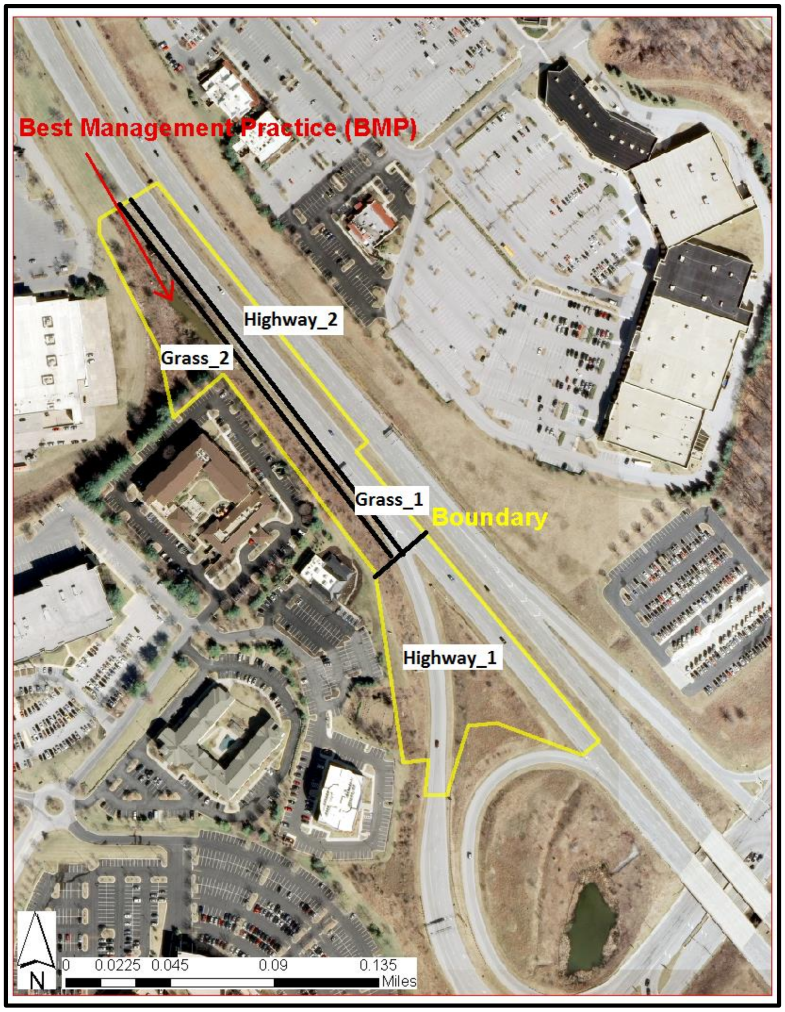

Figure 3.3.1.1.-1. Topographic delineation of the study site.

3.3.1.1.1. Water Quantity

This study aims to evaluate the performance of SWMM during storm events when the actual air vapor pressure is close to saturation. Therefore, it is reasonable to assume there is negligible evaporation in the subcatchments during the storm period.

To simplify the model, the internal routing of runoff between pervious and impervious areas in one subcatchment was set to “outlet”, which means all the runoff from both areas flows directly to an outlet (Rossman 2010). Based on an investigation of the topography, groundflow in this area can be neglected. Snow pack melting is not considered in this study either since most of the measured storm events took place during relatively warm weather. All candidate subcatchment hydrology-related parameters are listed in Table 3.3.1.1.1.-1.

Table 3.3.1.1.1.-1. Parameters Related to Hydrology.

Hydrology Parameters	Definition
Width	Width of overland flow path
%Slope	Average surface slope
N-imperv	Manning’s N for impervious area
N-per	Manning’s N for pervious area
S-Imperv	Depth of depression storage on impervious area
S-Perv	Depth of depression storage on pervious area
PctZero	Percent of impervious area with no depression storage
CurveNum	SCS runoff curve number
DryTime	Time for a fully saturated soil to completely dry

3.3.1.1.2. Water Quality

In SWMM, buildup and washoff of pollutants from subcatchments are associated with the “land uses” assigned to the subcatchment (Rossman 2010). Two land uses were created for the entire study area: grass land and paved highway.

Also for further simplification, three assumptions were made in the study: (1) the pollutants in infiltration flow was negligible, (2) all pollutants were assumed to be conservative (i.e., no decay) in the process, and (3) there were no co-pollutants for all kinds of pollutants. All candidate subcatchments pollutants parameters are listed in Table 3.3.1.1.2.-1.

Table 3.3.1.1.2.-1. Parameters Related to Pollutants.

Parameters	**Definition**
DRY_DAYS	Number of antecedent dry days prior to the start of the simulation
Rain Concen.	Concentration of the pollutant in rain water
Max. Buildup	Maximum possible buildup
Rate Constant	Rate constant of buildup function
Coefficient	Exponential coefficient in washoff function
Exponent	Runoff exponent in washoff function
% of Area	Assignment of land uses (percentage) to subcatchment

3.3.1.2. Runoff Routing

To reproduce the flow routing for the study domain, two channels and one culvert were established in SWMM. All candidate channels properties parameters are listed in Table 3.3.1.2.-1.

Table 3.3.1.2.-1. Parameters Related to Channels.

Parameters	**Definition**
Roughness	Manning’s roughness coefficient

3.3.1.3. Infiltration Basin

Based on previous field observations, the infiltration basin in the study area was ponded with water through the entire study period. The water level inside the infiltration basin was ranged from 0.18 m to 1.2 m (Natarajan 2012). Therefore, it is reasonable to treat the infiltration basin as a wet pond, which can be represented as a node “storage unit” in SWMM. The shape of the storage unit was described by a user-defined curve. All candidate infiltration basin properties parameters are listed in Table 3.3.1.3.-1.

Table 3.3.1.3.-1. Parameters Related to Infiltration Basin.

Parameters	**Definition**
InitDepth	Initial depth of water in the storage unit
Psi	Soil capillary suction head
Ksat	Soil saturated hydrologic conductivity
IMD	Difference between soil porosity and initial moisture content
MaxDepth	Maximum depth of the storage unit
Fevap	Fraction of evaporation rate realized

3.3.2. Data

3.3.2.1. Meteorological Boundary Conditions

Hourly precipitation observations were obtained from the NOAA’s National Climate Data Center Quality Controlled Local Climatological Database (QCLCD). There are about 1600 land-based observation stations in the United States. The station USW00093721, which is closest to the study site, was selected for this research. Figure 3.3.2.1.-1. shows the location of QCLCD stations relative to study area, where station USW00093721 is circled in yellow.

