ABSTRACT

Title of Document:	A DIAGNOSTIC DECISION SUPPORT SYSTEM FOR SELECTING BEST MANAGEMENT PRACTICES IN URBAN/SUBURBAN WATERSHEDS
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Best Management Practices (BMPs) have become the most effective way to mitigate

the non-point source pollution (NPS) problems. Much attention has been paid on NPS in

rural areas, where agricultural activities increase the nutrients, toxics, and sediments in

surface water. Urban and suburban areas are also major contributors of NPS, largely due

to stormwater. For watersheds bearing various soil types and land uses, a single type of

BMP cannot be the panacea to all stormwater and related water quality problems. There is

a need for a series of spatially distributed small-scale BMPs aimed at reducing flow volume and improving urban stormwater quality. This research seeks to develop a Diagnostic Decision Support System (DDSS) for urban BMP selection. The process-based distributed hydrologic model, Soil and Water Assessment Tool (SWAT), was used to simulate the hydrologic processes, estimate water quality variables, and to model the urban BMPs. The DDSS consists of three parts: a Hotspot Identifier, which locates the water quality and quantity hotspots; a Diagnostic Expert System (DES), which identifies the most likely physical reasons for excessive pollutants; and a Prescriptive Expert System (PES), which selects a proper set of spatially distributed BMPs. SWAT was calibrated and validated first to simulate pre-BMP watershed responses. The DDSS was then applied for BMP recommendation. The prescribed BMPs were modeled back into SWAT to quantify their effectiveness. Total Cost for BMP implementation was calculated as a function of BMP coverage area, BMP numbers and types, and residents' preferences. Protocols for urban BMP modeling were developed based on the BMPs' mechanism and the hydrologic processes involved. The DDSS was tested in Watts Branch, a small urban watershed in metropolitan Washington D.C., and Wilde Lake, a suburban watershed in Columbia, MD. Comparisons were carried out in terms of hotspots distribution and BMP recommendation between the two study areas. The hotspots identified and BMPs prescribed by the DDSS were also examined under future climate scenarios. The prescribed BMPs and GIS maps will be useful in agency-level decision making and in developing appropriate educational material for residents and the general public.

A DIAGNOSTIC DECISION SUPPORT SYSTEM FOR SELECTING BEST
MANAGEMENT PRACTICES IN URBAN/SUBURBAN WATERSHEDS

By

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1.1   Overview

Urban and suburban watersheds have not received enough attention in terms of the on-land NPS generation and location. In agricultural watersheds, much research has been carried out on identifying the NPS hotspots (critical areas), conservation practices, and BMP modeling. Relatively little research has been conducted in urban/suburban watershed in terms of hotspot identification. Some researchers tried to assign a simple type of BMP (or two) to a whole study area. However, little research has been done in assigning various types of BMPs to an urban watershed according to geophysical features. Although urban BMP modeling is already available in existing software such as SWMM and SUSTAIN, a BMP modeling method is still needed in order to quantity the BMPs' effectiveness in continuous distributed hydrologic models without specifying the BMP dimensions. A Decision Support System (DSS) is needed for urban NPS hotspot identification, LID BMP selection, and stormwater management plan evaluation.

This dissertation contributes new tools to (a) develop preliminary watershed-scale stormwater management plans by assigning an appropriate set of spatially distributed Low Impact Development (LID) Best Management Practices (BMPs) in urban/suburban watersheds; (b) assess the combined effectiveness of the recommended LID BMPs in reducing non-point source pollution (NPS); and (c) evaluate the preliminary plan under different changing climate conditions. This chapter provides a brief overview of non-point source pollution (NPS), decision support systems (DSS), and climate change consideration for NPS control plans.

1.2 Non-point Source Pollution (NPS) in Urban/Suburban Watersheds

The Clean Water Act (CWA) establishes the basic structure for regulating discharges of pollutants into the waters of the United States and regulating quality standards for surface waters (USEPA, 2013a). CWA has been instrumental in improving the health of rivers, lakes, and coastal waters. It has stopped billions of pounds of pollution from fouling the water, and dramatically increased the number of waterways that are safe for swimming and fishing (CTI, 2002).

In 1972, estimates were that only 30 to 40 percent of the assessed waters in the United States met water quality goals; sewage treatment facilities served approximately 140 million people in this country, many at only a primary treatment level (a level of treatment that screens and settles solid pollution); the country lost an estimated 450,000 acres of wetlands each year. Today, 60 to 70 percent of assessed waters meet those goals; more than 73 percent of the total population are serviced by more than 16,000 publicly owned treatment works providing secondary (a level of treatment that also incorporates bacteria to digest organic matter in wastewater) or more advanced treatment (additional measures typically intended to address nutrients); wetlands losses are estimated to be less than one-fourth that rate. (USEPA, 2013b)

Over the past 40 years, the modern Clean Water Act has made great advances in improving the quality of U.S. waters and controlling various sources of pollution, with one large exception: nonpoint sources − the unfinished agenda of the Clean Water Act. The United States Environmental Protection Agency (USEPA) estimates that, at a minimum, 28 percent of the nation's rivers, 44 percent of the lakes (excluding the Great Lakes), and

32 percent of the estuaries are impaired or threatened with impairment (USEPA, 1994). A significant portion of all pollutants results from nonpoint sources (NPS). Nonpoint source pollution (NPS) refers to the polluting of water by diffuse sources rather than single identifiable point sources. These diffuse sources are usually associated with land use activities as opposed to end-of-pipe discharges. Examples of common nonpoint source pollution include: sediments, pesticides, and nutrients running off of farms and urban lawns; oil, grease, heavy metals, and other toxic materials carried from streets, highways, rooftops, and parking lots into storm sewers; animal wastes (rural barns and urban pets); and soil washed away from logging and construction areas. (USEPA, 2013b)

The majority of the NPS pollutants, which accounts for approximately 60 percent of the total nonpoint source pollution load, are believed to be contributed from agricultural areas (USEPA, 1990). Much research has been carried out on agricultural NPS control and management accordingly (Section 2.2 and 2.3). However, NPS pollution from urban runoff is also a main contributor to water quality impairment. Urban runoff has been identified as one of the leading sources of water quality impairment in surface waters (USEPA, 2002). "Urban runoff/storm sewers" has been ranked as the fourth leading source of impairment in rivers, third in lakes, and second in estuaries (Table 1-1). Therefore, it is important to conduct a thorough research on NPS in urban watershed. The amount and the location of the NPS generated in urban/suburban watersheds are of great importance for a better understanding, stormwater management planning, and incentive programs development.

Table 1-1 Leading Sources in Different Waterbodies (USEPA, 2002)

Rivers and Streams	Lakes, Ponds, and Reservoirs	Estuaries
Agriculture (48%)	Agriculture (41%)	Municipal point sources (37%)
Hydrologic modifications (20%)	Hydrologic modifications (18%)	Urban runoff/storm sewers (13%)
Habitat modifications (14%)	Urban runoff/storm sewers (18%)	Industrial discharges (26%)
Urban runoff/storm sewers (13%)	General non-point source pollution (14%)	Atmospheric deposition (24%)

* Shaded areas indicate sources in urban area

1.3 Decision Support System Needed in Stormwater Management

In order to control the NPS pollution and improve the overall water quality of an urban/suburban watershed, stormwater Best Management Practices (BMPs) are introduced and implemented. Although large scaled BMPs, such as detention basins, are effective in storing large volumes of stormwater and improving the overall quality of urban watersheds, it is generally hard to find an empty space to build one in highly urbanized area. Moreover, such large-scale BMPs perform more as treatment facilities than as controls. They are effective at improving water quality in the receiving water bodies. However, the damage on land is already done: eroded land surface, increased nutrients concentration in soil and groundwater. Therefore, the concept of Low Impact Development (LID) is often a more appropriate approach to stormwater management and NPS control in urban watersheds (Geosyntec Consultants, 2009). Compared to the conventional large scale BMPs, these relatively less expensive and less space-consuming NPS control methods are more likely to be adopted by urban residents whose roofs, lawns, and back yards would be used/partially used for installing the BMPs. And the LID are more likely to benefit urban area where large open space is less available and large area of imperviousness accelerates

the stormwater recharge into MS4 (Municipal Separate Storm Sewer Systems, from which stormwater is often discharged untreated into local waterbodies).

Green Infrastructure (GI) elements, the small-scale BMPs (also called the LID BMPs), which treat the stormwater at its source and are used to support LID, have been increasingly popular in urban stormwater management (USEPA, 2014a). But no single LID BMP is the panacea to all water quantity/quality problems. Structural BMPs vary in their primary functions and pollutants being targeted. A vegetated filter strip is designed for sediment control while a rain barrel is designed for surface runoff control. A green roof controls surface runoff through reducing rainwater reaching the ground while an infiltration trench controls surface runoff by promoting infiltration. Geographical features such as soil types and topography are also crucial factors that determine the type of GI applicable to certain areas. GI elements, such as pervious pavement, may lose function when applied in area with steep slope. Infiltration trenches can be less useful in situation of being clogged by fine clay soil. Therefore, for watersheds bearing various soil types and land uses, different types of BMPs should be selected based on different targeted NPS pollutants and different geographical features.

The variation in geographical features of a watershed and the different nature of the GIs lead to large amount of input information and multiple criteria for decision making. In order to select proper types of BMPs for different types of NPS in various locations within a watershed, and to simplify the selecting process of this spatially distributed BMP series, the computer-aided information-based Decision Support System (DSS) is in great need. Since feasibility of the GIs is the primary concern, expert system based DSS is a more

suitable tool in LID BMP selection than mathematical optimization based solely on optimal reduction rate.

1.4   Hydrologic Models and BMP Modeling

In order to successfully carry out a thorough analysis on NPS in urban/suburban watersheds, and to gather detailed watershed information for a DSS, a distributed hydrologic model is needed to simulate the hydrological processes in the study watershed. A distributed hydrologic model allows for more spatial variation than a lumped model regarding the watershed characteristics such as soil types, landuses, and topography. Detailed watershed input required by the model can provide detailed model output/simulations, which is of great importance in analyzing on-land NPS generation and transport rather than analyzing the in-stream NPS at the watershed outlet.

For stormwater management planning, long-term effectiveness of a BMP is of great importance. It is more desirable to evaluate the annual reduction rather than a reduction of NPS in a single storm. Therefore, a continuous distributed hydrologic model is needed for developing a watershed model, and examining the long-term effectiveness of BMPs in a large spatial scale.

In order to validate the effectiveness of the DSS, the effectiveness of the BMPs should be quantified first. Because of the emphasis on NPS in agricultural area, the majority of the research on BMP modeling has focused on agricultural conservation practices such as contour farming, parallel terraces, and residue management. Modeling of urban BMPs has generally been applied to specific BMPs based on design storms, as is

seen in SWMM (Rossman, 2010) and SUSTAIN (Shoemaker, et al. 2009). SWMM and SUSTAIN are developed for urban BMP modeling, but specific dimensions of the BMPs are required. It is not practical to provide specific dimension to all spatially distributed BMPs when the goal is to quantify overall watershed-scale effectiveness of the BMPs for planning purposes. Therefore, a systematic method is needed for modeling a large number of urban BMPs simultaneously in a continuous distributed hydrologic model. The method should be easy to use to distinguish the different BMPs in different locations while requiring no specific dimension of the BMPs.

1.5   Climate Change and BMPs

In stormwater management planning, non-stationarity of climate needs to be taken into account as well. Without proper maintenance, the effectiveness of GIs and BMPs can decrease due to reduced water storage, leaching, and clogging (Bracmort et al., 2006). Besides the inherent BMP characteristics that contribute to decreased functionality, external drivers such as precipitation and temperature may also affect the long-term effectiveness of BMP and BMP recommendation.

Global warming has intensified in the past decades. According to IPCC (2007), higher average temperature, more precipitation, and more extreme climate conditions are expected in the future. Increased precipitation volume may result in higher surface runoff volume. More extreme precipitation increases the probability of weathering, erosion, and surface soil loss. Higher temperature may increase vegetation growth and lead to increasing needs of fertilization. The historical weather statistics are no longer valid in a changing

climate. A BMP designed to withhold a 100-yr (historical) storm may encounter decreased effectiveness due to increasing frequency of storms of that magnitude.

Therefore, it is crucial that people see further when making plans. Two questions should be answered first: 1) whether the stormwater management/ NPS control plan should be made based on future climate; and 2) if a plan has already been made based on the current climate condition, how future climate condition would affect the effectiveness of the already assigned BMPs. For stormwater management plans covering a large spatial area using continuous hydrologic models, little research has been conducted to examine how climate change would affect the combined effectiveness of a series of urban BMPs in an urban watershed. The analysis carried out in this study examined the effects of climate change on the overall stormwater management plan rather than on the individual BMPs. The results obtained from the climate change analysis in this research are an interesting and useful addition to the climate change and stormwater management research.

1.6   Research Objectives

The goal of this research is to develop a tool for researchers and policy makers which can provide a preliminary stormwater management plan in urban/suburban watersheds for LID BMP selection in terms of type and location. This goal was accomplished through four specific objectives:

1)   Develop virtual watershed models for the study areas. The calibrated models should be able to accurately simulate the current hydrological and water quality-related

features of the study area. Accurate simulations are crucial for hotspot identification in the following research steps.

2) Develop proper urban BMP expressions in the SWAT model. Each urban BMP should have a proper parameter-based representation in SWAT, which allows SWAT to accurately model the BMP and quantify its effectiveness. These expressions from a system that can also be used in future study related to urban BMP modeling. These BMP scenarios will be available for future application of SWAT to modeling the BMP impacts.

3) Develop a Diagnostic Decision Support System for urban BMP selection. This DDSS should be able to (a) identify the most problematic areas, (b) determine the most likely physical causes for highly polluted hotspots, and (c) select a proper set of spatially distributed BMPs/ GIs for stormwater quality improvement of the whole watershed.

4) Evaluate the long-term effects of the selected BMPs in different future scenarios. Different development patterns and climate change patterns may affect the allocation of the NPS hotspots and the effectiveness of BMPs. Temperature change, precipitation pattern change were considered in several future scenarios. The effectiveness of the BMPs was evaluated under different circumstances during their design lives.

This research provides researchers, designers, developers, and policy makers a better understanding of urban watershed and urban BMPs. The DDSS can be useful tool for BMP implementation, both in terms of location and BMP types. The estimation of BMP costs are also useful for policy makers to develop a proper incentive program which can promote BMP adoption. Please note that the proposed DDSS is designed for BMP selecting in a watershed scale, and it is ultimately a tool for assisting decision making related to stormwater management and NPS control. Therefore, the DSS is not developed for designing a specific BMP within a specific location under a specific storm event.

Research background, study areas, and literature review are presented in Section 2. The research methods and steps are detailed in Section 3. Section 4 provides the detailed research results and discussion based on the results. Section 5 is the conclusion and potential future work.

Chapter 2. Background and Literature Review

This chapter includes background information related to non-point source pollution (NPS), best management practices (BMPs), decision support systems (DSS), climate change conditions (CC), the tools used in this research, and introduction of the two study watersheds. Literature in the related topics is included here to provide an overview of what has already been done and what has not. The following sections follow the sequence of how the research idea was developed.

2.1 Nonpoint Source Pollution

This section raises the question of NPS in urban area. The section first presents the basic information related to NPS, such as the sources and the impacts of NPS, in general. Urban NPS impacts are then presented to illustrate the importance of studying and controlling NPS in urban area.

2.1.1 NPS Sources and Impacts

Nutrients and sediments are the most significant NPS pollutants. Nitrogen and phosphorus are introduced into the water cycle through both natural processes and human activities. Natural sources of nitrogen and phosphorus include weathering processes of rock, fixation of atmospheric nitrogen by leguminous plants, decomposition of organic material, and soil leaching (Khwanboonbumpen, 2006). Sources of nutrients related to human

activities are observed in both agricultural areas and urban areas. Manure and fertilizer inputs to crops significantly contribute to nutrient over-enrichment in agricultural areas (USEPA, 2005). In urban areas, the sources include fertilizers for lawns, pet wastes, failing septic systems, and atmospheric deposition from industry and automobile emissions (USEPA, 2005).

The concentration of nitrate-nitrogen in drinking water is limited to 10 mg/L (USEPA, 2005). High nutrient levels in receiving waters can lead to a higher level of nitrate-nitrogen in drinking water, but urban sources of nitrate are not high enough to pose a human health risk. However, nutrients concentrations at this level can result in eutrophication of sensitive receiving waters. These sensitive waters include oligotrophic or mesotrophic lakes where phosphorus is a limiting nutrient, or coastal or estuarine areas where nitrogen is limiting (USEPA, 2005). Eutrophication can result in changes in periphyton, benthic, and fish communities; extreme eutrophication can cause hypoxia or anoxia, leading to fish kills. Surface algal scum, water discoloration, and the release of toxins from sediment can also occur consequently (USEPA, 2005).

Sediment is another problem in streams and water bodies. Potential sources of sediment pollution include agricultural erosion, deforestation, overgrazing, silvicultural erosion, urban runoff, construction activities, and mining activities. Sediments can also be re-suspended and transported directly from the water body's shoreline, bank, or bottom. Atmospheric deposition is another major source (Urbonas & Doerfer, 2004; USEPA, 2005).

Table 2-1 Pollutants in Stormwater Runoff (Peluso & Marshall, 2002)

Pollutant	Source	Impact on Water Body
Sediments	Eroding rock, soil, or organic material from building sites, streets, and lawn	Clogged waterways, increased turbidity, and reduction of bottom living organisms
Nutrients	Nitrogen and Phosphorus from landscape runoff, atmospheric deposition, and faulty septic tanks	Unwanted growth of algae and undesirable aquatic weeds, scum, and water discoloration
Heavy Metals	Lead, cadmium, chromium, cooper, mercury, and zinc from vehicles, highway materials, atmospheric deposition, and industry	Disruption of fish reproduction, fish toxicity, and potential for ground water contamination
Oxygen Demanding Substances	Decaying organic matter	Death of fish and aquatic forms
Petroleum Hydrocarbons	Oil, grease, and various hydrocarbons from roads, parking lots, leaking storage tanks, and improper oil disposal	Toxicity to aquatic life and adverse impacts on benthic communities
Pathogens	Coliform bacteria and viruses from animal waste, septic systems, sewer cross-connections, and boats and marinas	Contamination of swimming, fishing areas, or drinking water
Toxics	Pesticides, solvents, and chemicals from lawns, gardens, and commercial and household activities	Interference with respiration of fish and aquatic life forms
Others	Changes in the temperature or physical properties of water	Increased oxygen demand by fish and aquatic life forms and increase availability of toxic elements that harm organisms

Excessive sediment may cause physical, chemical, and biological damages (Nelson, 2002). Physical damages include harm to water conveyance, treatment, and storage facilities. Increased coarse sediment supply can cause channel aggradation, resulting in reduced flow capacity that can lead to flooding or navigational problems and channel instability (USEPA, 2005). Chemical damages include deposition and storage of nutrients, metals, and pesticides associated with eroded sediments. The fine fraction of sediment is the primary carrier of other pollutants such as organic components, metals, ammonium ions, phosphates, and toxic organic compounds which contribute to lake eutrophication

(Novotny & Olem, 1994). Biological damages include harm to aquatic habitat. Fine sediment can impair sources of fish food, and can occupy pore spaces in spawning gravel, limiting permeability and reducing oxygen delivery to fish eggs deposited in the gravel, and reducing beneficial habitat structure in stream channels (Bjornn & Reiser, 1991). Table 2-1 lists the main pollutants in stormwater runoff (Peluso & Marshall, 2002).

2.1.2   Urban Stormwater and NPS

Over 50% of the global population live in urban centers and, therefore, an understanding of the processes acting upon urban systems is of great importance. The nature of man-made impervious land surfaces and heavily engineered waterways results in hydrological and sedimentological systems in urbanized basins which contrast significantly to those within more natural (i.e. pristine, forested, agricultural) aquatic systems (Taylor & Owens, 2009). Additionally, the abundance of contamination sources in urban systems results in high pollution loadings, which in turn have detrimental impacts on human and ecosystem health (Taylor & Owens, 2009).

Stormwater runoff is generated when precipitation from rain and snowmelt events flows over land or impervious surfaces and does not percolate into the ground (USEPA, 2013a). The runoff accumulates the over-land debris, sediment, nutrients and pollutants before discharging into the surface water bodies. Stormwater is part of a natural hydrologic process; however, human activities, especially urban development and agriculture, cause significant changes in patterns of stormwater flow from land into receiving waters (Muthukrishnan, 2004). Impervious land covers such as highways, streets, parking lots,

and rooftops, prevent the stormwater from percolating into the soil. The consequent surface runoffs with greater volume lead to worse soil erosion because of greater flow forces. Agricultural activities and automobiles significantly increase the overland chemicals (pollutants). If untreated, urban runoff can be or is often a significant source of water pollution, causing decline in fisheries, swimming, and other beneficial attributes of water resources (USEPA, 1994).

Increased stormwater flows from urbanization have several major impacts (FLOW, 2003). Increased stormwater flows can accelerate stream velocities and degrade stream channels. It may also result in declining water quality caused by washing off of accumulated pollutants from impervious surfaces and increases in siltation and erosion of soils from pervious areas. Groundwater recharge would be diminished accordingly, resulting in decreased dry-weather flows and poorer water quality of streams during low flows. Other impacts include increased stream temperatures, greater annual pollutant load delivery, increased flooding and sanitary sewer overflows due to stormwater infiltration and inflow, damages to stream and aquatic life resulting from suspended solids accumulation, and increased health risks to humans from trash and debris (FLOW, 2003). Besides the physical damage polluted stormwater may cause, other impacts from polluted urban runoff include: fish kills, health concerns of human and/or terrestrial animals, degraded drinking water, diminished water-based recreation and tourism opportunities, economic losses to commercial fishing and aquaculture industries, lowered real estate values, damage to habitat of fish and other aquatic organisms, inevitable costs of clean-up and pollution reduction, reduced aesthetic values of lakes, streams, and coastal areas, and other impacts (Muthukrishnan, 2004; Leeds et al., 1993).

2.2   Best Management Practices and Green Infrastructure

BMPs have been widely used as NPS controlling and stormwater management approaches. Following the previous discussion about NPS, basic information about BMPs and literature related to BMPs are presented in this section. The first two sub-sections provide information on the definition, types, and application of BMPs. The last sub-section lists previous research related to BMP in general, BMP related research using the SWAT model in particular, and BMP modeling.

2.2.1   Best Management Practices

The primary method to control stormwater discharges is the use of best management practices (BMPs). BMP refers to operational activities, physical controls or educational measures that are applied to reduce the discharge of pollutants and minimize potential impacts upon receiving waters. BMP refers to both structural and nonstructural practices that have direct impacts on the release, transport, or discharge of pollutants. (Muthukrishnan, 2004)

BMPs can be discussed in terms of individual structural practices and non-structural practices, as well as in terms of overall site designs such as Low Impact Development (LID) that combine a variety of structural and non-structural practices. Structural BMPs include a variety of practices that rely on a wide range of hydrologic, physical, biological, and chemical processes to improve water quality and manage runoff. Non-structural BMPs such as education and source control ordinances typically depend on a combination of behavioral change and enforcement. (Geosyntec Consultants, 2009)

Structural BMPs are engineered systems and methods designed to provide temporary storage and treatment of stormwater runoff for the removal of pollutants (MWLAP, 1992; MDE, 2000; Clar et al., 2003). These practices are aimed at controlling the total volume and peak discharge rate of stormwater runoff, reducing pollutants in the stormwater via chemical, physical, and/or biological approaches (Florida DER, 1988). Common examples of structural BMPs include detention ponds and constructed wetlands. (Muthukrishnan, 2004)

Table 2-2 Structural BMPs for Urban Stormwater Runoff (Muthukrishnan, 2004)

Major Categories	Structural BMPs
Ponds	Dry Detention Ponds
	Dry-Extended Detention Ponds
	Wet (Retention) Ponds
Stormwater Wetlands	Constructed Wetlands
Vegetative Biofilters	Grass Swales (Wet/Dry)
	Filter Strip/Buffer
	Bioretention Cells
Infiltration Practices	Infiltration Trench
	Infiltration Basin
	Porous Pavement
Sand and Organic Filters	Surface Sand Filter
	Perimeter Filter
	Media Filter
	Underground Filter
Technology Options and Others	Water Quality Inlets
	Multi-Chambered Treatment Train
	Vortex Separation/Continuous Deflection Systems

Nonstructural BMPs refer to those stormwater runoff management techniques that use natural measures to reduce pollution levels, do not require extensive construction efforts, and either limit the generation of stormwater runoff, or reduce the amounts of pollutants contained in the runoff (Muthukrishnan, 2004). They do not involve fixed,

permanent facilities and they usually work by changing behavior through government regulation (e.g., planning and environmental laws), persuasion, and/or economic instruments (Taylor and Wong, 2002). These BMPs include institutional, educational or pollution prevention practices. Because they improve runoff quality by reducing the use, generation and accumulation of potential stormwater contaminants at or near their sources in many cases, they are also termed as source control BMPs (WEF & ASCE, 1998).

Table 2-3 Non-structural BMPs for Urban Stormwater Runoff (Muthukrishnan, 2004)

Major Categories	Non Structural BMPs
Public Education	Public Education and Outreach
Planning and Management	Better Site Design
	Vegetation Controls
	Reduction/Disconnection of Impervious Areas
	Green Roofs*
	Low-Impact Development**
Materials Management	Alternative Product Substitution
	Housekeeping Practices
Street/Storm Drain Maintenance	Street Cleaning
	Catchbasin Cleaning
	Storm Drain Flushing
	Road and Bridge Maintenance
	BMP Maintenance
	Storm Channel and Creek Maintenance
Spill Prevention and Cleanup	Above Ground Tank Spill Control
	Vehicle Spill Control
Illegal Dumping Controls	Illegal Dumping Controls
	Storm Drain Stenciling
	Household Hazardous Waste Collection
	Used Oil Recycling
Illicit Connection Control	Illicit Connection Prevention
	Illicit Connection - Detection and Removal
	Leaking Sanitary Sewer and Septic Tank Control
Stormwater Reuse	Landscape Watering
	Toilet Flushing
	Cooling Water
	Aesthetic and Recreational Ponds

Low Impact Development (LID) – LID is an overall land planning and engineering design approach to managing stormwater runoff. LID emphasizes conservation and use of on-site natural features to protect water quality. This approach implements engineered small-scale hydrologic controls to mimic the pre-development hydrologic regime of watersheds through infiltrating, filtering, storing, evaporating, and detaining runoff close to its source. LID is similar to Sustainable Urban Drainage Systems (SUDS), a term used in the United Kingdom, and Water Sensitive Urban Design (WSUD), a term used in Australia. The term Green Infrastructure may also be used, particularly in areas with combined sewer overflow (CSO) issues. (Geosyntec Consultants, 2009)

2.2.2   Green Infrastructure Basics

Green Infrastructure (GI) is the network of natural and semi-natural areas, features and green spaces in rural and urban, and terrestrial, freshwater, coastal and marine areas, which together enhance ecosystem health and resilience, contribute to biodiversity conservation and benefit human populations through the maintenance and enhancement of ecosystem services (Naumann et al. 2010). The main elements of green infrastructure are hubs and links. Hubs tend to be large areas of natural vegetation and links tend to be linear features (e.g., streams) that connect hubs (Wickham et al. 2010).

Although there is no consensus on the definition of GI, all definitions tend to emphasize certain characteristics, which include critical mass, benefits to people, multi-functionality, substitutability with grey infrastructure (engineered stormwater management infrastructure such as underground pipes and combined sewers), and coordinated

interventions (Naumann et al. 2010). According to Naumann et al. (2010) and USEPA (2014a), the main objectives of using Green Infrastructure include:

Table 2-4 Objectives of Using Green Infrastructure

Objectives	Examples
Water quality and quantity/supply	Stormwater quality, nonpoint source pollution, flooding, water supply, rainwater harvesting, water purification.
Climate change adaptation and mitigation	Urban heat island, enhancing ecosystem resilience and functioning, help society to adapt to climate change.
Biodiversity conservation	Habitat restoration, habitats improvement, habitat connection.
Soil Protection	Sustainable agriculture, land management, afforestation.
Human health/quality of life/ well-being	Health benefits, recreation space, property values, job opportunities.
Sustainable management	Taking actions specifically aiming to improve the ecological quality and permeability of landscapes, therein addressing multiple ecosystem services and functions and adopting a long-term perspective.
Air quality	Smog, air temperature, particulate matter, health effects.
Energy	Cooling.

In the United Stated, GI is seen as intrinsically linked with the best management of stormwater (Wolff & Gleick, 2002). The USEPA (2014b) defines GI as infrastructure which uses vegetation, soils, and natural processes to manage water and create healthier urban environments. At the scale of a neighborhood or site, green infrastructure refers to stormwater management systems that mimic nature by soaking up and storing water. The table below lists several of the green infrastructure elements commonly used in the US.

Table 2-5 Most Common GI in US (USEPA, 2014b)

Name	Description
Downspout disconnection	The rerouting of rooftop drainage pipes to drain rainwater to rain barrels, cisterns, or permeable areas instead of the storm sewer. Downspout disconnection stores stormwater and/or allows stormwater to infiltrate into the soil. This simple practice may have particularly great benefits in cities with combined sewer systems
Rain gardens	Shallow, vegetated basins that collect and absorb runoff from rooftops, sidewalks, and streets. They are also known as bio-retention or bio-infiltration cells. Rain gardens mimic natural hydrology by infiltrating and evapotranspiring runoff. Rain gardens are versatile features that can be installed in almost any unpaved space.
Rainwater harvesting	The collection and storage of rainfall for later use. When designed appropriately, rainwater harvesting systems slow and reduce runoff and provide a source of water. These systems may be particularly attractive in arid regions, where they can reduce demands on increasingly limited water supplies.
Planter boxes	Urban rain gardens with vertical walls and open or closed bottoms that collect and absorb runoff from sidewalks, parking lots, and streets. Planter boxes are ideal for space-limited sites in dense urban areas and as a streetscaping element.
Bioswales	Vegetated, mulched, or xeriscaped channels that provide treatment and retention as they move stormwater from one place to another. Vegetated swales slow, infiltrate, and filter stormwater flows. As linear features, vegetated swales are particularly suitable along streets and parking lots.
Permeable pavements	Paved surfaces that infiltrate, treat, and/or store rainwater where it falls. Permeable pavements may be constructed from pervious concrete, porous asphalt, permeable interlocking pavers, and several other materials. These pavements are particularly cost effective where land values are high and where flooding or icing is a problem.
Green streets and alleys	Integration of green infrastructure elements into the street and/or alley design to store, infiltrate, and evapotranspire stormwater. Permeable pavement, bioswales, planter boxes, and trees are among the many green infrastructure features that may be woven into street or alley design.
Green Parking	Integration of GI elements into parking lot designs. Permeable pavements can be installed in sections of a lot and rain gardens and bioswales can be included in medians and along a parking lot perimeter. Benefits include urban heat island mitigation and a more walkable built environment.
Green roofs	Roofs covered with growing media and vegetation that enable rainfall infiltration and evapotranspiration of stored water. Green roofs are particularly cost effective in dense urban areas where land values are high and on large industrial or office buildings where stormwater management costs may be high.
Urban Tree Canopy	Many cities set tree canopy goals to restore some of the benefits provided by trees. Trees reduce and slow stormwater by intercepting precipitation in their leaves and branches. Homeowners, businesses, and cities can all participate in the planting and maintenance of trees throughout the urban environment.
Land Conservation	Protecting open spaces and sensitive natural areas within and adjacent to cities can mitigate the water quality and flooding impacts of urban stormwater while providing recreational opportunities for city residents. Natural areas that are particularly important in addressing water quality and flooding include riparian areas, wetlands, and steep hillsides.

2.2.3 Previous Studies Related to BMP, LID, and GI

Ever since the U.S. government recognized the problem of non-point source pollution and established provisions in a major amendment to the Clean Water Act in 1987, BMP has been increasingly popular in addressing pollution from wet-weather flow (WWF) and polluted runoff and controlling runoff increases and reducing water quality degradation associated with new development (Muthukrishnan, 2004).

Soil and Water Assessment Tools (SWAT) model, in particular, has proven to be an effective tool for evaluating BMP implementation, alternate land use, and other factors contributing to lower pollutant levels (Stewart et al., 2006; Chaplot et al., 2004; Whitall et al., 2004; Santhi et al., 2001). Gassman et al. (2007) have also indicated that a key strength of SWAT is a flexible framework allowing the simulation of a wide variety of structural and nonstructural BMPs such as fertilizer and manure application rate and timing, cover crops (perennial grasses), filter strips, conservation tillage, cover crops, application rate and timing of fertilizers, nutrient management, buffer strips, flood prevention structures, grass water way, and parallel terraces.

Researchers have been interested in BMP applications in agricultural watersheds, large-scale BMPs for stormwater volume control, quantification of BMP effectiveness, comparisons between large-scale BMPs and LID BMPs, BMP/LID selection, agricultural BMP modeling, and other BMP related topics.

2.2.3.1   BMPs in agricultural watersheds

Ripa et al (2006) used GLEAMS to estimate the soil erosion and Phosphorus mobility in an agricultural watershed. The amount of eroded soil and transported Phosphorus was compared in two scenarios: with and without BMP. Only one type of BMP was selected to be applied for the entire watershed.

Gitau et al. (2008) applied SWAT to characterize P losses from a study watershed at both the watershed and field levels, for the pre- and post-BMP implementation periods. He concluded that the SWAT model performed well at the watershed level as well as at the field level and that the SWAT was suitable for evaluating BMP impacts.

O'Donnell et al. (2008) used SWAT to predict reduction of sediment erosion and transport over a 30-year period due to grass and woody-riparian establishment on cropland. This study indicated upland areas should be targeted for BMP establishment. The study also stated the need for better representation of channel and floodplain sediment processes in SWAT and other hydrological models if BMP were to be assessed by computer simulations instead of on-the-ground monitoring.

Ullrich et al. (2009) carried out a sensitivity analysis for conservation management parameters in SWAT. Results showed that the model is sensitive to applied crop rotations and in some cases even to small variations of management practices. Lee et al. (2010) evaluated the reduction effect of non-point source pollution by applying best management practices (BMPs) to a 1.21 km2 small agricultural watershed using a SWAT model. Four BMP scenarios were analyzed. The results indicated that 5m-resolution land use data gives more reliable spatial information of high potential soil loss and sediment yield area as

compared to the 30m-resolution land use data for soil and water conservation of a watershed.

Zhang and Zhang (2011) used SWAT model to simulate performances of agricultural BMPs in reducing organophosphates (OPs) in runoff at the watershed scale. BMPs studied included buffer strips, sediment ponds, vegetated ditches, usage reduction, and the combinations of all BMPs. This study has suggested that the SWAT model reasonably predicts BMP effectiveness at the watershed scale. The research also suggested that combining individual BMPs provides enhanced mitigation effects. The combination of vegetated ditches, buffer strips and use reduction decreases diazinon and chlorpyrifos load by over 94%.

Liu et al. (2012) investigated the effectiveness of selected BMPs on the Xiangxi River through analysis of several scenarios by SWAT. Changes in land use, fertilizer management, and tillage management measures were simulated in SWAT. The results revealed that when farmland was returned to forests, both runoff and NPS pollution loads showed a clear downward trend and the NPS pollution loads decreased by 20% or more when compared with the status of 2007. Conservation tillage and contour farming could help reduce runoff by 15.99% and 9.16%, total nitrogen (TN) by 8.99% and 8%, and total phosphorus (TP) by 7% and 5%, respectively.

Ahmadi et al. (2013) presented an integrated simulation-optimization approach for targeted implementation of agricultural conservation practices at the watershed scale. A multi-objective genetic algorithm (NSGA-II) with mixed discrete-continuous decision

variables was coupled with SWAT, to identify optimal types and locations of conservation practices for nutrient and pesticide control at the watershed scale.

Laik (2014) developed a more productive and sustainable approach to enhance productivity, alleviate environmental and management constraints, and enhance farmers' income in the rice–wheat cropping system. The results showed enormous untapped potential to improve overall system performance through the adoption of Conservation agriculture in integration with BMP.

2.2.3.2   Research related to large-scale BMPs

Carleton (2001) analyzed the effluent data from 35 studies on 49 wetland systems used to treat stormwater runoff or runoff-impacted surface waters. Regression equations between variables such as loading rate, detention time, and removal rate were developed, which could be used as preliminary wetland design tools. Barrett (2005) developed a method which used linear regression as the primary tool to compute the expected effluent concentration from a BMP, given a specific influent concentration of interest. He concluded that this is a better BMP evaluation method than the traditional reduction rates in situations where the "percent reduction" in a pollutant EMC is not an inherent characteristic of the BMP. Anta (2006) developed a relationship between the total rainfall and the sediment particle size distribution of each event, and concluded that sedimentation ponds was suitable for the elimination of the fine sediments associated with urban runoff. Martin (2007) used a survey to determine the main reasons for the use of BMPs. He then

used ELECTRE III multi-criteria analysis method and created a multi-criteria decision aid matrix for BMP selection.

Elizabeth (2006) presented results of an extensive field monitoring program of a proprietary stormwater treatment technology called the Stormvault. The Stormvault is a multi-baffled system designed to remove contaminants from stormwater runoff primarily via gravitational settling, while providing some peak flow attenuation. Multiple linear regression results indicated that interactions between site and storm characteristics significantly affect effluent EMC. Welker (2006) studied two 85 to 100 year old infiltration pits where soil samples were collected and tested for copper. His results showed that infiltration BMPs would not cause serious groundwater contamination in the study area. Hogan (2007) did an analysis on urban stormwater treated from a flood control stormwater detention basins (SDB-FCs) and a water quality improvement stormwater detention basins (SDB-BMPs). The analysis results were then compared to the statistics of effluent in natural riparian wetlands (RWs). He concluded that use of SDB-BMPs instead of SDB-FCs could foster more responsible urban development and be an appropriate mitigation action for receiving aquatic ecosystems.

2.2.3.3   Urban LID BMPs

Edgar (2004) studied the BMPs (green roofs and pond) used in an inner city suburb. The effectiveness of BMPs was assessed by comparing synthetic hydrographs for the 1/2, 2, 5 and 10-year design-storms assuming wet and dry initial conditions. It was found that

green-roofs were effective at lowering total runoff and that the ponds could successfully attenuate storm peak flows for even the 10-year rainfall.

Gilroy (2009) showed that cisterns alone were capable of controlling rooftop runoff for small storms. The results showed that the volume of BMP storage was positively correlated to the percent reduction in the peak discharge rate and total runoff volume; however, location was a factor in the peak reduction and a maximum volume of effective storage for both hydrologic metrics does exist.

Guo et al. (2013) developed a method and procedure used in an optimization and statistics computer model developed for determining the water quality capture volume (WQCV) for storm water best management practices (BMP) and low-impact development (LID) facility designs. The authors found out that typically, but not always, the optimal runoff volume and event capture ratios lie between the 80 and 90th percentile of the local runoff volume population.

Hamel et al. (2013) analyzed the physiographic and anthropogenic factors that affect the baseflow response to urbanization with the aim to better understand the potential role of stormwater infiltration source-control technologies in restoring predevelopment baseflow. The researchers suggested that the adoption of a clear framework for baseflow assessment in pre- and post-development states, along with fundamental research on the translation from site-scale processes to catchment-scale effects, are essential research steps to guide future stormwater management for baseflow in suburban catchments.

Shuster & Rhea (2013) compared the stream discharge monitored 3 years before and after implementation of the stormwater management treatments. The results concluded that

retrofit management of stormwater runoff quantity with green infrastructure in a small suburban catchment can be successfully initiated with novel economic incentive programs and that the efficiency of further retrofits may be increased by focusing on transportation surfaces, which account for large proportions of connected impervious area in urban areas.

2.2.3.4   BMP selection and comparison

Panagopoulos (2011) examined two kinds of agricultural Best Management Practices (BMPs) with respect to cost-effectiveness (CE) in reducing sediment, nitrate-nitrogen (N O3-N) and total phosphorus (TP) losses to surface waters of the agricultural catchment using SWAT. The methodology aimed to facilitate decision making for a cost-effective management of diffuse pollution by enabling modelers and researchers to make rapid and reliable BMP cost estimations and thus being able to calculate their CE at the local level in order to identify the most suitable areas for their implementation.

Laurent et al. (2011) used the SWAT model to model the impacts of climate, soils and agricultural practices on nitrate flows in a 1310 km2 catchment in western France. Five scenarios of alternative practices were simulated to evaluate their consequences for nitrogen flows: reduced fertilization, catch crops, shallow cultivation, no-till with catch crops and filter strips. The 9-year simulations showed a reduction in nitrate flow of 8% with filters strips, 11% with catch crops, 12% with no-till with catch crops, and 15% with reduced fertilization. The authors concluded that modelling can improve people's understanding of the impacts of agricultural practices on water quality at different scales.