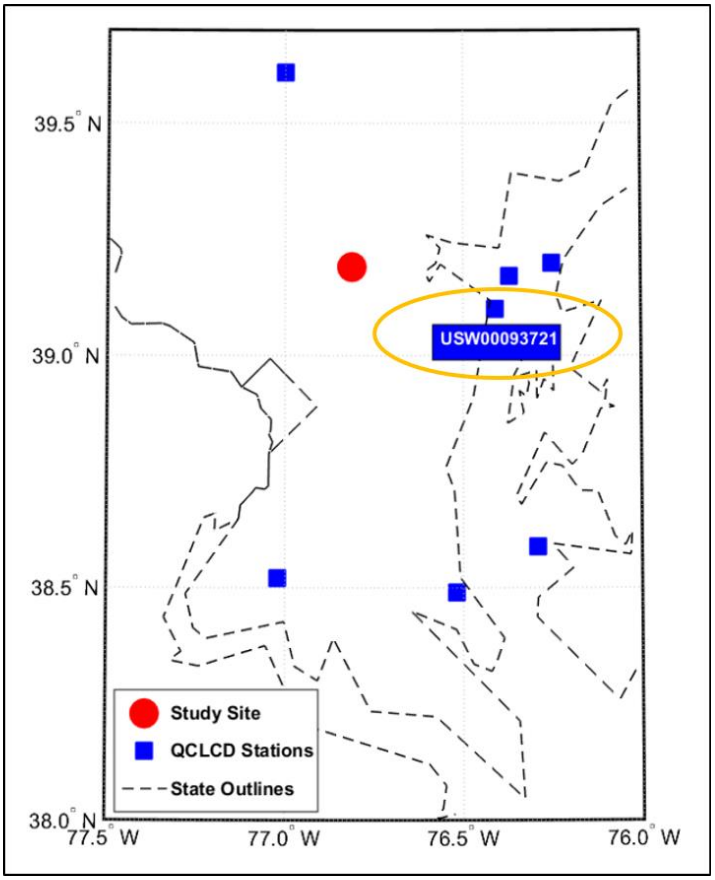

Figure 3.3.2.1.-1. QCLCD station location.

The QCLCD station is located southeast of the study area at distance of 12.5 km. This study assumed the precipitation at the station is similar to that at the study area. The average wind speed across whole period recorded by the station is about 3.5 m/s out of the west. Therefore, it is reasonable to assume the arrival time of precipitation at the study area is about one hour early than the recorded precipitation. This temporal lag was accounted for by shifting the timestamp of the QCLCD observations by one hour.

3.3.2.2. Topography

The topography of the study area was investigated by the Maryland State Highway Administration in 1999. The engineering drawing provides details about the elevation and physical properties of the constructions in this area.

3.3.2.3. Measurement Datasets

The runoff and water quality data collected from 2009 and 2012 by Dr. Allen Davis' research group were used for the model calibration and validation. The runoff flows at the inlet and outlet of the infiltration basin were recorded continuously at a 2-minute interval for 103 different storm events (Natarajan 2012). Meanwhile, water quality samples were collected at the inlet and the outlet of the infiltration basin during a subset of these rainfall events. A total of nine different kinds of pollutants were analyzed: total suspended solids (TSS), nitrate, nitrite, total Kjeldahl nitrogen (TKN), total phosphorus, total copper, total lead, total zinc, and chloride (Natarajan 2012).

Low flow discharge is unlikely to cause downstream flooding or exacerbate waterbody contamination. Therefore, two lower thresholds were used for selection of inflow and outflow measurement datasets,

$$M = \int_{t_1}^{t_2} Q\,dt > 10L \qquad (3.3.2.3-1)$$

where M is the integrated inflow (L); Q is the measured inflow discharge (LPS); t_1 is the start time (s) of the storm runoff event; and t_2 is the end time (s) of the storm runoff event. Similarly, the peak discharge was required to meet a minimum threshold defined as:

$$Q_{peak} = max(Q) > 2\ LPS \qquad (3.3.2.3-2)$$

where Q_{peak} is the maximum peak measured inflow discharge (LPS); and Q is the measured inflow discharge (LPS).

However, due to the limitation of in-situ sensors, measurements of outflow from the SCM may occasionally be inaccurate (e.g., Figure 3.3.2.3-1). Therefore, the selection for outflow measurements were more heuristic compared to the selection of valid inflow observation. An example of measurement errors selected out in this process is shown in Figure 3.3.2.3.-1.

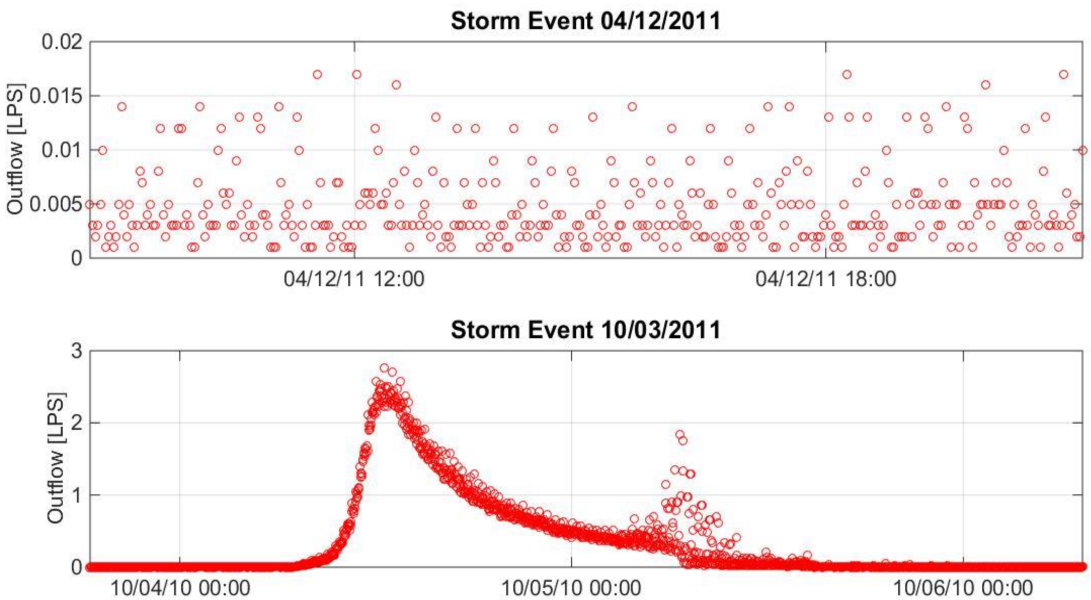

Figure 3.3.2.3.-1. Examples of measurement errors.

3.3.3. Model Calibration (and Validation)

The feasible ranges for each parameter were found in peer-reviewed literature (Gironas et al. 2009; Rossman 2010), as listed in Table 3.3.3.-1.and Table 3.3.3.-2.

Table 3.3.3.-1. Parameters Ranges for Flows.

Model Input	Definition	Value Ranges
Width [m]	Width of overland flow path	0.01~200

%Slope [%]	Average surface slope	0.0001~50
N-imperv [-]	Manning's N for impervious area	0.011~0.8
S-imperv [mm]	Depth of depression storage on impervious area	0.01~20
S-per [mm]	Depth off depression storage on pervious area	0.01~20
CurveNum [-]	SCS runoff curve number	10~98
PctZero [%]	Percent of impervious area with no depression storage	1~80
Roughness [-]	Manning's roughness coefficient for inlet channel	0.011~0.8
InitDepth [m]	Initial depth of water in the storage unit	0~0.91
Psi [mm]	Soil capillary suction head	40~320
Ksat [mm/hr]	Soil saturated hydrologic conductivity	1~125
IMD [-]	Difference between soil porosity and initial moisture content	0~50
Roughness [-]	Manning's roughness coefficient for outlet channel	0.011~0.8

Table 3.3.3.-2. Parameters Ranges for Water Quality.

Model Input	Definition	Value Ranges
Percent [%]	Assignment of land uses to each subcatchment	0~50
Coeff1 [kg/ha]	Maximum possible buildup	0.011~1.5
Coeff2 [kg/day]	Rate constant of buildup per day	0.01~0.9
Coeff1[kg/ha]	Washoff coefficient	1~200
Coeff2 [kg/day]	Runoff exponent in washoff	0.1~6
Crain [mg/L]	Concentration of the pollutant in rain water	0.01~100
Buildup [kg/ha]	Initial pollutant buildup on subcatchment	0~1000

In order to find the best estimate of the parameter set (i.e., $\hat{\alpha}$), the parameter dimensionality is sampled and systematically evaluated across the entire parameter space as defined in Table

3.3.3.-1.and Table 3.3.3.-2. Next, an individual replicate from $\hat{\alpha}$ is drawn and used to define a single SWMM simulation. This process is repeated for all J replicates within the parameter set α.