Dechmi & Skhiri (2013) tested 20 BMP scenarios in a modified SWAT-IRRIG model in an intensive irrigated watershed, evaluating the BMPs effectiveness in irrigation return flows (IRF), total suspended sediment (TSS), organic P (ORG P), soluble P (SOL P), and total P (TP). The results indicated that individual BMP (adjusted irrigation water use) could reduce IRF by 31.4%, TSS loads by 33.5% and TP loads by 12.8%. When individual BMPs were combined, the load reductions could be further increased, leading to a TP load reduction of about 22.6%.

Sommerlot et al. (2013) compared four methods employing some of the most cited models in field and watershed scale analysis to find a practical yet accurate method for evaluating field management strategies related to sediment transport at the watershed outlet. The impact of 20 best management practices on farmers' income and surface water quality in intensive irrigated systems was evaluated using a modified SWAT model. The tested BMPs showed differences in their environmental impact and gross margin and the most relevant conclusion is related to the use of several BMPs at the same time.

Chichakly et al. (2013) presented a multi-scale, multi-objective framework for generating a diverse family of stormwater best management practice (BMP) plans for entire watersheds. But the BMP selection was between detention pond and rain gardens only. Detention basin was modeled at the outlet of the watershed. And rain gardens were assumed to be applied throughout the watershed.

A new cooperative watershed management methodology was designed for developing an equitable and efficient BMP cost allocation among landowners in a watershed (Mohammad et al., 2013). The methodology combined SWAT, with an Ant

Colony Optimization (ACO) module and the cooperative game theory approach. Nash Bargaining Theory was used to investigate how the maximum saving on cost of the participating players in a coalition can be fairly allocated.

Artita et al. (2013) presented a methodology that integrates the semi-distributed watershed model SWAT with an evolutionary algorithm, Species Conserving Genetic Algorithm (SCGA). In addition to identifying an optimal watershed-scale BMP design (e.g., type, size, location), SCGA simultaneously produced several near-optimal design alternatives using a user-specified distance metric. Results yielded several high-quality alternative designs appropriate for solving integrated watershed management problems.

Liu et al. (2014) used SWAT to investigate the effectiveness and cost-benefit of several BMPs on agricultural NPS pollutant reduction in a large tributary of the Three Gorges Reservoir (TGR) in China. The authors concluded that reforestation was the most cost-benefit BMP for the specific watershed in terms of NPS reduction.

Chiang et al. (2014) compared the selection and placement of BMPs using SWAT and a genetic algorithm (GA) optimization and a targeting method and, evaluated the impacts of various BMP options. The results showed the importance of carefully selecting the BMP options for optimization in order to obtain more effective solutions in minimizing pollutant losses and BMP-implemented area in a watershed. The authors also concluded that other pollutants of concern, and cost and maintenance of selected BMPs options should be taken into consideration when applying this evaluation framework.

Ki & Ray (2014) illustrated a methodology of locating infiltration trenches at suitable locations from spatial overlay analyses which combine multiple layers that address

different aspects of field application into a composite map using fuzzy logic. The study demonstrated that the fuzzy logic analysis cannot only be used to improve spatial decision quality along with other overlay approaches, but also is combined with general water quality models for initial and refined searches for the best locations of BMPs at the sub-basin level.

Andrés-Valeri et al. (2014) compared the outflow water quality from two sustainable urban drainage systems (SUDS), a swale and a filter drain, with the water quality from one conventional drainage system, a concrete ditch. Results showed significantly smaller amounts of outflow pollutants in SUDS than in conventional drainage systems, especially in the filter drain which provided the best performance.

Rigge et al. (2014) evaluated the effects of rangeland BMP implementation with six commercial-scale pastures in the northern mixed-grass prairie. The results demonstrated that satellite imagery time series were useful in retrospectively evaluating the efficacy of conservation practices, providing critical information to guide adaptive management and decision makers.

Loperfido et al. (2014) evaluated the stream hydrologic data in four catchments located in the Chesapeake Bay watershed: one utilizing distributed stormwater BMPs, two utilizing centralized stormwater BMPs, and a forested catchment serving as a reference, to examine the effectiveness of centralized BMPs and distributed BMPs. Results highlighted the importance of both stormwater management strategy and land cover as factors dictating the magnitude and pattern of water export. Although hydrologic improvements provided

by distributed BMPs were substantial, land cover appeared to play a dominant role in reducing total runoff volume and decreasing stream response during precipitation events.

2.2.3.5   Social factors and BMP

Barbosa et al. (2012) pointed out several key elements in sustainable urban stormwater management. The authors concluded that BMPs should be seen as an opportunity for development and improvement of social, educational and environmental conditions in urbanized and surrounding areas. Therefore they require an ample perspective and the participation of different stakeholders.

Piemonti et al. (2013) determined the importance of incorporating sociological data, such as landowner tenure and attitudes of farming communities, in the design of conservation practice alternatives. Results showed that the practices proposed by optimized alternatives are less attractive to stakeholders/landowner operators because of the sociological conditions, the actual adoption of various practices will be lower and the planned benefits will be reduced.

Jacobs & Buijs (2011) studied stakeholders' concerns in two water management planning contexts, focusing on the meanings assigned to places and on attitudes toward proposed interventions. The results suggested that stakeholders' attitudes toward proposed interventions were, to a great extent, derived from their place meanings (Attitudes and constituent beliefs about proposed interventions firmly rooted in the meanings assigned to places). Place meanings include beauty, functionality, attachment, biodiversity, and risk. The concept of place meanings denotes any general belief, value, or affect in the mind of

a subject that relates that subject to a particular place in some way. Discussing place meanings during participatory planning processes could contribute substantially to successful water management.

2.2.3.6   BMP Modeling and Representation in SWAT

As indicated by Gassman et al. (2007), a key strength of SWAT is a flexible framework allowing the simulation of a wide variety of structural and nonstructural BMPs. Several researchers have successfully modeled agricultural BMPs, or conservation practices, in SWAT model by adjusting the values of existing parameters.

Vache et al. (2002) simulated riparian buffers, grassed waterways, filter strips, and field borders by modifying the channel cover factor and channel erodibility factor in SWAT to model the cover density and erosion resistance of the structures. Santhi et al. (2003) simulated grade stabilization structures in SWAT by modifying the land slope and soil erodibility factor. The impact of filter strips on sediment and nutrient reduction was simulated as a function of filter strip width.

Bracmort (2006) pointed out that appropriate model parameters for representation of the effect of parallel terraces are the curve number (CN2) and USLE support practice factor (USLE_P), along with slope length (SLSUBBSN). FILTERW (width of edge-of-field filter strip) was recognized to be the appropriate parameter for representation of field borders. Key parameters for representing grass waterway are the channel Manning's coefficient (CH_N2), channel slope (CH_S2), channel erodibility factor (CH_EROD), and channel cover factor (CH_COV).

Arabi (2007) developed and evaluated a method for the representation of several agricultural conservation practices with SWAT. The representation procedure entails identifying hydrologic and water quality processes that are affected by practice implementation, selecting SWAT parameters that represent the affected processes, performing a sensitivity analysis to ascertain the sensitivity of model outputs to selected parameters, adjusting the selected parameters based on the function of conservation practices, and verifying the reasonableness of the SWAT results. Ten important agricultural conservation practices were selected for representation with the SWAT2005 model, based on their relatively common use in water quality projects. These include contour farming, strip-cropping, parallel terraces, cover crops, residue management, field borders, filter strips, grassed waterways, lined water-ways, and grade stabilization structures. Parameters involved in BMP simulations include: SCS curve number (CN), USLE practice factor (USLE_P), USLE cover factor (USLE_C), Manning's roughness coefficient for overland flow (OV_N), slope length of the hillside (SLSUBBSN), channel width (CH_W2), channel depth (CH_D), channel Manning's roughness coefficient (CH_N2), channel cover factor (CH_COV), slope of the channel segment (CH_S2), and channel erodibility factor (CH EROD).

Wild (2009) developed a mathematical model of an idealized BMP in order to quantify the impact of variable hydrologic and pollutant concentration input on BMP performance. He suggested a need to incorporate into BMP performance guidelines the impact of the variable influent hydrologic and pollutant concentration characteristics. Emphasis should be placed on discharge water quality and statistical distributions of effluent concentration rather than on single-percent removal values.

Damodaram (2010) described a modeling approach to incorporate LID practices modeled using SWMM in an existing hydrologic model, HEC-HMS, to estimate the effects of LID choices on stream flow. LID included permeable pavement, green roof, and rainwater harvesting. BMP included a detention pond. Results demonstrate that use of LID practices yield significant stormwater control for small events and less control for flood events.

Zhang & Zhang (2011) used the pesticide transport and transformation module for lakes and reservoirs in SWAT to simulate pesticide processes in sediment ponds on farms. The parameters of channel roughness coefficient (CH_N2), channel erodibility (CH EROD) and channel cover (CH_COV) were increased to represent vegetated ditches, which reduce pollutants by increasing the channel roughness, sedimentation and pollutant adsorption to plant surfaces. Width of filter strip (FILTERW) used to calculate the mass of sediment, nutrients and pesticides trapped by filter strip in the SWAT model were changed to simulate this BMP.

2.2.3.7 Others

Several studies have analyzed the long-term effects of structural Best Management Practices (BMP) on water quality (e.g. Kirsch et al., 2002; Chaplot et al., 2004; Tripathi et al., 2005; Pandey et al., 2005 or Behera and Panda, 2006; Bracmort et al., 2006). Arabi et al. (2007) investigated the impact of modelling uncertainty on evaluation of management practices using a Monte Carlo-based probabilistic approach.

Bracmort et al. (2006) tried to determine the long-term (~20 year) impact of structural BMPs in two subwatersheds on sediment and phosphorus loads using the SWAT model. The BMPs were represented by modifying SWAT parameters to reflect the impact the practice has on the processes simulated within SWAT, both when practices are fully functional and as their condition deteriorates.

Lam et al. (2011) assessed the long-term impact of point and diffuse source pollution on sediment and nutrient load in a lowland catchment using the SWAT model and to evaluate the cost and effectiveness of BMPs for water quality improvement in the entire catchment. This study revealed that reduction only in one type of BMP did not achieve the target value for water quality according to the European Water Framework Directive. The combination of BMPs improved considerably water quality in the study area.

Koch et al. (2014) carried out a comprehensive synthesis of data from empirically based published studies and a widely used stormwater BMP database to assess the variability in nitrogen (N) removal performance of urban BMPs. The authors offered two broad recommendations for improving SW BMP implementation: (1) Properly accounting for the full distribution of SW BMP performance in setting nutrient reduction goals, and (2) Targeted long-term monitoring of SW BMPs that include standardized measurements of environment al factors and nutrient loads.

2.2.3.8   Summary

Despite the large numbers, the majority of the BMP related studies has been carried out in agricultural watersheds, focusing on evaluating and quantifying the effectiveness of

agricultural BMPs and conservation practices. As for the research carried out in urban watersheds, the research focus was either on urban surface runoff volume reduction, or evaluating the effectiveness of traditional large-scale BMPs. Studies related to LID BMPs were limited to the study of a single type of LID BMP, or applying the same type of small-scale BMP across the whole study area.

The limitations observed in literature related to BMP/Conservative Practices selection are 1) the candidate BMP options were generally limited to 2-4. The effective of each BMP option was quantified by applying the BMP to the entire watershed. The one that showed the highest NPS reduction rates or a best balanced reduction rate and cost would be the optimal BMP. No spatial variation nor genetic variation was taken into consideration in terms of BMP implementation. Secondly, some researchers have noticed that different BMPs should be applied in the study area. However, the various BMP types were applied solely based on landuse, or several BMPs were developed as a BMP set, which was still applied throughout the watershed. Finally, previous research generally focused on non-urban watersheds and non-LID BMPs. The selection process was based on optimization of reduction rate (or/and cost), which do not take feasibility into account.

Moreover, little research has been found for urban BMPs modeling in continuous hydrologic models such as SWAT. Research on BMP modeling has been closely related to the major concerns in different types of watershed. Nutrients and sediments are the main concern in agricultural watersheds. Therefore, BMPs being considered in agricultural watersheds are conventional practices such as couture farming and no tillage, which are modeled by adjusting parameters related to soil characteristics. Stormwater volume is the main concern in urban watersheds. So urban BMPs are usually modeled as a Continuous

Stirred Reactor (CSTR) with a desired volume [SUSTAIN (Lai, et al. 2007)]. However, the method requires BMP dimensions, which is less feasible in situations when the combined effectiveness of BMPs in various types and large numbers were to be quantified.

2.3   NPS Pollution Hotspots Targeting and Prioritizing

In most stormwater management plans, limited budget and resources do not allow for building BMPs throughout the watershed. This section explains why prioritizing the limited resources is needed. Literature is included to illustrate how researchers have been dealing with the problem and the limitation of current methods involved.

2.3.1   Need for Hotspot Identification

In order to improve the overall water quality of the watershed, a more effective way is to target the upland area for BMP implementation (O'Donnell et al., 2008). However, not all parts of a watershed are equally critical and responsible for producing high amounts of sediment and nutrient loads (Ouyang et al., 2008). In a watershed bearing various soil types, landuses, and topography, different part of the watershed may contribute different amount of NPS into the receiving waterbodies. Researchers have found out that typically, some small and well-defined areas contribute much of the sediment, P, and N into the watershed outflow (Walter et al., 2000; Pionke et al., 2000; Sharpley and Rekolainen, 1997; Pionke et al., 1997; Russell et al., 2000; Gburek et al., 2002; Agnew et al., 2006; Walter et al., 2009; Ballantine et al., 2009). These small definable areas are referred to as hotspots.

The NPS pollution hotspots are also known as Critical Source Areas (CSA) (Djodjic et al., 2002), and Hydrologically Sensitive Areas (HSAs) (Srinivasan & McDowell, 2007), which represent areas with high concentration of nutrients or sediment yield rate and are of priority in water quality treatment or management (Sadegh-Zadeh et al., 2007).

Cost has always been a concern in decision making related to stormwater management and NPS control. This is a main reason why hotspots need to be identified and be given priority in stormwater management plans. The District of Columbia Department of the Environment (DDOE) estimated that if stormwater retrofit is carried out in the entire city, the total cost would be $7 billion, but DDOE's annual budget is only about $17 million (DDOE, 2014). Philadelphia Water Department is facing the similar problem in achieving their "Greener City, Cleaner Water" goal (PWD, 2014).

Targeting mitigation measures at CSAs have been argued to provide a basis for cost effective protection and improvement in the chemical and biological quality of water bodies, to fulfil regulatory requirements such as the EU Water Framework Directive where good and high ecological status needs to be achieved and sustained (Doody et al., 2012; OJEC, 2000).

When resources are limited, studies recommended that management should be directed toward CSAs (Singh et al., 2010). Management practices implemented in these targeted areas have the potential to be more effective at treating larger quantities of pollution than randomly assigning the BMPs spatially (Djodjic et al., 2002; White et al., 2003; Sharpley et al., 2003; Srinivasan & McDowell, 2007; White et al., 2009) and

"generate the most profound or widespread environmental benefits for a given [cost]" (Hansen & Hellerstein, 2006).

2.3.2 Current research on Hotspot Identification

NPS hotspots have been defined both from the land resources and the water quality perspectives (Maas et al., 1985). One group of research uses soil properties such as soil erodibility and nutrient concentration as indices to identify hotspots, which is from land resources perspectives. Another group of research uses hydrologic models to simulate hydrological processes and uses water quality as indicator of NPS hotspots.

A number of studies have been carried out on the P index methods in US (Lemunyon and Gilbert, 1993; Buczko and Kuchenbuch, 2007; Sharpley et al., 2003) and Europe (Magette, 1998; Magette et al., 2007). Such P index tools classify fields based on the risk of P export during runoff events. The risk classification of the field is based on the P inputs, the risk of runoff occurring, and the connectivity between the field and adjacent waterbodies (Doody et al., 2012). Weights are also applied to the risk index based on various geographical features.

The widespread adoption of this risk based approach for identifying CSA at field scale in the US indicates a general consensus that it is a valid and flexible method for P management. However, researchers need to explicitly demonstrate that (a) areas categorized as high risk are the main source of P measured at catchment scale; (b) targeting mitigation measures at such areas will result in a decrease in P concentration in rivers and lakes; and (c) in low risk areas the continued application of P will not increase P export

(Sharpley et al., 2003). Besides these strict requirements, the majority of P indices can only predict indexed risk and cannot quantity of P loss (White et al., 2009).. These P index results compared favorably with measured in-stream water quality data, but the coarse discretization was ineffective for targeting CSAs. Therefore, process-based watershed models are increasingly used for targeting the CSAs.

SWAT (Arnold et al., 1998) is one of the most commonly used watershed models for predicting locations of CSAs in watersheds and for evaluating effectiveness of BMPs in controlling NPS pollution (Tripathi et al., 2003; Ouyang et al., 2008; Kalin & Hantush, 2009; Busteed et al., 2009; White et al., 2009; Singh et al., 2011; Gitau et al., 2004; Srinivasan et al., 2005).

Niraula et al. (2012) explored the effect of lumped calibration of the Soil and Water Assessment Tool (SWAT) on locations of sediment and nutrient critical source areas (CSAs). The study concluded that lumped calibration of the SWAT model using data at the watershed outlet has little effect on the locations of CSAs. Therefore, SWAT can be used without calibration for identification of CSAs in watersheds that lack sufficient data for model calibration, but not for all other modeling purposes.

Other modeling tools used for identifying CSAs include the Soil Moisture Distribution and Routing (SMDR) (Srinivasan et al. 2005), the Water Erosion Prediction Project (WEPP) (Pandey et al. 2009), and the Kinematic Runoff and Erosion model (KINEROS) (Kalin et al., 2004).

Kalin et al. (2004) used a modified unit sedimentograph approach to identify potential sediment-generating areas in two experimental watersheds in Iowa. Strauss et al. (2007)

defined the areas where source factors and transport factors coexisted, as being critical areas for P loss. They used the field scale simulation model GLEAMS and an additional meta-model, which was derived from the application of GLEAMS, to identify CSAs. They concluded that identification of critical source areas for targeting soil and phosphorus losses were crucial for correct allocation of BMPs.

In some studies NPS pollution was identified using different methods and in different perspectives. In one study carried out by Nickitas et al. (2009), used the Generalized Watershed Loading Functions (GWLF) model and its ArcView interface (AVGWLF) were used to estimate and examine the components of the total nitrogen (TN) nonpoint source (NPS) load. The authors found out that ground-water base flow was the largest pathway for NPS TN to the study stream, contributing about 54% of the total NPS TN load, septic systems were estimated to contribute about 17% of the total load, with the remaining TN load being mostly runoff from urban (17%), agricultural (5%), and low impact (e.g., forest) areas (6%). Proper BMP recommendation was made based on the study.

Shields et al. (2008) explored impacts of urbanization on magnitude and export flow distribution of nitrogen along an urban-rural gradient in a set of catchments studied by the Baltimore Ecosystem Study (BES). They found that increasing development in watersheds was associated with shifts in nitrogen export toward higher discharge, while total magnitude of export does not show as strong a trend. A simple statistical model relating export distribution metrics to impervious surface area was then used to extrapolate parameters of the N export distribution across the Gwynns Falls watershed in Baltimore County. The research method was good for identifying which sub-watersheds contribute the highest nutrients.

Rao et al. (2009) determined the effectiveness of BMPs using the Variable Source Loading Function (VSLF) model, which captures the spatial and temporal evolutions of variable source areas (VSA) in the landscape. The results demonstrated that BMPs, when sited with respect to VSAs, reduce P loss from agricultural watersheds, providing useful information for targeted water quality management.

Panagopoulos et al. (2012) demonstrated a new methodology and associated decision support tool that suggests the optimal location for placing BMPs to minimize diffuse surface water pollution at the catchment scale, by determining the trade-off among economic and multiple environmental objectives. The decision support tool consist s of a non-point source (NPS) pollution estimator, the SWAT model, a genetic algorithm (GA), and empirical economic function for the estimation of the mean annual cost of BMP implementation.

Giri et al (2012) used SWAT model to evaluate the performance of different targeting methods in identifying priority areas (high, medium, and low) based on various factors such as pollutant concentration, load, and yield in an agricultural watershed. NPS pollutant reduction in priority areas were compared among all targeting methods. The results indicated that emphasis should be placed on selection of the proper targeting method and BMP to meet the needs and goals of a BMP implementation project because different targeting methods produce varying results.

Panagopoulos et al. (2013) integrated the river basin SWAT model that serves as the nonpoint source pollution estimator into an optimization framework consisting of a multi-objective genetic algorithm that searches for optimal selection and location of BMPs in the

agricultural landscape. The proposed methodology helped to provide the basis for sustainable land-use planning and management in large agricultural landscapes, thus aiding decision-making and cost-effective implementation of Environmental Directives.

Giri et al. (2014) implemented ten best management practices (BMP) on agricultural areas using the SWAT model based on four targeting methods (Load per Subbasin Area Index (LPSAI), Load per Unit Area Index (LPUAI), Concentration Impact Index (CII), and Load Impact Index (LII)). The research concluded that proper utilization of limited resources is achieved through the right CSA selection criteria. Hence, the primary step before BMP implementation is to identify CSAs of pollutants in the watershed.

Chen et al. (2014) designed a multilevel PMA (ML-PMA) framework as a new tool to pinpoint the sensitive areas (hotspots), within a basin, that contribute the most to water quality deterioration. The main advantage of the ML-PMA framework is the integration of both watershed (SWAT) and river processes (QUAL2Kw) in addressing PMAs at the watershed scale. The authors concluded that if the PMAs can be spatially identified at high resolution, they can provide valuable information for designing on-site BMPs and forecasting their off-site impacts at the watershed scale.

A review of the literature shows that although the research on CSA (hotspots) has been popular, hotspots have not been identified for surface runoff. Majority of the CSA research has been limited to: 1) agricultural areas, because agricultural watershed is the No. 1 contributor of NPS in US; and 2) sediments and nutrients only, because excessive surface runoff has been naturally related to impervious surface which is more observed in the less

studied urban areas. Therefore, surface runoff has been less studied in agricultural watersheds. For urban stormwater and NPS control, large scaled BMPs such as detention basin and bio-retention basin seem more capable of controlling stormwater volume (Chichakly et al., 2013; Loperfido et al., 2014). The effectiveness of LID BMPs in reducing the runoff volume is more attractive to researchers as well (Shuster & Rhea, 2013; Hamel et al., 2013; Loperfido et al., 2014). But the water quality aspect of the urban LID has been somehow neglected, especially in the field of hotspots identification. Therefore, more research should be carried out in the usually neglected urban watersheds in terms of NPS CSA and surface runoff CSA.

2.4   Decision Support Systems

As stated earlier, NPS hotspots in urban watershed need to be identified; proper type of urban LID BMPs need to be assigned to each NPS hotspot. While the development of GIS and distributed hydrologic models improves the model simulation in general, large quantity of data are generated consequently. A decision support system (DSS) is need to identify hotspots and assign proper LID BMP at a watershed scale, and to process large volume of information in a timely fashion. This section provides basic information of DSS and its application.

2.4.1 DSS and EDSS

An effective protection of our environment largely depends on the quality of the available information used to make an appropriate decision. Problems arise when the quantities of available information are large and non-uniform (i.e., coming from many different disciplines or sources) and their quality could not be stated in advance (Cortés et al., 2000). Computers are central in contemporary environmental protection in tasks such as monitoring, data analysis, communication, information storage and retrieval, so it has been natural to try to integrate and enhance all these tasks with Artificial Intelligence knowledge-based techniques known as Decision Support Systems (DSS) (Cortés et al., 2000).

Many scientists have attempted to define the term "decision support system" (DSS), but the concept is extremely broad (Obropta, 2008). A common definition of DSS can be simplified as a computer-based information system that supports decision making. The term DSS has largely replaced the term "expert system", which was in wide use until 20 years ago. This change reflects the fact that our interest has shifted from replacing to assisting expert judgment. However, in order to provide substantial assistance to the expert decision maker, a DSS must provide efficient data gathering, organizing, storage, and manipulation capabilities; and it must communicate the resulting information effectively, through proper visualization, e.g. using geographical information systems (GIS) (Koutsoyiannis et al. 2003).

When applied to environmental issues, Decision Support Systems (DSS) are often called Environmental Decision Support Systems (EDSS). EDSS significantly reduce the

time in which decisions can be made while retaining the consistency and the quality of the decisions. These systems directly support decision-makers by offering criteria for the evaluation of alternatives or for justifying decisions. (Cortés et al., 2000)

Rizzoli and Young (1997) categorized the EDSS as a specialized type of DSS based on several aspects. One aspect is that the user of the EDSS are environmental scientists, environmental managers, and environmental stakeholders. The second aspect is the type of EDSS. Problem-specific EDSS can be used to tackle problems corresponding to a specific domain of knowledge. Situation-and problem-specific EDSS are tailored to a specific location and cannot be easily modified and applied in a new location. A third aspect is whether the EDSS is capable of handling spatial data management issues. Most EDSSs have a noticeable spatial dimension. This is addressed in terms of environmental modeling with spatially distributed models that demonstrate environmental phenomena in one (river models), two (air and water models), and three (land, air, and water quality models) components (Fedra1993; Lukasheh et al., 2001). The development of knowledge-based decision support systems for environmental planning requires the management of complex geospatial information, the integration of expert judgment with decision models, and the dynamic visualization of geographic terrain (Sikder, 2009).

2.4.2   Water Resource Management Decision Support System

A literature review by Cortés et al. (2000) of EDSS applications found that water management issues comprise the highest-ranked focus area with 25% of all references. DSS has also proven to be a useful and widely applied tool in environment (McIntosh et

al., 2011; Panagopoulos et al., 2012), policy support (van-Delden et al., 2011), and urban water management (Aulinas et al., 2011; Gualtieri, 2011).

Guariso et al. (1985) developed the first Water Resource Management Decision Support System (WRMDSS). Since then, many WRMDSSs have been developed, including WaterWare (Jamieson & Fedra, 1996a, b; Fedra & Jamieson, 1996), RiverWare (Zagona et al., 2001), L-THIA (Engel et al., 2003), mDSS (Mysiak et al., 2005), E2 (Argent et al., 2009), and other DSSs (David et al., 2012; Rowan et al., 2012).

The development of WRMDSS was prompted by two factors (Ge at al., 2013). One factor is that the ability of DSS to address semi- or un-structured problems is gradually increasing because of the integration of optimization methods (Azamathulla et al., 2008; Efendigil et al., 2008; Azamathulla et al., 2009), physical models (Mysiak et al., 2005; Zagona et al., 2001), geographical information systems (GIS) (Crossland et al., 1995; Liu, 2004; Qi & Altinakar, 2011), remote sensing (RS) (Jones and Barnes, 2000; Le Page et al., 2012), expert systems (ESs), and other technologies. GIS has ushered in a revolution in the development of distributed modeling (Ge at al., 2013). GIS has been widely applied to support the parameterization of many distributed models (Jamieson & Fedra, 1996a, b; Koutsoyiannis et al., 2003; Maia & Silva, 2009) due to its advantages in the analysis and visualization of spatial data. The other factor driving the development of WRMDSS is that each component of the water cycle with a higher spatial and shorter time resolution can be accurately calculated by means of the physical processes in the water cycle, which have been clearly described and simulated by scientists. In addition, the keys to developing a successful WRMDSS lie in fully understanding real water resources management problems

and dealing with the relationship among the applicability, maneuverability, and flexibility of systems (Mysiak et al., 2005;Argent et al., 2009).

2.4.3   Research in EDSS and WRMDSS

2.4.3.1   Water Resources Management

Waddle et al. (2007) developed a Decision Support Framework, which utilized the Commission's reservoir operations and stream flow routing model OASIS for water resources management in the Upper Delaware River. The framework included 1) the quantification of habitat metrics over a range of discharges and seasons; 2) development of a network-wide temperature simulation model; and 3) development of a prototype Delaware River Decision Support System (DRDSS) to assist the Commission and other stakeholders to analyze and interpret water management and reservoir operations alternatives.

Koutsoyiannis et al. (2003) developed a decision support system to support the management of the water resource system of Athens. The DSS included information systems that perform data acquisition, management and visualization, and models that perform simulation and optimization of the hydrosystem. Multiple, competitive targets and constraints with different priorities can be set with the system reliability and risk, the overall average operational cost and the overall guaranteed yield of the system.

Giordano et al. (2007) defined an integrated decision support system for consensus achievement (IDSS-C) which was able to support a participative decision-making process in all its phases. Problem structuring methods (PSM) and multi-group evaluation methods

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(MEM) were integrated in the IDSS-C. PSM was used to support the stakeholders in providing their perspective of the problem and to elicit their interests and preferences, while MEM were used to define not only the degree of consensus for each alternative, highlighting those where the agreement was high, but also the consensus label for each alternative and the behavior of individuals during the participative decision-making.

Almiñana (2010) presented the models and the algorithms which were being used in a decision support system (DSS) to determine water irrigation scheduling. The DSS provided dynamic scheduling of the daily irrigation for a given land area by taking into account the irrigation network topology, the water volume technical conditions and the logistical operations.

A decision support system was developed for supporting integrated water resources management in Daegu city, Republic of Korea (Zeng et al., 2012). The developed DSS contained four subsystems including database, model-base, and knowledge-base, as well as general user interface (GUI). It was then connected with the National Water Management Information System (WAMIS). The flow prediction was conducted through the incorporated HEC-HMS Version 3.0.1. Also, an urban water demand forecasting model was developed using an artificial neural network (ANN) based model. At the same time, a water resources management model based on genetic algorithm (GA) was developed in the DSS, facilitating efficient allocation of water resources among different regions within a city.

Ge et al. (2013) developed a DSS to provide an operative computer platform for decision makers to improve the water resource management of the inland river basins of

northwestern China. The DSS was used to aid in the decision-making process related to water allocation scheme planning and implementation and to aid real-time responses to changes in water supply, allowing a new water allocation scheme to be developed based on the actual relationship between the supply and demand for water.

Hadded et al. (2013) developed of a Decision Support System (DSS) for groundwater management using the WEAP-MODFLOW framework. Inputs to the hydrogeological model included natural recharge and inflow from higher neighboring aquifers. Outputs were mainly agricultural, touristic and urban water consumption. It was shown that the DSS developed was able to evaluate water management scenarios up to 2030, especially future water consumption, transmission link flow and active cell heads of the MODFLOW model for each time step.

The Dynamic Urban Water Simulation Model (DUWSiM) developed by Willuweit & O'Sullivan (2013) linked urban water balance concepts with the land use dynamics model MOLAND and the climate model LARS-WG, providing a platform for long term planning of urban water supply and water demand by analyzing the effects of urbanization scenarios and climatic changes on the urban water cycle in Dublin, the capital of Ireland.

Pierleoni et al. (2014) developed a Decision Support Systems for water resource allocation and management, the SimBaT. SimBaT was applied to the Montedoglio reservoir in the Tiber River Basin (Central Italy). The system returned information both on the distribution of the deficit at the weekly scale and on the likelihood that the critical events may occur depending on the availability and management of the volume stored in the Montedoglio reservoir. The case study showed how the combined use of models

addressing, on the one hand, the water resources management and, on the other hand, the climatic scenarios, can be useful in a field where data are highly variable in time.

2.4.3.2   Reservoir Management

Andreu et al. (1996) described a generic decision-support system (DSS) which was originally designed for the planning stage of decision-making associated with complex river basins.   Subsequently, it was expanded to incorporate modules relating to the operational stage of decision-making. These computer-assisted design modules allowed any complex water-resource system to be represented in graphical form, giving access to geographically referenced databases and knowledge bases.

Soncini-Sessa et al. (2003) developed a Decision Support System on water reservoir systems, which aimed at getting stakeholders and decision makers involved at every stage of the decisional process.

2.4.3.3   Crop Management

Sikder (2009) described the design and implementation of a knowledge-based interactive spatial decision support system for identifying the adaptability of crops at a given agro-ecological zone. The system (Eco-SDSS) illustrated the integration of an expert database ECOCROP 1 with Geographic Information Systems (GIS) to offer a flexible interface to identify tolerant plant species for a defined use and descriptions. The use of such tools offers increasing efficiency for potential extension and research in crop management and land use planning.

Balderama (2010) developed an integrated computer program called Cropping System and Water Management Model (CSWM) with a three-step feature (expert system—simulation—optimization) to address a range of decision support for rainfed farming, i.e. crop selection, scheduling and optimization. The system was used for agricultural planning with emphasis on sustainable agriculture in the rainfed areas through the use of small farm reservoirs for increased production and resource conservation and management.

2.4.3.4   Nonpoint Source Pollution (NPS)

Osmond et al. (1997) developed a computer-based decision support and educational software system, WATERSHEDSS, to aid managers in defining their water quality problems and selecting appropriate NPS control measures. This software was used to transfer water quality and land treatment information to watershed managers in order to assist them with appropriate land management/land treatment decisions; to assess NPS pollution in a watershed based on user-supplied information and decisions; and to evaluate, through geographical information systems-assisted modeling, the water quality effects of alternative land treatment scenarios.

Djodjic et al. (2002) developed a decision support system (DSS) consisting of the Maryland Phosphorus Index (PI), diagnosis expert system (ES), prescription ES, and a nonpoint-source pollution model, Ground Water Loading Effects of Agricultural Management Systems (GLEAMS), and applied the DSS to an agricultural watershed in southern Sweden. This system was used to identify critical source areas (CSAs) regarding phosphorus losses within the watershed, make a diagnosis of probable causes, prescribe

the most appropriate best management practices (BMPs), and quantify the environmental effects of the applied BMPs.

Zhang et al. (2006) introduced an integrated decision support system, NPSDSS (nonpoint source decision support system), to resolve the problem of setting up proper management practices in Dianchi Lake catchment area, a watershed with various landuses. The system was developed in a unique platform and integrated with the IMPULSE (integrated model of nonpoint source pollution processes) model, a stand-alone geographic information system (GIS) toolbox, a well-structured database, a measure screening model, and an expert system, as well.

Sadegh-Zadeh et al. (2007) used a decision support system in the framework of the geographic information system (GIS) and subsurface flow model to identify critical areas from simulated spatial distributions of relative nitrogen export. Diagnosis and prescription Expert Systems (ES) were developed and applied to the identification of probable causes of excessive nitrogen export and selection of appropriate Best Management Practices (BMPs) in a small agricultural watershed in Dorchester County, Maryland.

Panagopoulos et al. (2012) demonstrated a new methodology and associated decision support tool that suggests the optimal location for placing BMPs to minimize diffuse surface water pollution at the catchment scale, by determining the trade-off among economic and multiple environmental objectives. The decision support tool consists of a non-point source (NPS) pollution estimator, the SWAT (Soil and Water Assessment Tool) model, a genetic algorithm (GA), which serves as the optimization engine for the selection and placement of BMPs across the agricultural land of the wider Arachtos catchment

located in the western part of Greece, and of an empirical economic function for the estimation of the mean annual cost of BMP implementation.

2.4.3.5   Waste Treatment Plans

To assist in improving the solid waste decision-making process, which involve a variety of factors such as economic costs, legislative requirements, land use, pollution generation, resource usage and equity in the number and demographics of people affected by a plan, a specific spatial decision support system (SDSS) developed to address the multi-attribute and geographical nature of solid waste systems (MacDonald, 1996). The SDSS included expert systems and model management capabilities to supply, organize and analyze relevant data, and a GIS to help planners understand the spatial nature of particular programs and how they may impact the public and the environment.

A decision support methodology for the selection of a wastewater treatment system based on integrated urban water management principles for a remote settlement with failing septic systems was developed (Tjandraatmadja et al., 2013). Thirty-two service and treatment technologies options were considered. The options were assessed using a framework that considered technical, economic, environmental and social factors relevant to the local community and associated stakeholders (water utility, government agencies) and tools such as engineering design, life cycle assessment and multi-criteria analysis for evaluation of overall sustainability.

2.4.3.6   Landscape Ecological Evaluations

Young et al. (2000) developed a decision support system (DSS) which enables explicit prediction of the likely response of key features of the riverine environment to proposed flow management scenarios. The DSS did not include a detailed model of river hydrology or hydraulics, but rather, used the output from the range of such models currently in use in the BASINS (USEPA, 2013(g)) as inputs to the ecological models. The DSS provided a range of tools to allow user-defined evaluation of scenario results, as well as explanations and supporting information to elucidate the ecological modelling.

Engel et al. (2003) developed a DSS based, long-term hydrological impact assessment (L-THIA) web application to support decision makers who need information regarding the hydrologic impacts of water quantity and quality resulting from land use change.

Witlox et al. (2005) presented a state-of-the-art review of the use of expert systems in land-use planning in general and site selection in particular. It focuses on the theoretical discussion of different types of computer-based systems (i.e. expert systems, decision support systems, integrated systems) and tries to assess the usefulness of each system for the urban planner.

2.4.3.7   Others

Endreny (1999) took a developed statistical algorithm for combining the non-probability and probability data types and present an efficient process for implementing the desired data augmentation. In a case study simulated Environmental Protection Agency

(EPA) Environmental Monitoring and Assessment Program (EMAP) probability data were combined with auxiliary monitoring station data. The procedures for locating auxiliary stations, constructing an EMAP-SWS sampling frame, simulating pollutant exposure, and combining EMAP and auxiliary stations were developed as a decision support system (DSS). The benefit of using auxiliary stations in EMAP estimates was measured as the decrease in standard error of the estimation of water quality.

Water restoration and rehabilitation measures in the Netherlands had been realized, triggered by governmental subsidies, on a first-come-first-served basis. Claassen (2007) suggested an urgent need to have a simple, easily applicable DSS for regional water management more well-considered setting of priorities for selecting restoration projects. In his research, two examples were presented of methods used by setting priorities between areas, and three examples by making choices between measures within a limited area.

Chang et al. (2013) developed a Rule-based Decision Support System (RBDSS), a methodology to generate near-optimal sensor deployment strategies with low computational burden, such as those often encountered in large-scale optimization analyses. Three rules were derived to address the efficacy and efficiency characteristics of such a sensor deployment process: (1) intensity, (2) accessibility, and (3) complexity rules. The case study showed that RBDSS was able to generate the near-optimal sensor deployment strategies for small scale drinking water distribution networks relatively quickly. The RBDSS was transformative and transferable to drinking water distribution networks elsewhere with any scale.

2.5   Climate Change

A stormwater management plan is generally expected to be completed and maintain effective within a period of time.   Therefore, it is important for researcher and policy makers to take into account the changing climate when making a plan. This section briefly explains the IPCC climate change projections. Literature related to BMP under changing climate are included and research gap is presented.

2.5.1   IPCC Climate Projections in the Fourth Assessment Report (AR4)

IPCC SRES (Special Report on Emissions Scenarios) scenarios were constructed to explore future developments in the global environment with special reference to the production of greenhouse gases and aerosol precursor emissions. The IPCC SRES scenarios contain various driving forces of climate change, including population growth and socio-economic development. These drivers encompass various future scenarios that might influence greenhouse gas (GHG) sources and sinks, such as the energy system and land use change. The evolution of driving forces underlying climate change is highly uncertain. This results in a wide range of possible emissions paths of greenhouse gases. (ESS, 2014)

The SRES team defined four narrative storylines, labeled A1, A2, B1 and B2, describing the relationships between the forces driving greenhouse gas and aerosol emissions and their evolution during the 21st century for large world regions and globally. Each storyline represents different demographic, social, economic, technological, and

environmental developments that diverge in increasingly irreversible ways (ESS, 2014). The four development scenarios are:

- A1: globalization, emphasis on human wealth Globalized, intensive (market forces), moderate growth

- A2: regionalization, emphasis on human wealth Regional, intensive (clash of civilizations), rapid growth

- B1: globalization, emphasis on sustainability and equity Globalized, extensive (sustainable development), sustainable growth

- B2: regionalization, emphasis on sustainability and equity Regional, extensive (mixed green bag)

The A1 storyline and scenario family describes a future world of rapid economic growth, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies. Major underlying themes are convergence among regions, capacity building, and increased cultural and social interactions, with a substantial reduction in regional differences in per capita income. The A1 scenario family develops into three groups that describe alternative directions of technological change in the energy system. The three A1 groups are distinguished by their technological emphasis: fossil intensive (A1FI), non-fossil energy sources (A1T), or a balance across all sources (A1B).

The A2 storyline and scenario family describes a heterogeneous world. The underlying theme is self-reliance and preservation of local identities. Fertility patterns across regions converge slowly, which results in continuously increasing global population.

Economic development is primarily regionally oriented and per capita economic growth and technological change are more fragmented and slower than in other storylines.

The B1 storyline and scenario family describes a convergent world with the same global population that peaks in midcentury and declines thereafter, as in the A1 storyline, but with rapid changes in economic structures toward a service and information economy, with reductions in material intensity, and the introduction of clean and resource-efficient technologies. The emphasis is on global solutions to economic, social, and environmental sustainability, including improved equity, but without additional climate initiatives.

The B2 storyline and scenario family describes a world in which the emphasis is on local solutions to economic, social, and environmental sustainability. It is a world with continuously increasing global population at a rate lower than A2, intermediate levels of economic development, and less rapid and more diverse technological change than in the B1 and A1 storylines. While the scenario is also oriented toward environmental protection and social equity, it focuses on local and regional levels.