The model output from each of the J simulations is compared against the available observations after which the objective function, $\mathcal{L}$, is subsequently computed for that simulation. This process is repeated for all J replicates. Next, from this computed set the argument is then maximized (or minimized depending on the definition of the objective function) such that the "best" parameter fit, $\hat{\alpha}$, is determined automatically. Additionally, the parameter uncertainty (based on the parameter ranges listed in Table 3.3.3.-1.and Table 3.3.3.-2.) is implicitly contained in the output ensemble such that the model response with respect to parameter uncertainty can be illustrated in Figure 4.3.1.-1. The shaded gray area represents the range of model output with respect to the different combinations of parameter values. The blue line represents the single, "best" parameter set, which yields the closest agreement with the observations.

In this study, inflows and outflows were simulated at a 2-minute interval for all measured storm events. The objective functions for water quantity were calculated by weighting the importance of inflow and outflows,

$$\begin{cases} NSE = \alpha \cdot NSE_{inflow} + \beta \cdot NSE_{outflow} \\ Rel.B = \alpha \cdot Rel.B_{inflow} + \beta \cdot Rel.B_{outflow} \\ R = \alpha \cdot R_{inflow} + \beta \cdot R_{outflow} \end{cases} \qquad (3.3.3.-1)$$

where $NSE, Rel.B, and\ R$ are Nash-Sutcliffe coefficient, relative bias and correlation coefficient for the model, respectively; $NSE_{inflow}, Rel.B_{inflow}, and\ R_{inflow}$ are for model inflows; $NSE_{outflow}, Rel.B_{outflow}, and\ R_{outflow}$ are for model outflows; α is weighted factor for inflows ($0 < \alpha < 1$); and β is weighted factor for outflows ($0 < \beta < 1$). The values of α and β are based on the following equation,

$$\alpha + \beta = 1 \qquad (3.3.3.-2)$$

The objective functions for water quality were relative bias, root mean square error, and correlation coefficient. In this study, only the inflow water quality was calibrated due to the lack of outflow water quality data.

Chapter 4: Results and Discussion

In this chapter, the results of hydrologic and water quality model development are presented. The drainage area delineation is presented in section 4.1. The results of parameter sensitivity are presented in section 4.2. The results of model calibration and validation are presented in section 4.3 and 4.4.

4.1. Model Setup

The delineation of study area was based on the hydrologic behavior, which has been discussed in section 3.3. There are four “subcatchments”, two channels and one culvert established in SWMM model (Figure 4.1.-1). Subcatchments “highway_1” (0.7405 ha) and “highway_2” (0.4443 ha) represent disconnected impervious highways. Subcatchments “grass_right” (0.8145 ha) and “grass_left” (0.1481 ha) represent two grassy areas in the study area.

Runoff from “highway_1” flows into the culvert. Runoff generated from “highway_2” flows into one of the grassy areas labeled “grass_right”. Then runoff from “grass_right” and “grass_left” flow into the channel inlet. Finally, runoff from the entire drainage area flows into the infiltration basin (a.k.a., storage unit). Through a short outlet channel, the runoff from the infiltration basin flows out of the infiltration basin outlet.

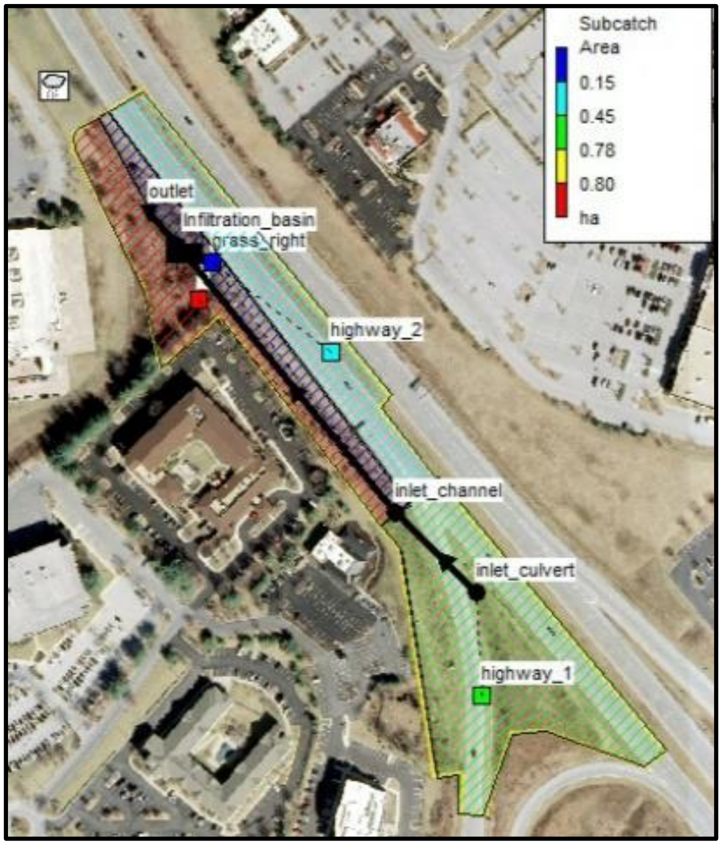

Figure 4.1.-1. Modeled study site in SWMM.

4.2. Parameter Sensitivity Analysis for Inflows

A sensitivity analysis was carried out to reduce the parameters dimensionality for model calibration (Section 3.2.3). In this study, parameters sensitivity was only analyzed for inflows. Parameter sensitivity on modeled outflows was not conducted due to water quantity outflow measurement noise. Initial calibration was conducted with all candidate inflow-related parameters to identify the most appropriate storm events ($NSE > 0.90$) in order to focus the parameter sensitivity investigation. The number of all candidate inflow-related parameters was 38. The results suggested five storm events had calibrated inflow with NSE greater than 0.93 (e.g., Figure 4.2.-1).

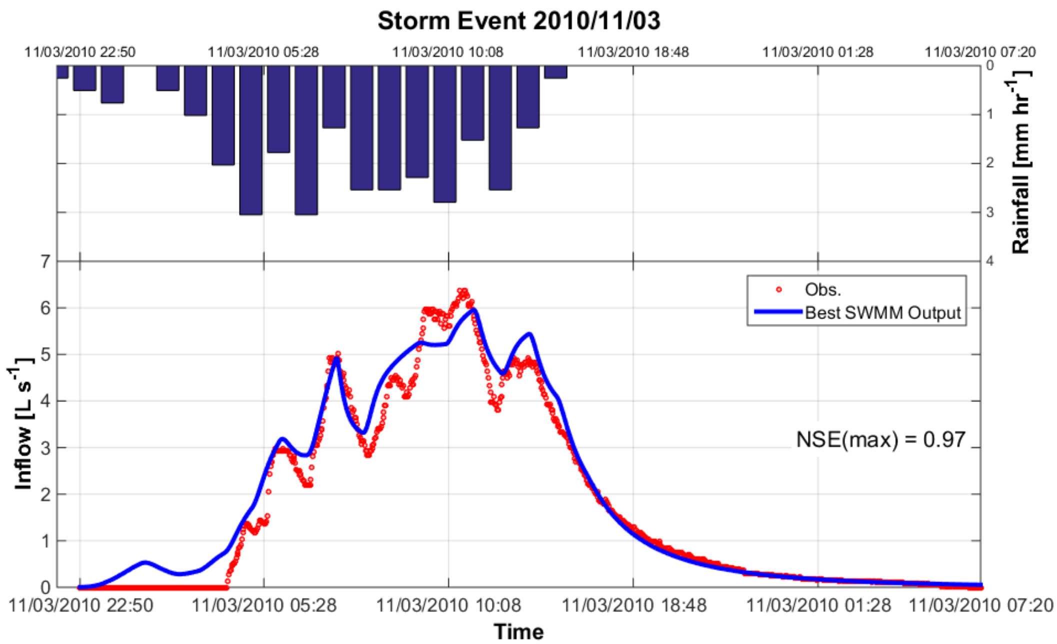

Figure 4.2.-1. Example of "best" calibrated storm event.