2.5.2   Research on BMP and Climate Change

Several studies have analyzed the long-term effects of structural Best Management Practices (BMP) on water quality (e.g. Kirsch et al., 2002; Chaplot et al., 2004; Tripathi et al., 2005; Pandey et al., 2005 or Behera and Panda, 2006; Bracmort et al., 2006). Researchers are increasingly worried about how climate change would affect the BMPs' effectiveness. However, the majority of the sensitivity analysis of BMPs under climate

change has been carried out in a one-BMP-at-a-time way and each type of BMPs has been applied to the entire study area in watershed scale studies.

Onuşluel Gül et al. (2010) provided a systematic procedure for sensitivity analysis, calibration, and validation in the SWAT model to evaluate existing flow regimes in a small-sized catchment in Denmark and examines a simple simulation to help quantify the effects of climate change on regional water quantities.

Karamouz et al. (2011) proposed an algorithm for selecting the BMPs to improve the system performance and reliability in dealing with urban flash floods that considers the anthropogenic and climate change effects. First, the future rainfall pattern of the study area under climate change impact was simulated. Then, the effectiveness of present and future development projects for improvement of drainage system performance was evaluated under different scenarios. Also, the effect of solid wastes and sediments carried with surface runoff in system performance was considered. Finally, feasibility of suggested BMPs and their effectiveness in urban flood management as well as their related costs and benefits are considered. The results of the study showed the significance of using analytical and management tools in assessing and improving the urban drainage system.

Wilson et al. (2011) predicted the future impacts of urban land use and climate changes on surface water quality within Des Plaines River watershed, Illinois, between 2010 and 2030. Land Change Modeler (LCM) was used to characterize three future land use/planning scenarios. Each scenario encourages low density residential growth, normal urban growth, and commercial growth, respectively. Future climate patterns examined include the Intergovernmental Panel on Climate Change (IPCC) Special Report on

Emission Scenario (SRES) B1 and A1B groups. The Soil and Water Assessment Tool (SWAT) was employed to estimate total suspended solids and phosphorus concentration generated at a 10 year interval. The combined land use and climate change analysis revealed land use development schemes that can be adopted to mitigate potential future water quality impairment.

Woznicki and Nejadhashemi (2012) determined how the sensitivity of BMPs performance vary due to changes in precipitation, temperature, and CO2 using the Soil and Water Assessment Tool. The monthly sensitivity analysis revealed that BMP sensitivity varies largely on a seasonal basis for all climate change scenarios. The results of this research suggest that the majority of agricultural BMPs tested in this study are significantly sensitive to climate change.

Chiang et al. (2012) evaluated 171 management practice combinations for their performances in improving water quality in a pasture-dominated watershed with dynamic land use changes during 1992–2007 by using the Soil and Water Assessment Tool. These selected BMPs were further examined with future climate conditions (2010–2069) for understanding how climate change may impact BMP performance. Results of this study demonstrate that watershed management should incorporate comparative analysis of various suites of BMPs, in addition to those implemented previously or under consideration for the future.

Woodbury and Shoemaker (2012) used a combination of two modified versions of the SWAT 2005 model to estimate the impact of several best management practices on phosphorus loading to the agricultural watershed. The long-term impacts of these scenarios

are investigated using historical data and stochastically generated weather data that incorporate projected climate change. The results indicated an increasing amount of total P loading to the reservoir in three out of the four management scenarios, regardless of increasing or decreasing precipitation. The results suggest that unless effective management practices are put in place, total P loading to the reservoir is projected to increase regardless of climate.

Jayakody et al. (2014) investigated climate change impacts on monthly sediment and nutrient transport, and efficiency of best management practices (BMPs) in the forest dominated watershed. The research found out that sediment, nitrogen and phosphorus loadings were increased in future climate conditions. The effectiveness of BMPs on sediment removal was reduced in future climate conditions, and the efficiency of nitrogen removal was increased, whereas phosphorus removal efficiency remained unchanged.

Woznicki and Nejadhashemi (2014) quantified the level of uncertainty in performance of seven agricultural BMPs due to climate change in reducing sediment, total nitrogen, and total phosphorus loads. The Soil and Water Assessment Tool coupled with mid-21st century climate data from the Community Climate System Model were used to quantify the spatial and temporal uncertainty for each BMP. Temporal uncertainty was determined to vary considerably for all BMPs. Spatial variation in BMP uncertainty was found to be prevalent in the study area and differed between climate scenarios and practices. The authors concluded that performance uncertainty should not be ignored when developing BMP implementation plans to address climate change adaptation.

Bosch et al. (2014) used the Soil and Water Assessment Tool to simulate various climate scenarios with a range of BMPs to assess possible changes in water, sediment, and nutrient yields from four agricultural watersheds. The results showed much greater yield increases associated with scenarios of more pronounced climate change, indicating that above certain threshold climate change may markedly accelerate sediment and nutrient export. The results also indicated the importance of targeting specific management strategies for individual watersheds.

Ahmadi et al. (2014) used the hydrologic model SWAT in a primarily agricultural watershed to simulate hydrologic and water quality processes on a daily basis over the 2015–2099 time horizon. Stream flow, sediment and total nutrient loads did not differ noticeably between assessment periods. However, the proportion of dissolved to total nutrients increased significantly from early-century to late-century periods. Changes in pollutant fluxes showed pronounced monthly variability.

Park et al. (2014) used SWAT to evaluate the present and future proper BMP scenarios for Chungju dam watershed, which includes rice paddy and upland crop areas. BMPs of streambank stabilization, building recharge structures, conservation tillage, and terrace and contour farming were examined individually in terms of reducing nonpoint source pollution loads by applying MIROC3.2 HiRes A1B and B1 scenarios for present (1981–2010) and future (2040s and 2080s). The results showed that streambank stabilization achieved the highest reductions in sediment and T-N, and slope terracing was a highly effective BMP for sediment and T-P removal in both present and future climate conditions.

Newcomer et al. (2014) carried out a field and HYDRUS-2D modeling study in San Francisco, California, USA to quantify urban recharge rates, volumes, and efficiency beneath a LID BMP infiltration trench and irrigated lawn considering historical El Nino/Southern Oscillation (ENSO) variability and future climate change using simulated precipitation from the Geophysical Fluid Dynamic Laboratory (GFDL) A1F1 climate scenario. The results demonstrated a clear benefit for recharge and local groundwater resources using LID BMPs.

Bär et al. (2015) used SWAT to identify the most vulnerable regions under three different climate change scenarios for agricultural water resources. The research concluded that the reasons of this vulnerability was because of diminishing irrigation potential caused by reduced precipitation.

2.6 Hydrologic Model SWAT

In need of hotspot identification and BMP recommendation in high spatial resolution, and urban LID BMP modeling in a simpler way, SWAT was selected as the modeling environmental in this study. This section provides some basic information of SWAT. Literature related to SWAT are included to demonstrate SWAT's ability of simulating various type of watersheds. This section is not included in Chapter 3 because most material are summarized from SWAT's user manual (Neitsch, 2005) and based on literature review.

2.6.1   SWAT Basics

In this research, Soil and Water Assessment Tool (SWAT) was selected as the modeling system. One reason is that SWAT is powerful enough to model almost all characteristics in different watersheds. Another reason is as indicated by Gassman et al. (2007), its key strength is a flexible framework allowing the simulation of a wide variety of structural and nonstructural BMPs. SWAT is also capable of simulating vegetation and simulate long-term effects. It can easily facilitate any change related to watershed characteristics or climate.

Soil and Water Assessment Tool (SWAT) (Arnold, 1985) is semi-distributed watershed scale modeling environment developed for predicting the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, land use and management conditions over long periods of time (Neitsch, 2005).

As a distributed model, SWAT represents a watershed at three levels: basin level, subbasin level, and Hydrologic Response Units (HRU) level. Basin level representations refer to characteristics that are uniform throughout the whole watershed. Subbasins are determined according to geological location and stream network. HRUs are defined as a unique combination of soil types, land used conditions, and topography (land slope).

Simulation of the hydrology of a watershed in SWAT can be separated into two major categories: land phase and the routing phase of the hydrologic cycle. The land phase controls the amount of water, sediment, nutrient and pesticide loading to the main channel from each HRU. The land phase includes simulations in climate, hydrology, land cover,

erosion, nutrients, pesticides, and management. The routing phase determines the movement of water, sediments, nutrients and other constituents through the channel network and waterbodies of the watershed to the outlet. In routing phase, SWAT also simulates the transformation of chemicals in the stream and streambed. The land phase generally represents the water cycles within subbasins and the routing phase represents the water flow among subbasins. (Neitsch, 2005)
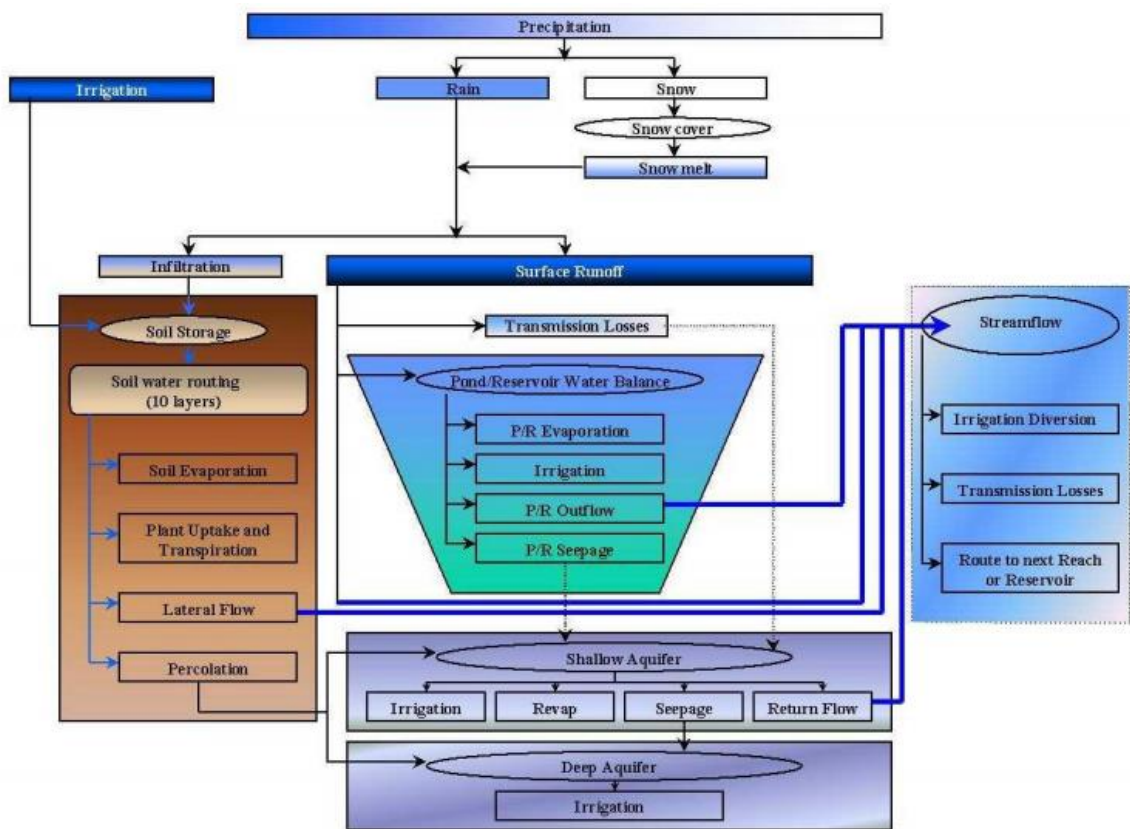
Figure 2-1 The land phase hydrologic processes modeled in SWAT (Neitsch, 2005)

The land phase of the hydrologic cycle simulated by SWAT is based on the water balance equation:

$$SW_t = SW_o + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}) \qquad Eq.\,2.1$$

where t is the time, i is the time index, SWt is the final soil water content on day i, SWo is the initial soil water content on day i, R$_{day}$ is the amount of precipitation on day i, Q$_{surf}$ is the amount of surface runoff on day i, E$_a$ is the amount of evaporation on day i, w$_{seep}$ is the amount of water entering the vadose zone from the soil profile on day i, Q$_{gw}$ is the amount of return flow on day i.

Erosion and sediment yield are estimated for each Hydrologic Response Unit with the Modified Universal Soil Loss Equation (MUSLE). MUSLE uses the amount of runoff to simulate erosion and sediment yield. The hydrology model supplies estimates of runoff volume and peak runoff rate which, with the subbasin area, are used to calculate the runoff erosive energy variable. Erosion and sediments are modeled using a modified Universal Soil Loss Equation (MUSLE). (Neitsch, 2005)

$$sed = 11.8\big(Q_{surf} \cdot q_{peak} \cdot area_{hru}\big)^{0.56} \cdot K_{USLE} \cdot C_{USLE} \cdot P_{USLE} \cdot LS_{USLE} \cdot CFRG \qquad Eq.\,2.2$$

where sed is the sediment yield on a given day (tons), Q_{surf} is the surface runoff volume (mm/ha), q_{peak} is the peak runoff rate (m^3/s), K_{USLE} is the soil erodibility factor, C_{USLE} is the cover and management factor, P_{USLE} is the support practice factor, LS_{USLE} is the topographic factor, and $CFRG$ is the coarse fragment factor.

SWAT tracks the movement and transformation of several forms of nitrogen (N) and phosphorus (P) in the watershed. The different forms of N and P are subjected to transport in solution, transport with sediments, uptake by plants, and other processes. Nutrients may be introduced to the main channel and transported downstream through surface runoff and

lateral subsurface flow. Major nutrients (N and P) partitioning are represented in Fig. 2-2 and Fig. 2-3. (Neitsch, 2005)
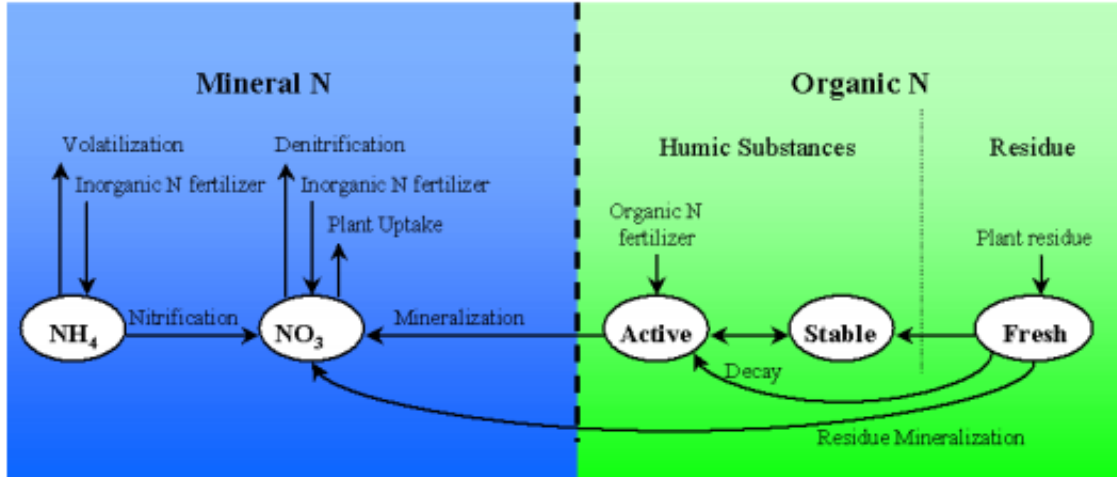
Figure 0.6: Partitioning of Nitrogen in SWAT

Figure 2-2 The partitioning of Nitrogen in SWAT (Neitsch, 2005)
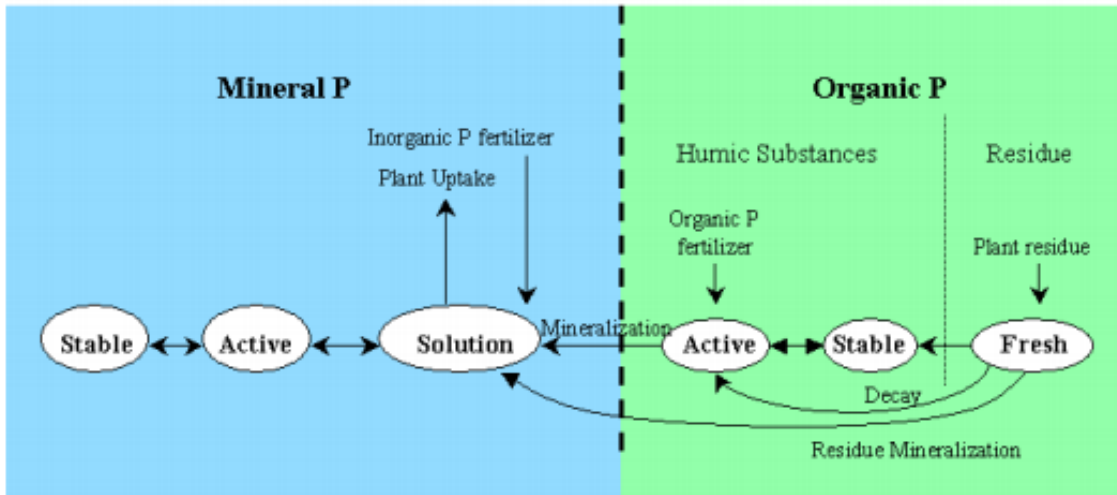
Figure 0.7: Partitioning of Phosphorus in SWAT

Figure 2-3 The partitioning of Phosphorus in SWAT (Neitsch, 2005)

2.6.2   SWAT Input and Output Files

Input for SWAT is defined at one of several different levels of detail: watershed, subbasin, and HRU. Unique features such as reservoirs or point sources must have input data provided for each individual feature included in watershed simulation.

Watershed level inputs are used to model processes throughout the watershed. Subbasin level inputs are inputs set at the same value for all HRUs in the subbasin if the input pertains to a process modeled in the HRU. HRU levels inputs are inputs that can be set to unique values for each HRU in the watershed. Each subbasin needs 3 required input files, and each HRU needs 4 required input files. For more information about other input files, please refer to Neitsch (2005).

A number of output files are generated in every SWAT simulation: the summary input file (input.std), the summary output file (output.std), the HRU output file (output.hru), the subbasin output file (output.sub), and the main channel or reach output file (output.rch). The most useful output file in this reach is the output.rch file and the output.hru file. The main channel output file contains summary information for each routing reach in the watershed. The variables that are included in this file and are used in this research include average daily stream flow (cms), sediment transported (tons), nitrogen transported (kg), and phosphorus transported (kg). The HRU output file contains summary information for each of the hydrologic response units in the watershed. The variables that are included in this file and are used in this research are variable per-area values being simulated for each HRU: surface runoff (mm), sediment yield (tons/ha), nitrogen (kg/ha) in different forms, and phosphorus (kg/ha) in different forms.

2.6.3   ArcSWAT

The ArcSWAT ArcGIS extension is a graphical user interface for the SWAT model (Winchell et al., 2007). The ArcSWAT ArcGIS extension evolved from AVSWAT2000, an ArcView extension developed for an earlier version of SWAT. The interface requires the designation of landuse, soil, weather, groundwater, water use, management, soil chemistry, pond, and stream water quality data as well as the simulation period, in order to ensure a successful simulation.

The key procedures included in SWAT input preparation and SWAT simulation are: Delineate the watershed and define the HRUs, Edit SWAT databases, Define weather data, Apply the default input files writer, Edit the default input files, Setup and run SWAT, Apply a calibration tool, Analyze, plot, and graph SWAT output (Winchell et al., 2007).

2.6.4   Customizing SWAT for Simulating Various Types of Watersheds

SWAT has been widely used in modeling water quantity and water quality. Not only can SWAT simulate various type of watersheds, and facilitation changes, it also provide the opportunity for modelers to modify the program itself to accommodate special cases and situations in each watershed.

By adding a snowfall–snowmelt routine for mountainous terrain in SWAT, Fontaine (2002) was able to make SWAT to simulate hydrology of a non-agricultural mountainous region with a large snowmelt component.

Vazquez-Amabile (2005) expanded SWAT's capabilities to compute perched groundwater table depth. Van Griensven (2005) used a time step of a user-defined fraction of an hour and an hourly time step to calculate the rainfall/runoff and the in-stream river routing processes, respectively. And he further improved the hydrologic module by including a convolution module and modifications of the evapotranspiration module of SWAT.