Based on the five storm events, the relative sensitivities as measured with NSC of inflow peak discharge, peak time, and integrated inflow to parameters were analyzed. The perturbation size was set to be $\pm 10\%$. The mean relative sensitivity (Rel. Sens.) over the five storm events and the standard deviation of NSCs are listed in Table 4.2.-1.

Based on the sensitivity analysis result, parameter sensitivity to peak discharge time was much lower relative to peak discharge and integrated inflow. The order of magnitude for parameters sensitivities relative to peak discharge and integrated inflow were similar. The results indicate that all inflow hydrology-related parameters were much more sensitive to peak discharge and integrated inflow compared to peak discharge time in this model.

Two subjective thresholds were chosen for the selection of sensitive parameters relative to peak discharge and integrated inflow,

$$\begin{cases} \left|\overline{Rel.Sens.}\right| > 0.01 \\ Std.Sens. > 0.1 \end{cases} \qquad (4.2.-1)$$

where $\left|\overline{Rel.Sens.}\right|$ is the absolute value of mean relative sensitivity across the five storm events; and $Std.Sens.$ is the standard deviation of these five relative sensitivities.

Similar subjective thresholds were chosen for the selection of sensitive parameters relative to peak discharge time,

$$\begin{cases}\left|\overline{Rel.Sens.}\right| > 1 \times 10^{-8} \\ Std.Sens. > 1 \times 10^{-9}\end{cases} \qquad (4.2.-2)$$

where $\left|\overline{Rel.Sens.}\right|$ is the absolute value of mean relative sensitivity across the five storm events; and $Std.Sens.$ is the standard deviation of these five relative sensitivities.

Table 4.2.-1. Relative Sensitivity of Parameters.

Hydrology Parameters	**Peak Discharge (LPS)**		**Peak Time**		**Integrated Inflow (L)**	
	Rel. Sens.	Std	Rel. Sens.	Std	Rel. Sens.	Std
Curve Number [-]	$6.2 \cdot 10^{-1}$	$6.5 \cdot 10^{-1}$	$-1.5 \cdot 10^{-8}$	$3.5 \cdot 10^{-8}$	$4.6 \cdot 10^{-1}$	$3.8 \cdot 10^{-1}$
Drying Time [day]	$2.2 \cdot 10^{-2}$	$3.7 \cdot 10^{-2}$	$-3.8 \cdot 10^{-9}$	$5.2 \cdot 10^{-9}$	$1.6 \cdot 10^{-2}$	$2.3 \cdot 10^{-2}$
N-imperv [-]	$-3.5 \cdot 10^{-3}$	$2.3 \cdot 10^{-1}$	$5.7 \cdot 10^{-9}$	$5.2 \cdot 10^{-9}$	$1.2 \cdot 10^{-1}$	$2.7 \cdot 10^{-1}$
N-per [-]	$-4.7 \cdot 10^{-2}$	$2.4 \cdot 10^{-2}$	$5.7 \cdot 10^{-9}$	$5.2 \cdot 10^{-9}$	$-1.3 \cdot 10^{-3}$	$4.3 \cdot 10^{-3}$
S-imperv [mm]	$-2.3 \cdot 10^{-1}$	$3.5 \cdot 10^{-1}$	$1.1 \cdot 10^{-8}$	$1.7 \cdot 10^{-8}$	$-3.9 \cdot 10^{-1}$	$5.5 \cdot 10^{-1}$
S-per [mm]	$-1.5 \cdot 10^{-2}$	$3.2 \cdot 10^{-1}$	$7.6 \cdot 10^{-9}$	$1.2 \cdot 10^{-8}$	$-4.4 \cdot 10^{-2}$	$3.9 \cdot 10^{-1}$
Channel Rough [-]	$-1.7 \cdot 10^{-1}$	$1.1 \cdot 10^{-1}$	$1.3 \cdot 10^{-8}$	$1.1 \cdot 10^{-8}$	$7.7 \cdot 10^{-3}$	$3.5 \cdot 10^{-3}$
Culvert Rough [-]	$-6.4 \cdot 10^{-4}$	$3.9 \cdot 10^{-3}$	$3.8 \cdot 10^{-9}$	$5.2 \cdot 10^{-9}$	$1.2 \cdot 10^{-4}$	$3.1 \cdot 10^{-4}$
PctZero [%]	$6.0 \cdot 10^{-2}$	$1.2 \cdot 10^{-1}$	$-3.8 \cdot 10^{-9}$	$5.2 \cdot 10^{-9}$	$1.2 \cdot 10^{-1}$	$1.6 \cdot 10^{-1}$
%Slope [%]	$2.7 \cdot 10^{-2}$	$1.0 \cdot 10^{-1}$	$1.9 \cdot 10^{-9}$	$1.6 \cdot 10^{-8}$	$-1.3 \cdot 10^{-2}$	$4.2 \cdot 10^{-2}$
Width [m]	$1.3 \cdot 10^{-1}$	$6.5 \cdot 10^{-2}$	$-1.1 \cdot 10^{-8}$	$1.0 \cdot 10^{-8}$	$7.0 \cdot 10^{-3}$	$1.4 \cdot 10^{-2}$

Therefore, the final parameter dimensionality for model inflow calibration was reduced from 38 to 29. Critical parameters selected for model inflow calibration included subcatchment width, slope, Manning's N for impervious area, depression storage for impervious/pervious area, runoff curve number, percent of impervious area with no depression storage and inlet channel roughness.

4.3. Model Calibration and Validation Results for Flows

4.3.1. Model Calibration and Validation Results

The model calibration period was from August, 2009 to April, 2011, while the validation period was from April, 2011 to August, 2012. There were total 36 storm events used during calibration period. And during validation period, there were a total of 36 storm events used. The parameter dimensionality for model inflow and outflow was 34. A total of 20,000 input replicates were simulated. The parameters and their calibrated values are listed in Table 4.3.1.-1.

Table 4.3.1.-1. Parameters Being Calibrated for Flows.