Tolson and Shoemaker (2007) used a modified version of SWAT 2000 to simulate excess soil water movement in frozen soils in Cannonsville Reservoir Watershed. Abbaspour et al. (2007) used SWAT to simulate all related processes affecting water quantity, sediment, and nutrient loads in the Thur River basin (area 1700 km2). The main objectives were to test the performance of SWAT and the feasibility of using this model as a simulator of flow and transport processes at a watershed scale.

Baffaut and Benson (2008) modified the SWAT 2005 code to simulate faster aquifer recharge in Karst environments for the James River Basin in Southwest Missouri. Echegaray (2009) further modified the SWAT-Karst to represent Karst environments at the HRU scale. Liu and Yang (2008) used a mass balance algorithm and created an SWAT extension which can simulate riparian wetlands hydrologic processes.

To develop a distributed hydrological cycle model of an irrigation district, Zheng et al. (2010) modified the SWAT model in the aspects of the extraction of ditches, distributed subbasins and hydrologic response units, and the calculation method of the crop's actual ET. To improve SWAT performances in runoff simulation in small basins, Kim (2010)

improved the channel routing module of SWAT by developing a new channel routing mechanism.

White et al. (2010) changed the curve-number based SWAT into a new water-balance-SWAT, improving watershed runoff simulation in conditions such as monsoonal climates and areas dominated by variable source area hydrology. To address the special hydrological processes and crop yields in paddy rice areas, Xie (2011) developed the SWAT model by incorporating new processes for irrigation and drainage.

Pisinaras et al. (2010) used SWAT2005 to simulate the Kosynthos River watershed located in Northeastern Greece. The study showed that SWAT model, if properly validated, can be used effectively in testing management scenarios in Mediterranean watersheds. The SWAT model application, supported by GIS technology, proved to be a flexible and reliable tool for water decision-making, especially under the need for harmonization with the Water Framework.

Bonumá et al. (2012) modified the Soil and Water Assessment Tool to simulate the landscape transport capacity of sediment. The results suggested that integration of the sediment deposition routine in SWAT increased accuracy in steeper areas while significantly improving its ability to predict the spatial distribution of sediment deposition areas.

Ficklin (2012) used the SWAT to model hydrology, sediment, nitrate and pesticide transport components for the Sacramento River watershed. Results indicated that best management practices, such as pesticide use limits during wet seasons, could improve water quality in the Sacramento River watershed.

Einheuser et al. (2012) identified influential stream variables simulated from SWAT that correlate with macroinvertebrate indices using biophysical and statistical regression models. The models developed were used to evaluate the impact of three agricultural management practices on stream integrity.

2.7   Calibration Tool PEST

Parameter Estimation (PEST) was utilized for auto-calibration of the SWAT models. Some basic concepts used in PEST are presented here as background information. References related to PEST are included to illustrate the wide application of the software.

2.7.1   Basic Features of PEST

PEST (acronym for Parameter ESTimation) is a nonlinear parameter estimation package. The purpose of PEST is to assist in data interpretation, model calibration and predictive analysis, where model parameters need to be adjusted until model-generated numbers fit a set of observations as closely as possible then, provided certain continuity conditions are met. Thus PEST, as a nonlinear parameter estimator, can exist independently of any particular model, yet can be used to estimate parameters and/or excitations, and carry out various predictive analysis tasks, for a wide range of model types (Doherty, 2004).

PEST must be provided with three types of input files containing the data which it needs in order to effectively take control of a particular model. The template files, instruction files, and a PEST control file which "brings it all together.

Of the masses of data of all types that may reside on a model's input files, those numbers must be identified which PEST is free to alter and optimize. This is a simple process which can be carried out using input file "templates". To construct a template file, simply start with a model input file and replace each space occupied by a parameter by a set of characters that both identify the parameter and define its width on the input file.

In order to peruse a model output file and read the observation values calculated by the model, PEST must be provided with a set of instructions. PEST requires, then, that for each model output file which must be opened and perused for observation values, an instruction file be provided detailing how to find those observations.

Once interfaced with a model, PEST's role is to minimize the weighted sum of squared differences between model-generated observation values and those actually measured in the laboratory or field; this sum of weighted, squared, model-to-measurement discrepancies is referred to as the "objective function".

2.7.2   Optimization Algorithm in PEST

PEST adjusts the parameter values to minimize the value of the objective function, which is the squared-weighted-residual, or the sum of squared weighted differences between model-generated observation values and those actually measured in the laboratory or field. Residuals are weighted to overcome the issue of non-constant variance of the residuals, to adjust for order-of-magnitude differences among observations having different units, or to impose priority on a user-selected set of observations. The objective function is:

$$\Phi = \sum_{i=1}^{m} (r_i w_i)^2 \qquad\qquad Eq.\,2.3$$

where w_i is the weight attached to the i'th observation; r_i (the i'th residual) equals the difference between the model outcome and the measurement for the i'th observation.

2.7.3   PEST Research

The model-independent program PEST has been widely used for parameter estimation and sensitivity analysis for soil and water related models. The modeling package Annualized Agricultural Nonpoint Source Model (AnnAGNPS) was applied to predict the export of nitrogen and phosphorus from Currency Creek, a small experimental catchment within the Hawkesbury–Nepean drainage basin of the Sydney Region. PEST was applied for sensitivity testing to determine and assess the relative importance of the key parameters of the model (Baginska et al., 2002)

George Zyvoloski (2003) presented several different conceptual models of the Large Hydraulic Gradient (LHG) region north of Yucca Mountain and described the impact of those models on groundwater flow near the potential high-level repository site. The numerical models were calibrated by matching available water level measurements using PEST, along with more informal comparisons of the model to hydrologic and geochemical information.

Wang and Melesse (2005) used PEST to adjust their SWAT model. They further modified the PEST-generated parameter values and determined that SWAT performs well in snowmelt hydrology. Islama and Wallender (2005) auto-calibrated their MIKE SHE

model with PEST to invest the effects of winter cover cropping practices on water availability.

In order to link the Army Remote Moisture System with the Land Information System (LIS), PEST was integrated into the process to optimize soil porosity and saturated hydraulic conductivity (Ksat), using the remotely sensed measurements, in order to provide a more accurate estimate of the soil moisture (Tischler & Garcia, 2006).

Iskra and Droste (2007) conducted a study on the effects of three automatic optimization techniques, Levenberg-Marquardt Method (PEST), Random Search Method and Shuffled Complex Evolution Method, on calibrating an HSPF model. The research found out that SCE performs best. And PEST can perform as well as SCE if the variables are properly adjusted, initial guess is good and insensitive parameters are eliminated from the optimization process.

In one study, PEST was used to calibrate the Noah land surface model and run at high spatial resolution across the Walnut Gulch Experimental Watershed. And the results demonstrated the potential to gain physically meaningful soil information using simple parameter estimation with few but appropriately timed remote sensing retrievals (Santanello, 2007).

In another study, methods of global analysis (Latin hypercube sampling, LHS) and gradient-based optimization (PEST, parameter estimation software) were explored to calibrate soil hydraulic parameters in the Root Zone Water Quality Model (RZWQM2). Errors in simulated soil water contents were reduced by using LHS to initialize and

constrain the PEST parameter space, which also stabilized the cross-validation results (Fang, 2009).

2.8   Study Areas

Two watersheds were selected in this research. One is the highly urbanized Watts Branch watershed. The other one is a small sub-urban watershed called Wilde Lake. More detailed description of the two watersheds are presented in this section. The basic information of Watts Branch and Wilde Lake watersheds is listed in Table 2-7.
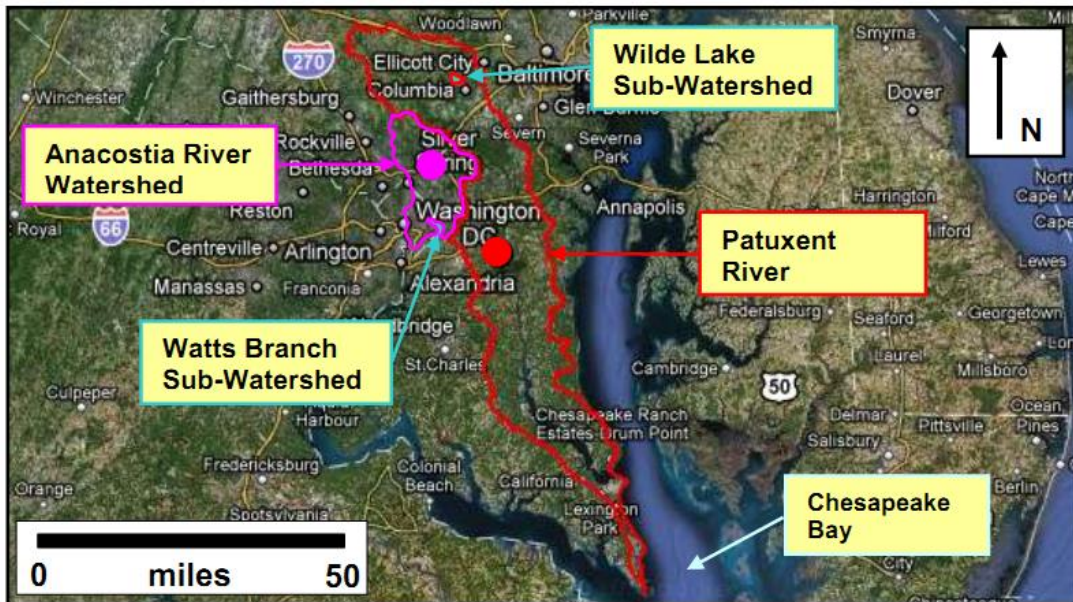
Figure 2-4 Area Map of the Two Study Watersheds (Leisnham et al., 2012)

2.8.1   Watts Branch

Watts Brach is the largest tributary that flows into the Anacostia River. It begins in Prince George's County, Maryland, and flows three miles northwest from the eastern

corner of Washington DC to meet the Anacostia River in Kenilworth Park (US EPA, 2013(d)). Watts Branch has a total length of approximately four miles, with drainage area of 3.53 square miles (US EPA, 2003). There is also a 0.3-mile tidal influenced section in Kenilworth Park.

The general soil associations found in the watershed can be broken down into three broad groups. Watts Branch itself flows through the Luka-Linside-Codorus association. These soils are deep, nearly level, moderately well drained ones that are underlain by stratified alluvial sediment or man-deposited dredged material on flood plains. The most prevalent general soil association in the DC portion of the watershed is the Urban land-Christiana-Sunnyside association. These soils are deep and are nearly level to steep, well drained soils that are underlain by unstable clayey sediment and are predominantly on uplands. A third minor association that Watts Branch flows through is the Urban land-Galestown-Rumford association which are also deep, nearly level to moderately sloping and somewhat excessively drained soils that are mostly sandy throughout and are a part of old terraces. (DC DOH, 2003)

The stream bed is dominated by gravels and sand, with silt and organic deposits in shallow pools. Numerous undercut banks are clays and some highly erodible sandy loams (DC DOH, 2003).

Watts Branch Watershed Hotspots
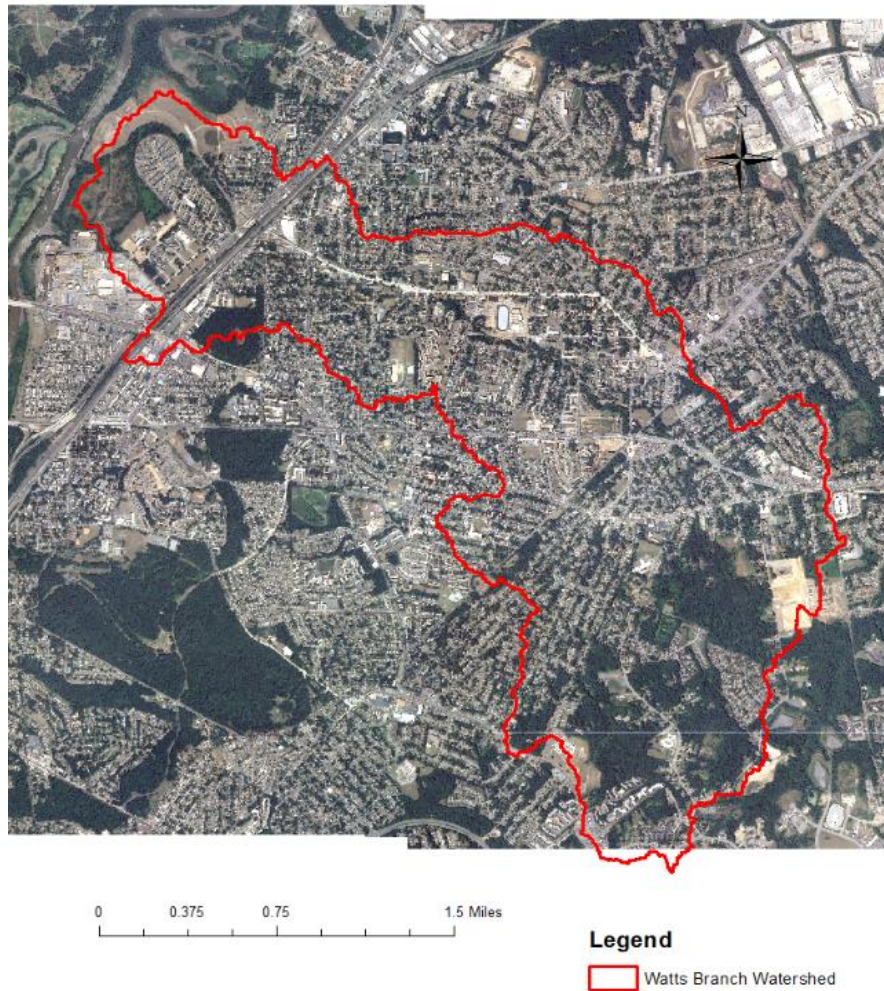
Figure 2-5 Satellite Image of Watts Branch Watershed

Prior to the twentieth century, large portion of the Anacostia watershed were converted from forests and meadows to crop land. Following World War II, the Anacostia watershed developed and grew in population (Shepp and Cummies, 1997). Now, the Watts Branch watershed is heavily urbanized, encompassing 3.03 square miles (85%) of urban residential land and 1.13 square miles (32%) of impervious surface. The change and development of the land use has caused serious water problem in this area. A major concern is total suspended solids (TSS) (US EPA, 2013(d)). Urbanization and stream alterations,

including channelization and floodplain loss, have contributed to increased volumes of stormwater runoff. The runoff severely eroded stream banks and mobilized high levels of total suspended sediment (TSS), which prevented the stream from supporting all of its designated uses (US EPA, 2013(d)).

According to the D.C. DOH (2003), "both the upper and lower reaches of Watts Branch exhibit moderate to high bank erosion. A lack of floodplain over time led to lateral erosion of the channelized stream, causing a higher width/depth ratio and elevated TSS levels. Monitoring conducted in 1997 indicated that the high TSS levels caused poor habitat conditions in the creek." The Upper Reach lost access to its floodplain due to fill and/or channel capacity enlargement. The loss of floodplain caused the stream to incise and entrench because it was forced to accommodate higher discharges within the active channel. Additionally, the channelization reduced the stream length and increased the stream slope, causing higher flow velocities which also promotes vertical and lateral erosion. A decrease in the sediment transport capacity in the Lower Reach is the result of two major conditions: 1) an increase in width/depth ratio and 2) a decrease in stream slope, due to the stream's proximity to the Anacostia River. Additional stream bank erosion may occur as the stream continues to aggrade and then attempts to develop a floodplain and meander pattern.

2.8.2   Wilde Lake

Wilde Lake is a man-made impoundment located in the Village of Wilde Lake, the first of Columbia's (Maryland) nine villages and Town Center (KCI, 2009). The site was originally a low-lying meadow covered with rough grass, with a small stream running

through it. The lake was constructed in 1966 as a regional stormwater facility. The lake is 22-acre and has a depth range from 13 feet at the back of the dam to 7-8 feet in the central part of the lake (Lakes of Columbia, 2013).

Wilde Lake watershed is 1.9 square miles and is almost fully built-out with most of the development occurring in the 1970s. Its development is primarily residential with some commercial, public schools, and active recreation parks. The Wilde Lake watershed is approximately 32% impervious cover and, based on zoning, is fully built out (KCI, 2009). The impervious cover in Wilde Lake changes the hydrology of streams, wetlands and floodplains. Higher pollutant loadings in urban stormwater have been observed. Higher transporting power of surface runoff increases channel erosion and transport the sediments into the lake, where dredging is needed periodically to maintain normal operations of the reservoir.

Most development above the lake was constructed in the 1960s and 1970s, with no on-site stormwater management controls (KCI, 2009). Because of this, the streams in this subwatershed have been affected by moderate to severe sediment loading and associated nutrients. Nonpoint sources of pollution stemming from stormwater runoff and associated stream channel erosion are the primary concern. Nutrient loads from residential areas in the Wilde Lake subwatershed and from agricultural areas in the Centennial Lake subwatershed are also of concern.
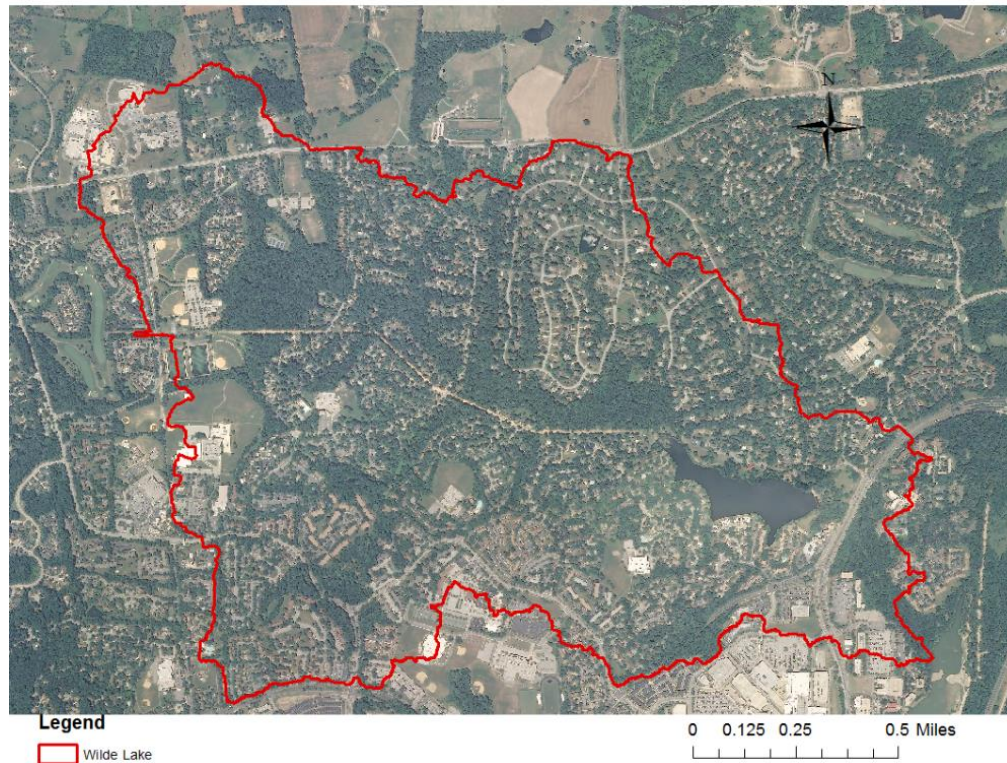
Figure 2-6 Satellite Image of Wilde Lake Watershed

Table 2-6 Basic Information of Watts Branch and Wilde Lake Watersheds

		WB	WL
Area (mi2)		3.72	1.95
Elevation (m)	Mean	41.43	125.06
	Min	1.57	90.98
	Max	92.53	152.32
Impervious area (%)		32.10	14.50
Land slope (%)	Mean	8.63	7.53
	Min	0.00	0.00
	Max	83.56	64.90
Dominant landuse types		Mid density residential area; High density residential area; Industrial and commercial	Low density residential; Forest
Mean soil erodibility		0.22	0.30

Chapter 3.   Research Methods

In this research, the distributed hydrologic model Soil and Water Assessment Tool (SWAT) was utilized as the modeling environment. It modeled the target watersheds and simulated the before-and-after-BMPs conditions. Parameter ESTimation (PEST) was used to auto-calibrate the SWAT model to ensure that the model accurately simulated the pre-BMP watershed conditions. The simulation results obtained from the calibrated SWAT model were used to identify the hotspots where pollutant level was high and critical for water quality improvements. The Diagnostic Expert System (DES) was developed to identify the possible causes of high NPS yield in the hotspots. The Prescriptive Expert System (PES) was then used to select a series of best BMPs for each hotspot. Total cost estimation was carried out for each prescribed BMP series. The whole DDSS and the cost estimation was coded in MATLAB. All results were visualized in GIS maps. The research methods are described in detail in this chapter.