Model Elements	Model Input	Definition	Calibrated Value
Highway_1	Width [m]	Width of overland flow path	147
	%Slope [%]	Average surface slope	49.5
	N-imperv [-]	Manning’s N for impervious area	0.53
	S-imperv [mm]	Depth of depression storage on impervious area	10.2
	S-per [mm]	Depth off depression storage on pervious area	19.4
	CurveNum [-]	SCS runoff curve number	17.1
	PctZero [%]	Percent of impervious area with no depression storage	25
Highway_2	Width [m]	Width of overland flow path	78.8
	%Slope [%]	Average surface slope	40.4
	N-imperv [-]	Manning’s N for impervious area	0.10

	S-imperv [mm]	Depth of depression storage on impervious area	5.85
	S-per [mm]	Depth off depression storage on pervious area	3.48
	CurveNum [-]	SCS runoff curve number	43.4
	PctZero [%]	Percent of impervious area with no depression storage	25
Grass_left	Width [m]	Width of overland flow path	138
	%Slope [%]	Average surface slope	34.8
	N-imperv [-]	Manning's N for impervious area	0.63
	S-imperv [mm]	Depth of depression storage on impervious area	0.26
	S-per [mm]	Depth off depression storage on pervious area	3.46
	CurveNum [-]	SCS runoff curve number	19.3
	PctZero [%]	Percent of impervious area with no depression storage	25
Grass_right	Width [m]	Width of overland flow path	173
	%Slope [%]	Average surface slope	32.6
	N-imperv [-]	Manning's N for impervious area	0.07
	S-imperv [mm]	Depth of depression storage on impervious area	10.5
	S-per [mm]	Depth off depression storage on pervious area	7.72
	CurveNum [-]	SCS runoff curve number	31.7
	PctZero [%]	Percent of impervious area with no depression storage	25
Inlet_Channel	Roughness [-]	Manning's roughness coefficient	0.66
BMP	InitDepth [m]	Initial depth of water in the storage unit	0.83
	Psi [mm]	Soil capillary suction head	233
	Ksat [mm/hr]	Soil saturated hydrologic conductivity	29.6

	IMD [-]	Difference between soil porosity and initial moisture content	38.0
Outlet_Channel	Roughness [-]	Manning's roughness coefficient	0.09

It is possible to find more than one "best" estimate given the maximization (or minimization depending on the selected objective function) given the vast parameter dimensionality searched during the auto calibration routine. Therefore, the selection of parameter sets is based on rationality. As listed in Table 4.3.-3., the calibrated model results yielded a Nash-Sutcliffe Coefficient (NSE) equal to 0.95 for storm event 2010/11/03 (Figure 4.3.1.-1.). However, the parameters values for subcatchment "Highway_1" are much different.

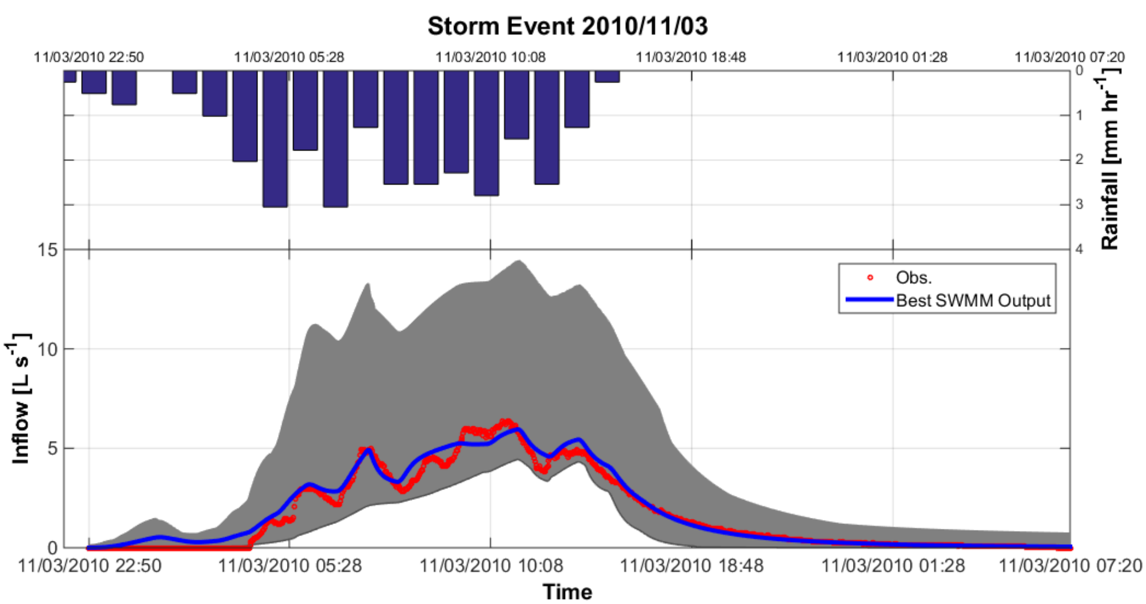

Figure 4.3.1.-1. Storm event 2010/11/03.

Table 4.3.1.-2. Calibrated Parameters Values.

Element	Model Input	$\boldsymbol{NSE = 0.95}$	$\boldsymbol{NSE = 0.95}$
Highway_1	Width [m]	182	104
	%Slope [%]	27.1	41.5
	N-imperv [-]	0.56	0.17
	S-imperv [mm]	19.1	1.73
	S-per [mm]	4.13	4.23
	CurveNum [-]	40.0	90.5
	PctZero [%]	25	25

It is also possible to find the different "best" estimate based on different objective functions. As listed in Table 4.3.1.-2, the calibrated model results yielded a NSE equals to 0.95, R equals to 0.98, and Rel. B equals to 0.0014. But the parameter values for subcatchment "Highway_1" are much different.

Table 4.3.1.-3. Calibrated Parameters Values.

Element	Model Input	$\boldsymbol{NSE = 0.95}$	$\boldsymbol{R = 0.98}$	**Rel. B = 0.0014**
Highway_1	Width [m]	182	18.9	47.2
	%Slope [%]	27.1	47.9	7.69
	N-imperv [-]	0.56	0.09	0.08
	S-imperv [mm]	19.1	14.6	8.63
	S-per [mm]	4.13	6.83	13.3
	CurveNum [-]	40.0	12.8	38.7
	PctZero [%]	25	25	25

In this study, the statistics for model inflows and outflows including the model Nash-Sutcliffe Coefficient (NSE), relative bias (Rel-B), and correlation coefficient (R), were computed as

$$\begin{cases} NSE = \alpha \cdot NSE_{inflow} + \beta \cdot NSE_{outflow} \\ Rel.B = \alpha \cdot Rel.B_{inflow} + \beta \cdot Rel.B_{outflow} \\ R = \alpha \cdot R_{inflow} + \beta \cdot R_{outflow} \\ \alpha = 0.8 \\ \beta = 0.2 \end{cases} \qquad (4.3.1.-1)$$

in which NSE, $Rel.B$, and R are the model Nash-Sutcliffe Coefficient, model relative bias, and model correlation coefficient, respectively; NSE_{inflow}, $Rel.B_{inflow}$, and R_{inflow} are the Nash-Sutcliffe Coefficient, relative bias, and correlation coefficient for inflow, respectively; $NSE_{outflow}$ $Rel.B_{outflow}$, and $R_{outflow}$ are the Nash-Sutcliffe Coefficient, relative bias, and correlation coefficient for outflow, respectively; α is the weighting factor for inflows; and β is the weighting factor for outflows.

In this study, measured outflow discharge was much smaller in magnitude than inflow. To represent the importance of inflow and outflow, the weighting factor α for inflows was assigned as 0.8, while the weighting factor β for outflows was assigned as 0.2 in this study. This explicitly represents more confidence in the inflow observations relative to the outflow observations. The calibration and validation results for flows are listed in Table 4.3.1.-4.

Table 4.3.1.-4. Statistics of Model Flows.

Hydrology Parameters	Calibration Period 2009/08-2011/04	Validation Period 2011/04-2012/08
NSE [-]	0.430	0.16
R [-]	0.69	0.40
Relative Bias [%]	−8.38%	−39.6%

The NSE in both the calibration and validation periods were greater than 0, which indicated the flow discharges simulated by SWMM model was better than the mean of observed discharge. For the calibration period, the values indicates good model performance. As expected, statistics in the validation period were slightly worse than those obtained in the calibration period. Generally speaking, the statistics suggested a robust calibration of the calibrated model in terms of water flows during storm events. Figure 4.3.1.-2 and Figure 4.3.1.-3 shows the comparison of hydrographs between SWMM and field-observations for water flows in calibration and validation periods.

For calibration period, the relatively high values of NSE indicate good model performance in capturing SCM response. The correlation coefficients R shows a relatively good linear relationship between the simulations and the observations. Relative bias was -8.38%, which showed a fair model simulation accuracy. The negative sign of relative bias indicated the model, in general, underestimated the discharge.

To investigate the model performance for inflow and outflow, the objective functions were calculated in calibration and validation periods for both inflow and outflow. The results are listed in Table 4.3.1.-4 and Table 4.3.1.-5.

Table 4.3.1.-5. Statistics of Calibrated Model Inflow and Outflow in Calibration Period.

Calibration Period 2009/08-2011/04	Inflow	Outflow
NSE [-]	0.45	0.36
R [-]	0.69	0.66
Relative Bias [%]	4.58%	−60.2%

Table 4.3.1.-6. Statistics of Calibrated Model Inflow and Outflow in Validation Period.

Validation Period 2011/04-2012/08	Inflow	Outflow
NSE [-]	0.16	0.14
R [-]	0.41	0.40
Relative Bias [%]	−32.4%	−68.3%

For the calibration period, the inflow statistics were relatively good, especially for relative bias. The relative bias value of 4.58% suggests a significant model accuracy. During the validation period, the inflow statistics were relatively poor. The model underestimated the inflow by about 32.4%. One possible reason is the model was unable to capture the characteristics of several big storm events, especially the extreme storm event at Sep. 05, 2011 (Figure 4.3.1.-3).

In both calibration and validation periods, the statistics for outflow were worse than inflow, which indicated the model had relatively poor performance in reproducing outflow. The most likely explanation is the outflow discharges were too low to be measured accurately by sensors through the V-notch weirs.

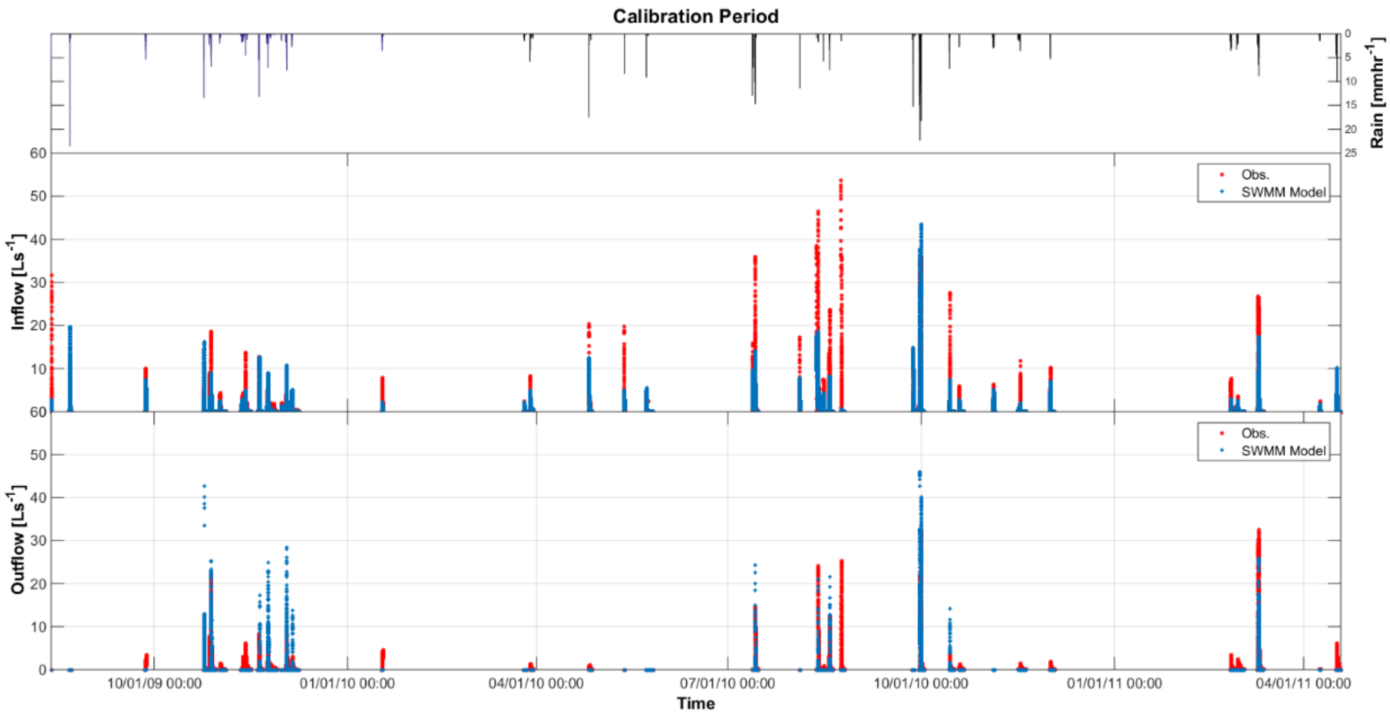

Figure 4.3.1.-2. Inflow and outflow in field-observation and SWMM (calibration).

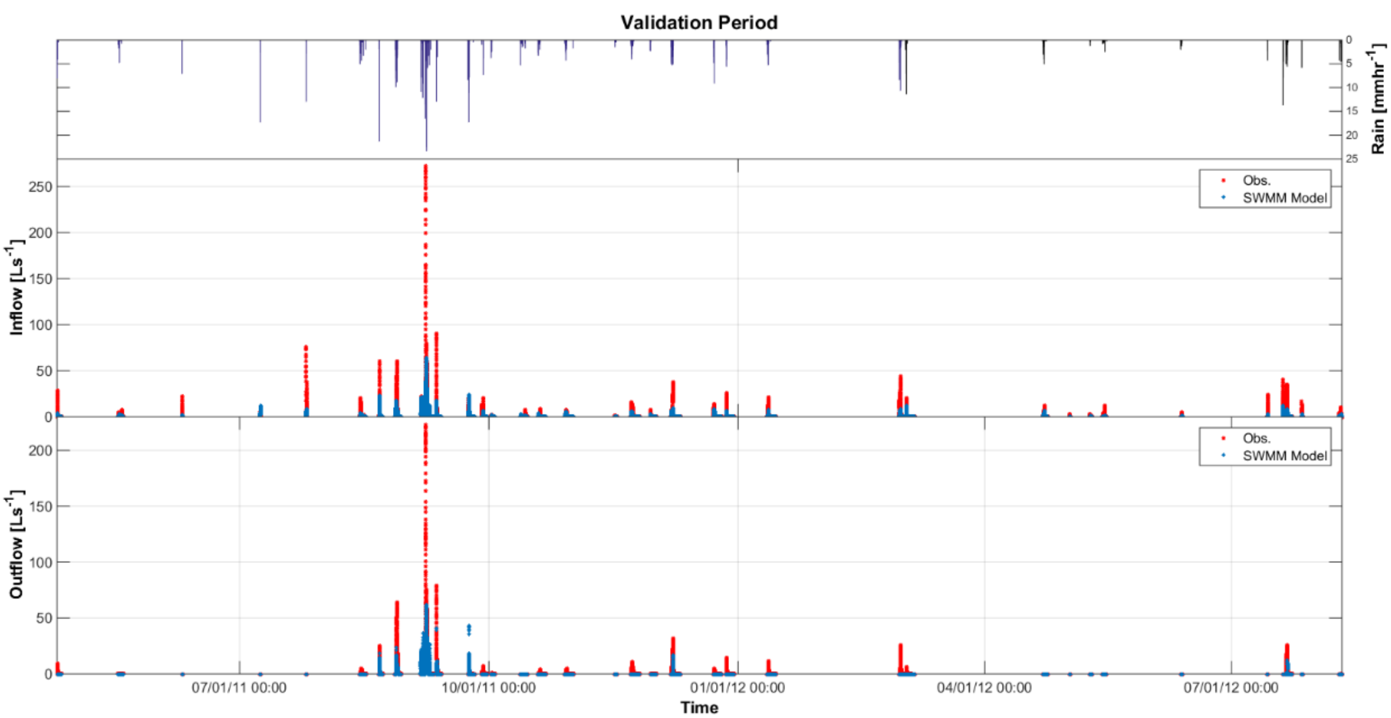

Figure 4.3.1.-3. Inflow and outflow in field-observation and SWMM (validation).