3.1   Development of Watershed Models

The development of hydrologic models for the two study watersheds was performed in two major steps: model setup and model calibration (and validation). The SWAT model setup section (3.1.1) describes all input data needed for a successful SWAT run. The SWAT calibration section (3.1.2) details the model optimization process which is essential for a more accurate, site specific SWAT simulation.

3.1.1   SWAT Model Setup

The SWAT input files for the study watersheds were prepared using ArcSWAT (Winchell et al., 2007). The 1 arc/s Digital Elevation Model (DEM), which has a cell size of approximately 10m by 10m, was obtained from the USGS National Map Viewer (USGS, 2013a). This elevation map is needed for land slope calculation, flow-direction calculation, stream accumulation, and watershed delineation. Once the stream network is determined, the number of subbasins, location of point-source discharge, and location of reservoirs can be defined accordingly.

A 2006-version of landuse/ land cover map was retrieved from the National Map Viewer (USGS, 2013a). This map detailed the type of landuses within the study area. Major Landuses include forest land, agricultural land, wetlands, and urban land in general. The Soil map was retrieved from the US SSURGO database (USDA, 2013), which was available from USDA's Data Mart. Compared to STATSGO (USGS, 2013b), SSURGO data is substantially more spatially detailed. Land slope, landuse, and soil types are needed to define Hydrologic Response Unit (HRU) which is a smallest calculation unit in SWAT.

Besides the terrestrial information, weather data is also needed. The weather data includes precipitation, daily temperature, solar radiation, wind speed, and relative humidity. The data can be observed or simulated. In this study, each watershed was given one set of weather station values including daily temperature and precipitation data. The data were obtained from NOAA National Climate Data Center. The other three variables were not available for the weather station selected. Instead, the weather generation program embedded in SWAT generated series of simulated weather data based on the historical statistics provided in the SWAT database. The weather data covered the entire study period

of Oct.1, 2000 to Sept. 30, 2012. Table 3-1 summarizes the data name, type, version, and sources. The weather station name, location, and data availability are listed in Table 3-2.

Table 3-1 ArcSWAT Input Files

Data Name	Data Version/Type	Data Sources
Elevation DEM	1/9, 2008, Wilde Lake 1/1, Watts Branch	The national map viewer http://viewer.nationalmap.gov/viewer/
Land Cover	2006	
Soil	Shape Files	USDA http://soildatamart.nrcs.usda.gov/

Table 3-2 ArcSWAT Weather Input Files

Station Name	Station ID	Location	Elevation	Data Available
Washington National Airport, VA (Watts Branch)	448906	38.848 -77.034	3m	Daily Precipitation* Daily Max/Min Temperature* Oct.1, 2000 to Sept. 30, 2012
Baltimore Washington International Airport, MD (Wilde Lake)	180465	39.166 -76.683	47.5m	Daily Precipitation* Daily Max/Min Temperature* Oct.1, 2000 to Sept. 30, 2012

*Units: Pcp: tenth of mm; Tmp: tenth of degree C

3.1.2   SWAT Model Calibration

Parameter ESTimation (PEST) (Doherty, 2004) is a model-independent nonlinear parameter estimation package developed to assist in data interpretation, model calibration and predictive analysis (Doherty, 2004). PEST was used for SWAT auto-calibration in this study. Its sensitivity analysis package, SENSAN, was used for preliminary sensitivity analysis for the SWAT parameters.

3.1.2.1   Sensitivity analysis for SWAT parameters

Based on the literature (Gitau et al., 2008; Bracmort et al., 2006; Liu et al., 2012), 44 parameters which have the greatest influence on the stream discharge and water quality estimation were selected for sensitivity analysis. Although all these parameters are closely

related to hydrology and water quality, parameters might show different sensitivity when modeling different watersheds. Therefore, sensitivity analysis was conducted before calibrating the urban/suburban watersheds in this study. All candidate parameters are listed in Tables 3-3 to 3-5.

Table 3-3 Parameters Related to Hydrology

Hydrology Parameters	Definition
ALPHA_BF	Base flow recession factor
AWC	Available water capacity
CH-K1	Effective hydraulic conductivity in tributary channel alluvium
CH-K2	Effective hydraulic conductivity in main channel
CH-N1	Manning's n value for tributary channels
CH-N2	Manning's n value for main channel
CH-S1	Average Slope of tributary channels
CH-S2	Average Slope of main channel
CN2	Curve number antecedent moisture condition II
DELAY	Groundwater delay
ESCO, EPCO	Soil and plant evaporation compensation factors
GW-DELAY	groundwater delay time
GWQMN	Threshold depth of water in shallow aquifer
GW-REVAP	groundwater re-evaporation time
KSAT	Saturated hydraulic conductivity
SLOPE	Average slope steepness
SLSOIL	Slope length for lateral flow
SMFMX, SMFMN	Snow melt factor
SURLAG	Surface runoff lag coefficients

SENSAN is a utility in the PEST package developed for sensitivity analysis (Doherty, 2004). Sensitivity analysis on parameters in this study was carried out using this utility. The required input files are SENSAN control file, instruction files, and template files. SENSAN instruction files and template files are exactly the same as those used in PEST. Template files define which parameters should be adjusted during the calibration. Instruction files define what outputs would be used to be compared with the observations.

Table 3-4 Parameters Related to Sediments

Sediment Parameters	Definition
ADJ_PKR	Peak rate adjustment factor for sediment routing (tributary channels)
BIOMIX	Biological mixing efficiency
CANMX	Maximum canopy index
CH-COV	Channel cover factor
CH-EROD	Channel erodibility of the soil layer
PRF	Peak rate adjustment factor for sediment routing
SLSUBBSN	Average slope length
SPCON	Linear coefficient for sediment routing
SPEXP	Exponent coefficient for sediment routing
USLE-C	USLE cropping factor
USLE-P	USLE support practice factor

Table 3-5 Parameters Related to Nutrients

Nutrients Parameters	Definition
A10	Ratio of chlorophyll-a to algae biomass
A12	Fraction of algal biomass that is phosphorus
BC4	Rate constant for mineralization of P to dissolved P
NPERCO	Nitrogen percolation coefficient
PHOSKD	Phosphorus partitioning coefficient
RHOQ	Algal respiration rate @ 20ºC
RS1	Local algae settling rate @ 20ºC
RS2	Benthic source rate for dissolved P
RS5	Organic P settling rate in the reach @ 20ºC
SOL_LABP	Initial soluble P concentration in soil layer
SOL_NO3	Initial NO3 concentration in the soil layer
SOL_ORGN	Initial organic N concentration in soil layer
SOL_ORGP	Initial organic P concentration in soil layer
UBP	Phosphorus uptake distribution parameter

The sensitivity analysis was based on the one-at-a-time method. The SWAT default values were defined as a base-parameter set. The model simulation using this specific parameter set was defined as the base-simulation. In each simulation, only one parameter value was changed. Each parameter was given 4 different values other than the default

value. A general rule for the four values were set to be ±10% and ±20% of the default value. If the default values were zero, a fixed increment was applied to each of the four values. For the 44 parameters, 176 SWAT simulation were carried out by SENSAN. Three sets of reports were generated and further analyzed for parameter sensitivity.

The most influential adjustable parameters were determined based on the sensitivity analysis results. The PEST tool was then asked to calibrate the SWAT models by adjusting the selected influential parameters. To take into account the geographical differences of the whole watershed, the parameters were further divided into sub-parameters which were grouped based on soil types, land uses, or plant types. The grouping method is similar to Wang & Brubaker (2013).

3.1.2.2   PEST model setup

In this study, both water quantity and water quality variables were of interest. Therefore, observations of stream discharge, sediment yield, total N yield, and total P yield were required for model calibration.

The Watts Branch SWAT model (WB_SWAT) was calibrated over daily stream discharge obtained from the USGS gauging station No. 01651800 (Watts Branch at Washington DC) which is located at the outlet of subbasin 9 (Fig. 4-1). The station keeps a record of over 20 years of daily stream discharge values (available from 06/19/1992 until now). The data coverage rate is nearly 100%. The entire study period was from Oct. 1, 2000 to Sept. 30, 2012. Water years were used in order to keep the continuity of hydrological processes during the winter months. The first 9 years were selected as model

calibration period, the remaining 3 years as model validation period. No missing discharge data was observed in the study period. A warm-up/spin-up period is needed for SWAT in order to avoid the effects of non-realistic initial model conditions such as initial soil water content and initial curve number. Therefore, the 2000 and 2001 water years were not included in the calibration process in order to gain a better calibrated model with which to represent the watershed. Similarly, water year 2008 was excluded from any statistical analysis needed for model validation.

There were also a few water quality data collected sporadically in water years from 2006 to 2009. The water quality data included event-based total sediments, nitrogen, and phosphorus. Calibrating over these water quality data may not give the most accurate simulation results, but the magnitude of the model outputs were expected to become more reasonable than with an un-calibrated model. The samples can at least provide some reference data points.

Limited hydrologic and water quality data were available for calibrating the Wilde Lake SWAT model (WL_SWAT). The USGS gauging station located at Little Patuxent River Tributary above Wilde Lake at Columbia was not functioning until Oct. 1, 2012. The water quality samples were taken in 2008 to 2011. Therefore, WL_SWAT model was calibrated in a slightly different time period. Water years from 2002 to 2011 were selected for model calibration. Water years from 2012 to 2014 were selected for model validation. The paucity of data was somewhat representative of the conditions that modelers face when modeling the hydrology of small urban watersheds.

The PEST is directed to extract the desired SWAT model outputs and compare the simulated values with the observations. This is done through the user defined instruction files, which tell PEST the location (rows and columns) of the desired data in a specific SWAT output file. In this study, daily stream discharge were extracted from the "Flow_Out" column in the "output.rch" file. Sediments and nutrients were compared with the columns "Sediment Yield", "Total N", and "Total P" in the same output file.

The PEST template files were produced based on the SWAT input files. A parameter name identified by "##" was applied to all adjustable parameters in SWAT input files that contain the sensitive parameters. PEST adjusted those parameters in each iteration according to the parameter range provided in the PEST control file.

3.2   Urban BMP Modeling

The BMPs of concern in this study were the small-scaled structural and non-structural BMPs referred to as Green Infrastructures (GI) elements and usually used as part of Low Impact Development (LID). The term LID BMP is used in this document to represent this type of BMPs. These relatively less expensive and less space-consuming BMPs are more likely to be adopted by urban residents whose roofs, lawns, and back yards would be used/partially used for installing the BMPs. Compared to the conventional large scale BMPs such as detention basins, the LID BMPs are more likely to benefit urban areas where large open space is less available and large area of imperviousness accelerates the stormwater recharge into MS4.

Eight candidate BMPs were included in this research: Pervious Pavements (PP), Vegetated Filter Strips (VFS), Rain Barrels (RB), Green Roof (GR), Native Landscaping (NL), Rain Gardens (RG), Fertilizer Reduction (FR), and Infiltration Trench (IT). These BMPs were represented by one or several SWAT parameters. A four-step procedure, similar to Arabi et al. (2008) was developed to determine how each BMP should be expressed in SWAT. Different BMPs work via different mechanisms. Some function through rainwater storage, some through filtration or infiltration. Therefore, the first step was to identify the main working mechanism, the hydrological and chemical processes involved in each BMP. Secondly, SWAT parameters which represent the hydrological/chemical processes were identified. The parameters can be existing ones clearly defined as part of a BMP in the SWAT model, such as filter strip width (FILTERW) which is already defined in the SWAT model for modeling vegetated filter strips. The parameters can also be general ones related to the physical characteristics of the HRU, such as curve number and soil erodibility factor which are used in SWAT to model general HRU level hydrology. Thirdly, sensitivity analysis was carried out for the selected parameters to test whether changes of the parameters would change the hydrologic response of the HRU and how much. This step was not important though. Sometimes, even if a parameter did not influence the overall simulation results, the parameter was still worth editing in order to mimic certain characteristics of the BMP. Finally, the parameter values and how much these values should be changed were determined according to observed reduction rates gathered from real world BMP projects and literature. When no observed data were available, the value changes were estimated based on physical reasoning.

In the following section, the definition and main function of each BMP is obtained from EPA. The mechanism of each BMP are described in detail. Some special requirement and limitations for BMP implementation are included. SWAT parameters related to each BMP are also listed. The observed NPS reduction rates are listed in Section 3.2.3. Results from sensitivity analysis and the determined parameter values are described in Section 4.2.

3.2.1   Mechanism of the BMPs

Pervious Pavement

Pervious pavement has been classified as structural BMP working through infiltration (EPA, 2014a). It is an alternative to asphalt or concrete surfaces that allows stormwater to drain through the porous surface to a crushed stone reservoir underneath. The reservoir temporarily stores surface runoff before infiltrating it into the subsoil. Underdrains may also be used below the stone reservoir if soil conditions are not conducive to complete infiltration of runoff (Muthukrishnan, 2004). Permeable pavement is not effective on steep slopes (VA DEQ, 2014). Therefore, it is suitable for areas with a slope of 5% or less.

The main function of pervious pavement is decreasing surface runoff. It works via decreasing impervious area, promoting infiltration, and increasing surface roughness coefficients. The related parameters in SWAT include: FIMP (fraction of impervious pavement), CN2 (curve number), Ksat (hydrologic conductivity at saturation), and N_OV (overland roughness of coefficients). There is also potential soil character change.

Vegetated Filter Strip

Vegetated filter strips are classified as vegetated bio-filter (Muthukrishnan, 2004). Filter strips are bands of dense vegetation planted downstream of a runoff source (EPA, 2014a). The use of natural or engineered filter strips is limited to gently sloping areas where vegetative cover can be established and channelized flow is not likely to develop. Filter strips are well suited for treating runoff from roads and highways, roof downspouts, small parking lots, and impervious surfaces. They are also ideal components for the fringe of a stream buffer, or as pretreatment for a structural practice.

The main function of filter strip is to trap sediment and nutrients in surface runoff. It has limited effects on reducing surface runoff (EPA, 2014a). The main mechanism for filter strips is filtration/ trapping. The vegetated filter strips function via trapping and filtering, increasing canopy storage, and infiltration, increasing water ponding, and possibly decreasing curve number. SWAT has incorporated the BMP into the model by introducing the parameter FILTERW, the width of the filter strip. The recommended filter strip width ranges from zero to eight meters (OSUE, 2014). The trapping efficiency for sediment, nutrients and pesticides ($Trap_{ef}$) is expressed as

$$Trap_{ef} = 0.367 \times FILTERW^{0.2967} \qquad\qquad Eq.\,3.1$$

Besides filter strip width, FILTERW, CANMX (maximum canopy storage) can be included to model the filter strips in order to better mimic the filter strip functions. The FILTERW should not exceed 30 meters in order to keep the trapping efficiency less or equal to one.

Rain Barrel

Rain barrels have been identified as non-structural BMP designed for stormwater reuse (EPA, 2014a). Rain barrels are placed outside a building at roof downspouts to store rooftop runoff/rainwater for later reuse in lawn and garden watering. They can be implemented without the use of pumping devices by relying on gravity flow instead. Rain barrels are low-cost water conservation devices that reduce runoff volume and, for small storm events, delay and reduce the peak runoff flow rates. Rain barrels can provide a source of chemically untreated "soft water" for gardens and compost, free of most sediment and dissolved salts.

Rain barrels work by collecting rainwater at the storm event and releasing the water later on to the lawns/ to the drainage systems. It is unknown where the water goes afterward. Therefore, it is more suitable to consider the water be transported outside the watershed. Then the stored water can be considered as initial abstract from the canopy. CANMX was used to model the effects of a rain barrel.

Green Roof

Green roofs consist of an impermeable roof membrane overlaid with a lightweight planting mix with a high infiltration rate and vegetated with plants tolerant of heat, drought, and periodic inundations (EPA, 2014a). In areas of high-density development, green roofs are one of the best ways to reduce runoff volumes via evapotranspiration losses. The soil and vegetation layer provide a means of replacing the impermeable surfaces of building roofs to reduce stormwater runoff volumes, control stormwater peak flows, improve

stormwater quality, and reduce stormwater runoff temperature (Muthukrishnan, 2004). Green roofs are especially effective in controlling intense, short-duration summer storms (Muthukrishnan, 2004; Berghage, 2009). Green roofs also appeared to be beneficial for the removal of atmospheric nitrate (Berghage, 2009). However, green roof is suitable on flat-top buildings. Most single family houses, are not suitable for installing green roof because of the tilted roof surface; additionally, their structural capacity is inadequate for the weight of the soils and water included in the green roof.

Green roofs have been widely used to control storm water and surface runoff. They work via decreasing impervious area, increasing canopy storage, increasing canopy evaporation, filtering the nutrients, increasing overland roughness coefficients, decreasing peak runoff. SWAT parameters involved in these processes are: FIMP, CANMX, OV_N, and CN2.

Native Landscaping

Native landscaping, sometimes called conservation landscaping, uses plants that were native to a given region prior to European settlement (EPA, 2014a). It is usually done by converting lawn into low-maintenance native plants in residential areas. These native plants, once established, can require minimal irrigation, mowing, and chemical treatments, which offers substantial savings and environmental benefits by improving the quality of the air, soil and water, preventing flooding, and controlling erosion (RM, 2014).

Native landscaping, as a BMP, works via increasing canopy, increasing surface roughness, increasing infiltration, reducing irritation and fertilizer, filtering the sediments

and nutrients, and increasing evapotranspiration. The related parameters in SWAT include: CANMX, OV_N, AWC (available water capacity, water available for plant = field capacity − wilting point), FILTERW, and parameters representing management operations. Parameters related to management operations include: type of plant, amount of water and frequency needed for irrigation, amount of N and P needed annually, the fertilizer application efficiency and frequency.

Rain Garden

A rain garden or bioretention cell is a depressed area with porous backfill (material used to refill an excavation) under a vegetated surface (EPA, 2014a). It can also be classified as vegetative bio-filters (Muthukrishnan, 2004). These areas often have an under-drain to encourage filtration and infiltration, especially in clayey soils. Bioretention cells provide groundwater recharge, pollutant removal, and runoff detention. Bioretention cells are an effective solution in parking lots or urban areas where green space is limited. Bioretention as a BMP is not recommended for areas with slopes greater than 20%. Bioretention BMPs have the potential to create attractive habitats for mosquitoes and other vectors (Muthukrishnan, 2004).

The main mechanism involved in a rain garden includes: increasing water ponding, increasing canopy storage, decreasing impervious area when installed in parking lots, promoting infiltration, filtering sediments and nutrients, decreasing curve number when installed in residential area, and decreasing soil erodibility. The related parameters in

SWAT are: CANMX, CN2, FIMP, USLE_K (universal soil lose equation K factor, for erodibility), AWC, and Ksat.

Fertilizer Reduction

Reducing the use of fertilizer or using slow-release fertilizer might be the easiest way to decrease the nutrients contribution to streams. Advantages of slow release fertilizers are that the nutrients are available gradually over time (SRF, 2014). This means that the gardener can fertilize less often, and the nutrients are provided slowly and steadily. This is how most plants prefer to be fed and helps them grow well.

To model less fertilizer usage in SWAT, parameters related to management operations include: amount of N and P needed annually, the fertilizer application efficiency and frequency. This type of BMP was only recommended in agricultural area. Because of agricultural activity, using NL is not an idea way to reduce nutrients. It is unreasonable to replace agricultural crops with native plants for NPS control purposes.

Infiltration Trench

Infiltration trenches are rock-filled ditches with no outlets. These trenches are designed to collect runoff during a storm event and release it into the soil by infiltration (the process through which stormwater runoff penetrates into soil from the ground surface) (EPA, 2014a). Infiltration may not be appropriate in areas where groundwater is a primary source of drinking water due to this method's potential for contaminant migration. This

holds true when runoff is from a commercial or residential area with a higher potential for metal or organic contamination. Also, the performance is limited in areas with poorly permeable soils, and these BMPs can experience reduced infiltrating capacity and clogging due to excessive sediment accumulation (Muthukrishnan, 2004). Runoff that contains high levels of sediments or hydrocarbons (for example, oil and grease) that may clog the trench are often pretreated with other techniques such as water quality inlets (series of chambers that promote sedimentation of coarse materials and separation of free oil from storm water), inlet protection devices, grassed swales, and vegetated filter strips (EPA, 2014a).

Infiltration trench works mainly through infiltration. The main mechanism include: 1) ponding of water; 2) promote infiltration /ground water recharge; 3) decrease curve number; 4) increase surface roughness. Related parameters are: Ksat, CN2, OV_N. Canopy (CANMX) should also be increased to simulate initial abstraction. Percentage of impervious area (FIMP) should also be decreased in order to mimic the effects of having an infiltration trench.