4.3.2. Seasonal Water Quantity Calibration Results

To further investigate the model performance, the seasonality effect of model inflows during the calibration period was analyzed in this study (Spring: March, April, Mary; Summer: June, July, August; Fall: September, October, November; Winter: December, January, February). The results are listed in Table 4.3.2.-1.

Table 4.3.2.-1. Seasonal Statistics of Model Calibrated Inflows.

Calibration Period	Spring (03 /04 /05)	Summer (06/07/08)	Fall (09/10/11)	Winter (12/01/02)
NSE [-]	0.61	0.20	0.59	0.42
R [-]	0.78	0.46	0.82	0.72
Relative Bias [%]	−3.28%	−9.28%	15.7%	−9.93%

The statistics for spring and fall were the best among the four seasons. The high values of NSE, R, and small relative bias suggested the model had high accuracy in reproducing inflows in spring and fall. These two seasons had modest inflows. Summer season had the poorest performance statistics with the highest inflows among the four seasons. The model highly underestimated the inflows in summer time. Winter had fair model accuracy with lowest inflows among the four seasons. Figure 4.3.2.-1 shows the comparison of hydrographs between SWMM and field-observations for water inflows in four seasons. To better visualize the results, the x-axis represents the number of measurements instead of date or time.

One possible reason to explain the seasonality effect is the uncertainty between forcing data and true data, in this case, QCLCD precipitation and local precipitation. In this study, the field-measured precipitation (2-minute interval) was treated as "true" precipitation (locally measured adjacent to the study site). To compare field-measured and QCLDC (hourly) precipitation data, field-measured precipitation was integrated hourly. The results of seasonal statistics of precipitation are listed in Table 4.3.2.-2.

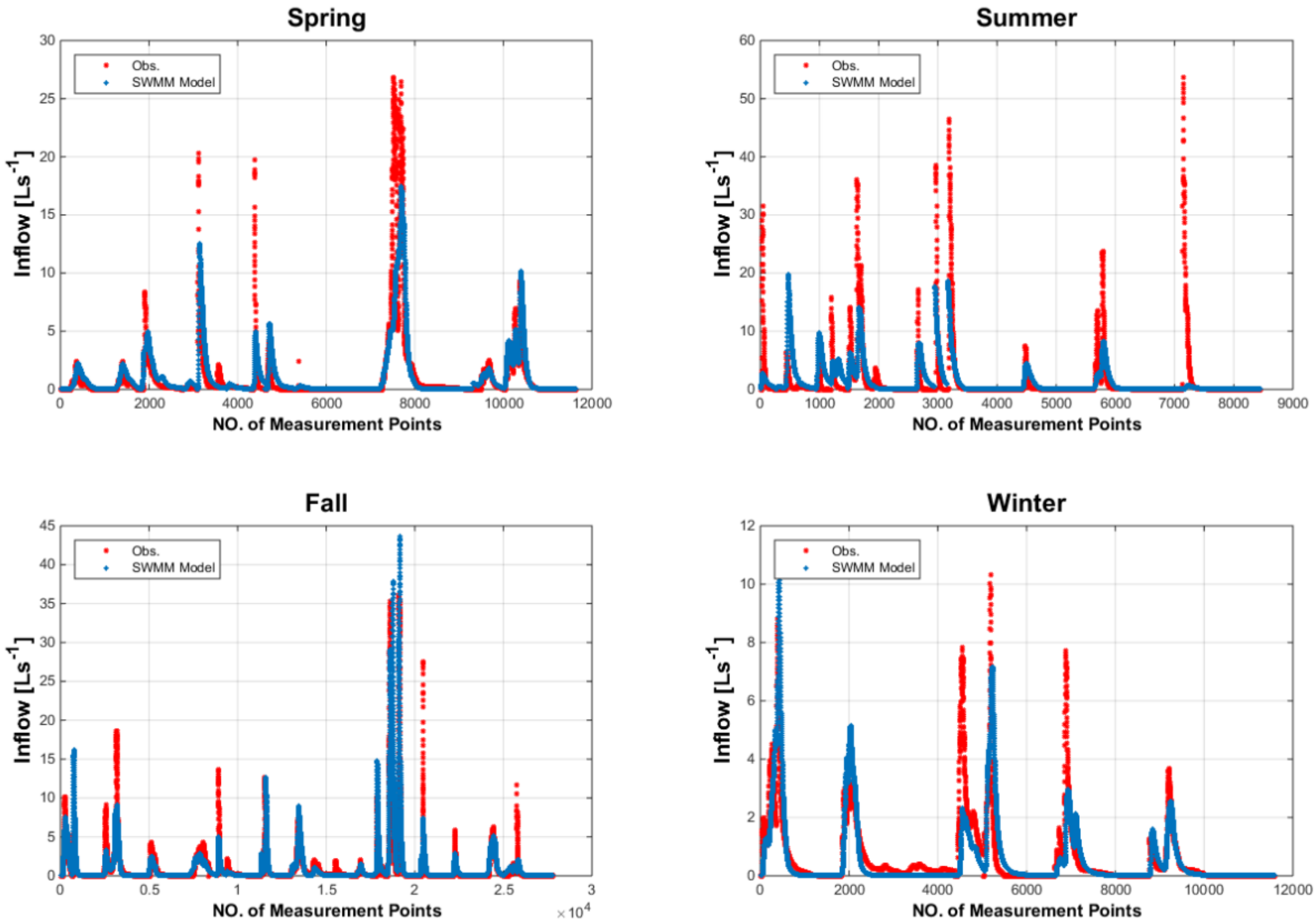

Figure 4.3.2.-1. Inflow in field-observation and SWMM (four Seasons in calibration period).

Table 4.3.2.-2. Seasonality Statistics of Precipitation.

Calibration Period	Spring (03 /04 /05)	Summer (06/07/08)	Fall (09/10/11)	Winter (12/01/02)
RMSE [mm/hr]	1.32	3.07	1.32	0.72
R [-]	0.61	0.40	0.65	0.60
Relative Bias [%]	5.67%	−48.3%	6.66%	6.20%

The statistics of spring and fall were the best among the four reasons. It suggests QCLCD precipitation in these two seasons had the best fit with “true” precipitation. Summer season had the poorest performance statistics, which indicate the QCLCD precipitation had relatively big errors. Winter season had the best statistics with low RMSE, relative bias, and relatively high R. However, the model inflow in winter was not the best fit. It further indicated the relatively poor model performance in reproducing low flows in this study.

The seasonal phenomena can be explained by the formation of clouds and precipitation. During the summer time, the mechanism of cloud formation is associated with strong vertical ascent over fairly small horizontal areas, which tends to generate heavy and local precipitation. During spring and fall season, the mechanism of cloud formation is largely frontal convergence with gradual air uplift, which tends to generate relatively light precipitation with wide spatial coverage (Shuttleworth 2012). Considering the location of QCLCD station and study area (Section 3.3.2.1.), the distance effect is negligible during the spring and fall seasons.

4.4. Model Calibration and Validation Results for Water Quality

The model calibration period for water quality was from August, 2009 to December, 2010, while the validation period was from February, 2011 to May, 2012. There were total 13 storm events during the calibration period. And during the validation period, there were a total of 13 storm events. In this study, only inflow water quality was simulated due to the lack of outflow water quality observations. The parameter dimensionality for model inflow and outflow was 21. A total of 1,000 input replicates were simulated. Although there were 9 kinds of pollutants in field-measured datasets, only one pollutant (TSS) was simulated in this study due to the lack of peer-reviewed parameters ranges for use during constraint of relevant parameter values. The parameters are listed in Table 4.4.-1.

Table 4.4.-1. Parameters Being Calibrated for TSS.

Model Input		Definition	Calibrated Value
Crain [mg/L]		Concentration of the pollutant in rain water	22.1
Highway_1	Buildup [kg/ha]	Initial pollutant buildup on subcatchment	796
	Percent [%]	Assignment of “grass” land uses to this subcatchment	40.1
	Percent [%]	Assignment of “high” land uses to this subcatchment	39.2
Highway_2	Buildup [kg/ha]	Initial pollutant buildup on subcatchment	738
	Percent [%]	Assignment of “grass” land uses to this subcatchment	43.2
	Percent [%]	Assignment of “high” land uses to this subcatchment	29.9
Grass_left	Buildup [kg/ha]	Initial pollutant buildup on subcatchment	294
	Percent [%]	Assignment of “grass” land uses to this subcatchment	18.3
	Percent [%]	Assignment of “high” land uses to this subcatchment	10.6
Grass_right	Buildup [kg/ha]	Initial pollutant buildup on subcatchment	185
	Percent [%]	Assignment of “grass” land uses to this subcatchment	42.5
	Percent [%]	Assignment of “high” land uses to this subcatchment	43.6
Land-Use Grass	Coeff1 [kg/ha]	Maximum possible buildup	1.47
	Coeff2 [kg/day]	Rate constant of buildup per day	0.21
	Coeff1[kg/ha]	Washoff coefficient	166
	Coeff2 [kg/day]	Runoff exponent in washoff	1.78
	Coeff1 [kg/ha]	Maximum possible buildup	1.05

Land-Use Highway	Coeff2 [kg/day]	Rate constant of buildup per day	0.89
	Coeff1[kg/ha]	Washoff coefficient	121
	Coeff2 [kg/day]	Runoff exponent in washoff	3.51

The statistics for model water pollutant TSS include model root mean square error (RMSE) and correlation coefficient (R). Figure 4.4.-1. shows the comparison between SWMM and field-observations for inflow TSS concentration in calibration and validation periods. The model calibration and validation results are listed in Table 4.4.-2.

Table 4.4.-2. Statistics of Model Inflow Water Quality.

Water Quality Parameters	Calibration 2009/08-2010/10	Validation 2011/02-2012/05
R [-]	0.35	0.23
RMSE [mg/L]	169	138
Relative Bias [%]	-1196%	5772%

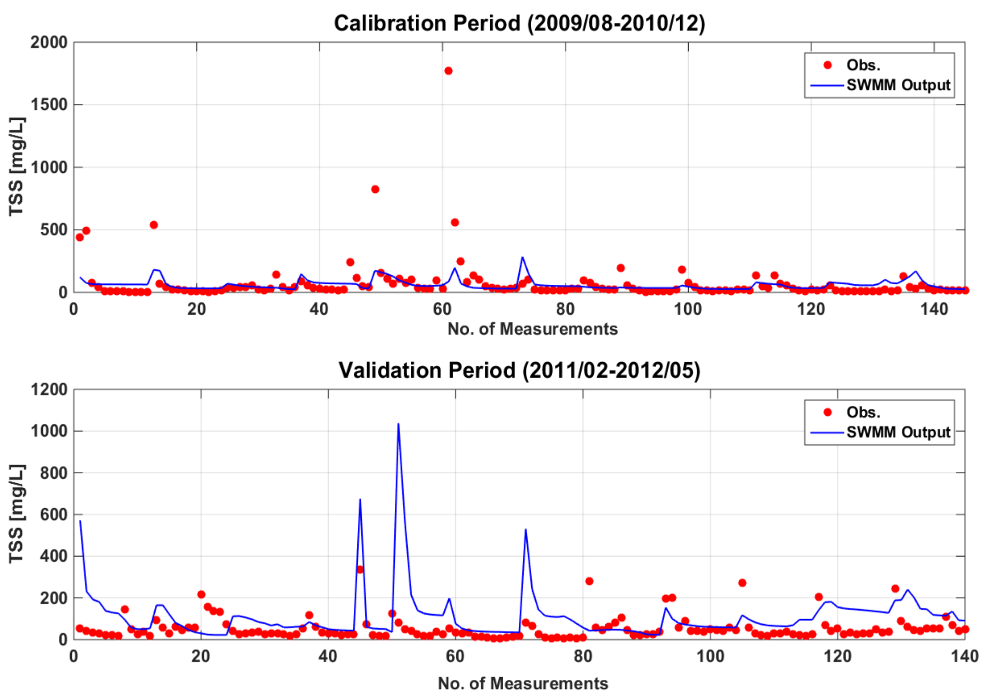

Figure 4.4.-1. Inflow TSS concentration in field-observation and SWMM.

The statistics for inflow quality (TSS) were poor for both calibration and validation. The results reflect that simulation of urban runoff quality is difficult. Large uncertainties arise both in the representation of the physical, chemical and biological processes and in the acquisition of data and parameters for model algorithm (Gironas et al. 2009).

Chapter 5: Conclusion and Discussion

5.1. Summary and Discussion of the Study

In this research, SWMM model was developed for a small urban basin with an infiltration basin. The model was calibrated to simulate the performance of the SCM in terms of inflow, outflow, and inflow water quality during storm events. An auto-calibration procedure was developed that accelerated the calibration process for this study. The sensitivity analysis for inflows reduced the parameters dimensionality and improved the calibration efficiency. It further testified that parameter sensitivity varies with study area.

The model calibration and validation results suggested the model can reproduce relatively accurate water discharge, especially during the spring and fall. However, the model had poor performance for simulating low flows, in this case, outflows from the infiltration basin during summer time. The model underestimated the outflow. The results of seasonal analysis suggested one possible reason to explain the model poor performance was inaccurate forcing data (i.e., precipitation data). The QCLCD product (precipitation data) had better fit with “true” values measured adjacent to the study site (i.e., field-measured precipitation data) during the spring and fall.

The model was unable to reproduce accurate pollutant concentration in water. One of the reason was that empirical model can not fully represent the complex behavior for water pollutants. Moreover, the limited field-measured data also restrained the model calibration.

Generally speaking, the SWMM model had a good performance in simulating water flows during storm events and a relatively poor performance in simulating water quality results. These findings suggest the “storage unit” in SWMM can fully represent the “ponded” infiltration basin in the study.

5.2. Recommendations for Future Research

One of the most important advantages of model is to predict the future. Coupled with future climate change projections (i.e., projected rainfall amounts), the calibrated model could potentially predict the performance of the infiltration basin and the hydrologic behavior of the urban site under a changing climate. Moreover, more precipitation products can be tested as forcing data for the model to find the best for calibration in this study area. In addition, the parameter sensitivity can be analyzed using outflows to further improve calibration efficiency.

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