3.2.2   Sensitivity Analysis on Parameters Representing BMPs

In section 3.2.1, several parameters have been chosen to model the LID BMPs. A sensitivity analysis was carried out to see whether the changes in these parameters could result in changes in SWAT simulation. The sensitivity analysis was based on the uncalibrated WB_SWAT model. Sensitivities were calculated on the four variables at watershed level, namely the average annual surface runoff (mm), sediment loading (tons/ha), total N (kg/ha), and total P (kg/ha). The four variables were total watershed yield

represented in unit of mass/area, which were calculated by total amount of watershed yield divided by the total watershed area.

Firstly, one baseline simulation was carried out using the un-calibrated WB_SWAT model. All parameters were set as default or were calculated by ArcSWAT using the information available. Similar to Section 3.1.2.1, the sensitivity analysis was carried out in the one-at-a-time way. Only one parameter was changed in each simulation while all other parameters remained the same as the baseline simulation. For each of the parameters of interest, four to five alternative values were provided in different SWAT simulations. According to the characteristics and the initial values of the parameter, alternative values with an absolute fixed value or with a relative percentage change were given to different parameter. After each simulation, the SWAT simulation results were compared with those obtained in the baseline simulation. For the eight parameters of interest, a total of 33 simulations were carried out. The alternative parameter values are listed in Table 3-6.

Table 3-6 Parameter Values Experimented in Sensitivity Analysis

Parameter	Value 1	Value 2	Value 3	Value 4	Value 5	Value 6
AWC	Orig.	Orig. + 0.1	Orig. + 0.2	Orig. + 0.3	Orig. + 0.4	Orig. + 0.5
USLE_K	Orig. * 0.5	Orig.	Orig. * 1.5	Orig. * 2.0	Orig. * 2.5	
Ksat	Orig. * 0.5	Orig.	Orig. * 1.5	Orig. * 2.0	Orig. * 2.5	
CN2	Orig. * 0.6	Orig. * 0.7	Orig. * 0.8	Orig. * 0.9	Orig.	
CANMX	Orig.	Orig. * 2.0	Orig. * 4	Orig. * 6	Orig. * 8	
FILTERW	Orig.	Orig. + 1.0	Orig. + 2.0	Orig. + 3.0	Orig. + 4.0	
OV_N	Orig.	Orig. * 1.2	Orig. * 1.4	Orig. * 1.6	Orig. * 1.8	Orig. * 2.0
FIMP	Orig.	Orig. * 0.8	Orig. * 0.5	0		

Note: only one parameter value was adjusted in each simulation. The table lists all possible parameter changes.

"FIMP" is a parameter value related to land use types. This value is not directly supplied in SWAT, but through a land use database where "FIMP" is one characteristic of

each urban land use (urban.dat). Therefore, in order to change this parameter, one needs to change the database values or change the landuse types. Changing the database is not recommended. This is because the data based is shared by all HRUs in one SWAT model. Assuming there were two HRUs with the same landuse type, if a BMP was to be modeled in one HRU while no BMP built in the other, then changing the data base would cause a change in both HRUs, which is not reasonable.

3.2.3   Observed BMP Reduction Rate

The criteria used to determine how much each parameter should be changed to represent the BMPs were obtained from observed BMP reduction rates of the exiting urban BMPs. This section listed some major findings in literature regarding the observed reduction rate in terms of runoff and NPS. The approximate pollutant removals of the most common structural BMPs are presented in terms of percent removals in the tables 3-7 through 3-15.

Table 3-7 Pollutant Removals of the Most Common Structural BMPs (Muthukrishnan, 2004)

BMP	TSS	TN	TP
Infiltration trench	75	60-70	55-60
Porous pavement	82-95	65	80-85
Bio-retention basin	80	65-87	49
Vegetated filter strip	54-84	-65	20

Pervious Pavement

More than a dozen studies carried out in various locations are now available to characterize the runoff reduction potential for permeable pavement that are designed with the requisite amount of storage to enable infiltration beneath the paver (Table 3-8).

According to different design level, the surface runoff and NPS reduction rate of pervious

pavement can also be different (Table 3-9) (VA DEQ, 2014).

Table 3-8 Runoff Reduction Rate for Pervious Pavement (Collins et al., 2008)

Location	ONT	PA	FRA	NC	NC	WA	CT
Runoff Reduction Rate (%)	99	94	98	100	95-98	97-100	72
Location	UK	NC	PA	NC	UK	MD	Lab
Runoff Reduction Rate (%)	78	38-66	25-45	66	53	45-60	30-55

Table 3-9 The Overall Stormwater Functions of Pervious Pavement (VA DEQ, 2014)

Stormwater Function	Level 1 Design	Level 2 Design
Annual Runoff Volume Reduction (RR)	45%	75%
Total Phosphorus (TP) EMC Reduction	25%	25%
Total Phosphorus (TP) Mass Load Removal	59%	81%
Total Nitrogen (TN) EMC Reduction	25%	25%
Total Nitrogen (TN) Mass Load Removal	59%	81%

Vegetated Filter Strip

Table 3-10 Average Percent Removal of Pollutants by Vegetated Filter Strip (OSUE, 2014)

Location	Soil Texture	Slope (%)	Flow Conditions	Filter Strip Width (feet)	Sediment	N	P
Virginia (1989)	Silt loam	11-16	OLF	15	70	54	61
				30	84	73	79
			CF	15	83	83	85
				30	93	82	87
Maryland (1989)	Sandy loam	3-4	OLF	15	66	0	27
				30	83	48	46
Iowa (1991)	Silt loam	7	OLF	10	72	-	-
				20	83	-	-
				30	97	-	-
		12	OLF	10	88	-	-
				20	90	-	-
				30	96	-	-
Virginia (1992)	Silt loam	4-12	OLF	13	65	-	-
				26	65	-	-
Iowa (1993)	Silt loam	3-6	OLF	15	72	-	-
				30	76	-	-

* CF: concentrated flow; OLF: overland flow

The results summarized in Table 3-10 are typical sediment reduction rates of most filter-strip studies, with nutrients trapping rates recorded in several studies. Other research also summarized the NPS reduction rate of VFS. Negative nutrients reduction rates have been observed for VFS with large width (Table 3-11). The values indicated that fertilizer application is needed for maintenance of VFS. As the width increases, the nutrients reduced by VFS will not be able to compensate for the increasing fertilizer needed for VFS growth.

Table 3-11 Average Pollutant Removal Capability (SC DHEC, 2014)

	50 feet in width	75 feet in width	150 feet in width	Average
TSS	50%	54%	84%	70%
Total Phosphorus	20%	-25%	-40%	10%
Nitrate Nitrogen	20%	-27%	-20%	30%

Because effectiveness of VFS is determined by the filter width in SWAT (Eq. 3.1). A proper width should be determined for VFS modeling in SWAT. The SCS has developed general recommendations, based upon research, on the minimum filter-strip width for particular ranges of slope steepness (Fig. 3-1). A 4-meter VFS was modeled in SWAT based on this recommendation.
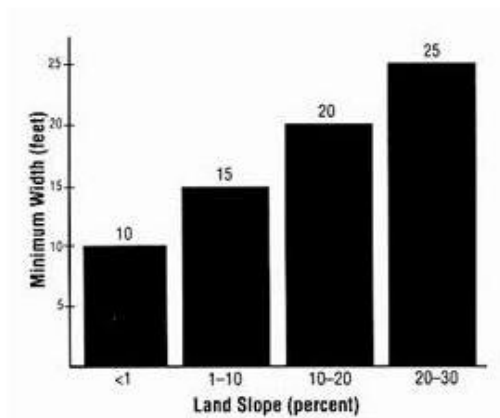
Figure 3-1 SCS Recommended VFS Width (OSUE, 2014)

Green Roof

Considerable research has been conducted in recent years to define the runoff reduction capability of extensive green roofs (Table 3-12). Reported rates for runoff reduction have been shown to be a function of media depth, roof slope, annual rainfall and cold season effects. Based on the prevailing climate for the region, a conservative runoff reduction rate for green roofs of 45% to 60% is recommended for initial design. However, reduction was not obvious in terms of nutrients.

Table 3-12 Runoff Reduction Capability of Green Roofs (Collins et al., 2008)

Location	USA	Germany	MI	OR	NC
Runoff Reduction Rate (%)	40-45	54	30-85	69	55-63
Location	**PA**	**MI**	**ONT**	**GA**	**Average**
Runoff Reduction Rate (%)	45	50-60	54-76	43-60	45-40

Native Landscaping

According to Recreational Management (2014), native landscaping can dramatically reduce the total cost of maintaining the vegetated area. At the same time, no fertilizer is needed in area planted with native vegetation. Therefore, native landscape can reduce applied N by 100%, thus reducing substantial amount of nutrients contained in surface runoff and stormwater.

Table 3-13 Cost Comparison between Conventional Lawn and Native Landscaping (RM, 2014)

		Year 1	Year 5	Year 10	Year 20
Existing Turf Grass	Mowing	$3,500	$3,824.54	$4,433.70	$5,958.52
	Fertilizer	$525	$573.68	$665.05	$893.78
New Prairie, Savanna or Wetland from Seed	Herbicide	$330			
	Maintenance		$546.36	$633.39	$851.22

Rain Gardens

More than 10 studies are now available to characterize the runoff reduction rates for bio-retention areas, or rain gardens (Table 3-14) (Collins et al., 2008). A conservative runoff reduction rate of 80% is assigned to designs that rely on full infiltration.

Table 3-14 Runoff Reduction Rates for Bioretention Areas (Collins et al., 2008)

Location	CT	PA	FL	AUS	ONT	Model
Runoff Reduction Rate (%)	99	86	98	73	40	30
Location	**NC**	**NC**	**NC**	**NC**	**MD**	
Runoff Reduction Rate (%)	40-60	20-29	52-56	20-50	52-65	

Infiltration Trench

The runoff reduction capability of infiltration practices is presumed to be high, given that infiltration is the design intent of the practice. Some surface overflows do occur when the infiltration storage capacity is exceeded. Assuming the practice is designed with adequate pretreatment and soil infiltration testing, a conservative runoff reduction rate of 90% is assigned to infiltration practices (Table 3-15). If an underdrain must be utilized, the recommended runoff reduction rate drops to 50%.

Table 3-15 Runoff Reduction Rates for Infiltration Trench (Collins et al., 2008)

Location	NH	VA	PA	NC
Runoff Reduction Rate (%)	90	60	90	96-100

Researchers have different opinions towards infiltration trench. Some state that the runoff reduction rate of infiltration trench is minimal to small, while the reduction rates of sediment yield and nutrients are substantial. Others state that the primary function of infiltration trench is to reduce runoff. Runoff needs to be pre-treated before entering the trench in order to get rid of sediments. Despite the argument, the reduction rates of nutrients

should be 15% for N and 25% for P for initial design (CSN, 2009; CWP, 2007). Different design of the same type of BMP would result in different reduction rate. Even if the designs were the same, geological and climatological differences would result in differences in the working efficiency of the BMPs. Therefore, the reduction rates observed for all BMPs of the same kind were averaged to obtain a mean reduction rate, which would be used as the criteria in this study (Table 3-16). Not all urban BMPs have exiting data. Therefore, reasonable estimates were used instead. The values summarized in Table 3-16 served as targets to quantify SWAT parameter changes that represent BMPs in the SWAT model.

Table 3-16 Observed Reduction Rates for GI

BMP	Surface Q	Sediments	Total N	Total P
Pervious Pavement	80%	85%	80%	65%
Filter Strip	---	70%	20%	30%
Rain Barrel	---	---	---	---
Green Roof	50%	---	---	---
Native Landscaping	---	---	---	---
Rain Garden	50%	80%	50%	70%
Fertilizer Reduction	---	---	---	---
Infiltration Trench	50%	---	15%	25%

3.3   Diagnostic Decision Support System

The Diagnostic Decision Support System (DDSS) developed in this study includes three components: 1) hotspot identifier, 2) Diagnostic Expert System, and 3) Prescriptive Expert System. These three components correspond to the sequence in which the tools of the system are expected to be used in practice, starting with the identification of critical areas of runoff and pollutant yield and proceeding to the development of a spatial control plan rooted in the implantation of effective BMPs. DES and PES is incorporated in one process, since a prescription is usually provided immediately after the diagnosis.

3.3.1 Hotspots Identification

The first step in making stormwater management plans using the DDSS is to identify the most problematic hotspots where excessive surface runoff, sediments or nutrients are generated. In this study, hotspots were identified using the process based hydrologic model as described in Section 2.3.1. The distributed hydrologic model SWAT, which has been demonstrated to be a suitable tool for this research (Section 2.2.3 and Section 2.6.4), was calibrated and used to simulate the water quality and water quantity related variables. The hotspots were geographically based on Hydrologic Response Unit (HRU), the smallest unit of modeling in SWAT model. The variables of interest were on-land variables (Section 2.6.2), including surface runoff (mm), sediment yield (Ton/ha), total N (Kg/ha), and total P (Kg/ha) contributed to streams from each HRU. These four per-area yields are called *yield at the HRU level* in the later parts of this document.

Surface runoff and sediments yield were retrievable directly from SWAT output.hru files on a HRU basis. Total nitrogen generated in each HRU included organic N, NO3 in surface runoff, NO3 in lateral flow, and NO3 in groundwater flow. Total phosphorus included organic P, soluble P in flow, and P attached to sediment. Annual surface runoff, sediment yield, total N, and total P were averaged from water year 2002 to 2011 respectively. Values in water year 2000 and 2012 were not included because they were partial years. Values in water year 2001 were not included because it was still in the model warm-up period. The average annual per-area yields of the four on-land variables were used for hotspot identification.

For each variable of interest, the average annual values generated from each HRU were ranked from the highest to the lowest. A certain number of HRUs that produce the highest per-area amount of the variables were identified as hotspots. In this study, the hotspots were defined as the top 20% of HRUs. It needs to be noted that in the hotspot identification process, the average annual values were compared and ranked in terms of per-area-yield. Taking sediment as an example, the annual sediment yield at the HRU level was the annual total amount of sediment generated in one HRU divided by its area. The philosophy of using per-area-values as hotspot identifier instead of the total amount was to find the area with the highest concentration. An area with small NPS concentration but large area may contribute a large amount of NPS. However, this specific area may not be a problematic area. BMPs should be installed in the most problematic areas where the HRUs account for a small percent of total watershed area while producing most of the pollutants in order to produce the largest benefit/cost ratio.

Four sets of hotspots were identified for the four on-land variables. For simplicity, the four sets are called runoff hotspots (or SurfQ_hs), sediment hotspots (Sed_hs), nitrogen hotspots (N_hs), and phosphorus hotspots (P_hs) in the remaining text.

3.3.2   Development of the Diagnostic Expert System (DES)

The Diagnostic Expert System (DES), the second component of the Diagnostic Decision Support System, was developed to identify the possible reasons why certain areas contribute high level of nutrients and sediments into the receiving water bodies. The whole process is similar to a medical process of diagnosis and treatment (prescription). Before

prescriptions (BMPs) can be made, the diseases (main reasons) for the symptom (high runoff or NPS) should be determined. Take medical examination as an example. If a patient is feeling dizziness, a test of blood glucose level (79.2 to 110 mg/dL, normal values in humans) would determine whether or not the dizzy condition is caused by low blood sugar. A similar concept was employed in the DES. As a process based model, SWAT uses series of parameters to represent the hydrological and chemical processes involved in the study watershed. Therefore, given a properly calibrated SWAT model, the parameter values which represent certain watershed characteristics were used as indicators for the problems involved in each hotspot. In order to determine the diagnosis, threshold values for the parameters of concern had to be selected.

For runoff hotspots (SurfQ_hs), the simulated amount of surface runoff were highly correlated to the fraction of impervious pavement (*fimp*). High impervious coverage was therefore, defined as one of the main reasons for high surface runoff generation. Additionally, surface runoff is calculated using the SCS curve number method in SWAT (Eq. 3.2 &3.3). High curve numbers can therefore be another reason for large amount of surface runoff. The threshold value for FIMP and CN2 were set to be 0.5 and 50.

$$Q_{surf} = \frac{\left(R_{day} - 0.2S\right)^2}{\left(R_{day} + 0.8S\right)} \qquad Eq.\,3.2$$

$$S = 24.5\left(\frac{1000}{CN} - 10\right) \qquad Eq.\,3.3$$

where Q_{surf} is the daily surface runoff, R_{day} is daily rainfall, CN is curve number.

Sediment yield is calculated using the Modified Universal Soil Loss Equation (MUSLE) in SWAT (Eq. 3.4).

$$sed = 11.8 \left(Q_{surf} \cdot q_{peak} \cdot area_{hru} \right)^{0.56} \cdot K_{USLE} \cdot C_{USLE} \cdot P_{USLE} \cdot LS_{USLE} \cdot CFRG \quad Eq. 3.4$$

$$q_{peak} = \frac{\alpha_{tc} \cdot Q_{surf} \cdot Area}{3.6 \, t_{conc}} \qquad\qquad Eq. 3.5$$

$$t_{conc} = t_{ov} + t_{ch} \qquad\qquad Eq. 3.6$$

where sed is the sediment yield on a given day, Q_{surf} is the surface runoff volume, q_{peak} is the peak runoff rate, $area_{hru}$ is the area of the HRU, K_{USLE} is the USLE soil erodibility factor, C_{USLE} is the cover and management factor, P_{USLE} is the support practice factor. LS_{USLE} is the topographic factor, and $CFRG$ is the coarse fragment factor. α_{tc} is the fraction of daily rainfall. t_{conc} is the time of concentration.

Based on MUSLE, four major factors were identified for high sediment yield hotspots (Sed_hs): high surface runoff volume (and high peak flow), high soil erodibility, poor soil cover, and steep slope. Besides surface runoff, which is one of SWAT's simulation outputs, the other three factors were represented in SWAT in form of parameters: K_{USLE}, C_{USLE}, and HRU slope. Based on the literature (Djodjic et al., 2002; Sadegh-Zadeh et al., 2007), the threshold values for the three parameters were set at 0.25, 0.20, and 0.10, respectively. One or more major factors can be observed in each sediment hotspot. Therefore, the possible reasons for Sed_hs can be defined as either a single or a combination of several factors.

In urban areas, NO_3 is the major N source. Total nitrogen generated in each HRU includes NO_3 in surface runoff, in lateral flow and in groundwater flow. The amount of N is related to forcing parameters such as N concentration in rain, atmospheric composition, and N application; terrestrial parameters such as N percolation rate and initial N concentration in soil; and modeled forcing variables - surface runoff. In SWAT model, the first two factors were defined at basin level, which means the same parameter values were applied to the entire watershed, thus resulting in no difference in N amount in the first three components. Soil N concentration in this model was also defined as the same value in all HRUs. Therefore, the difference in total N yield predicted by the model is due to differences of flow and amount of N applied to each HRU. Accordingly, possible reasons for high N yield are: high surface runoff, high groundwater discharge, low soil re-evaporation, and high fertilizer application. High groundwater discharge is generally caused by high soil permeability, which is parameterized by hydraulic conductivity at saturation K_{sat} and Curve Number CN2. Soil re-evaporation is related to soil water content, which can be partly represented by soil water available for plant uptake AWC. In this study, the factors for high N yield (N_hs) were classified as high surface runoff, high sub-surface runoff (including lateral flow and groundwater flow), and high N application. The thresholds included SurfQ_hs (whether the HRU was identified as a SurfQ_hs), and CN2 of 50.

The identification of P_hs was relatively easier. Phosphorus is generally in forms of soluble P in flow and P attached to sediment. In urban areas, P is related to soil P concentration, P sorption rate, surface runoff, sediment yield, and P application. Again, the first two factors were defined by a single value for the entire watershed. Therefore there

are only three main reasons for high P yield: high surface runoff, high sediment yield, and high fertilizer application. The first two factors were indicated as SurfQ_hs and Sed_hs. Therefore, possible reasons for high P yield are relatively easily identified. A detailed flow chart for the DES is plotted in Fig.3-2. The DES process was coded in MATLAB.

3.3.3   Development of the Prescriptive Expert System (PES)

Having determined the causes for water quality problems, the PES was used to determine the proper LID BMPs for the whole watershed. Instead of applying a mathematical optimization process based on optimal reduction rate, the PES was developed using Expert System (or DSS in Section 2.4), which is knowledge based and is more suitable for BMP feasibility consideration. Besides the physically feasible BMP recommendations, the total cost of installing all recommended BMPs in the study area (BC) was calculated. Residents' preferences (RP) were incorporated into the calculation of total cost of promoting the recommended BMPs (TC) as an Incentive Adjustment Factor K_{RP}, which is assumed to be a function of RP.
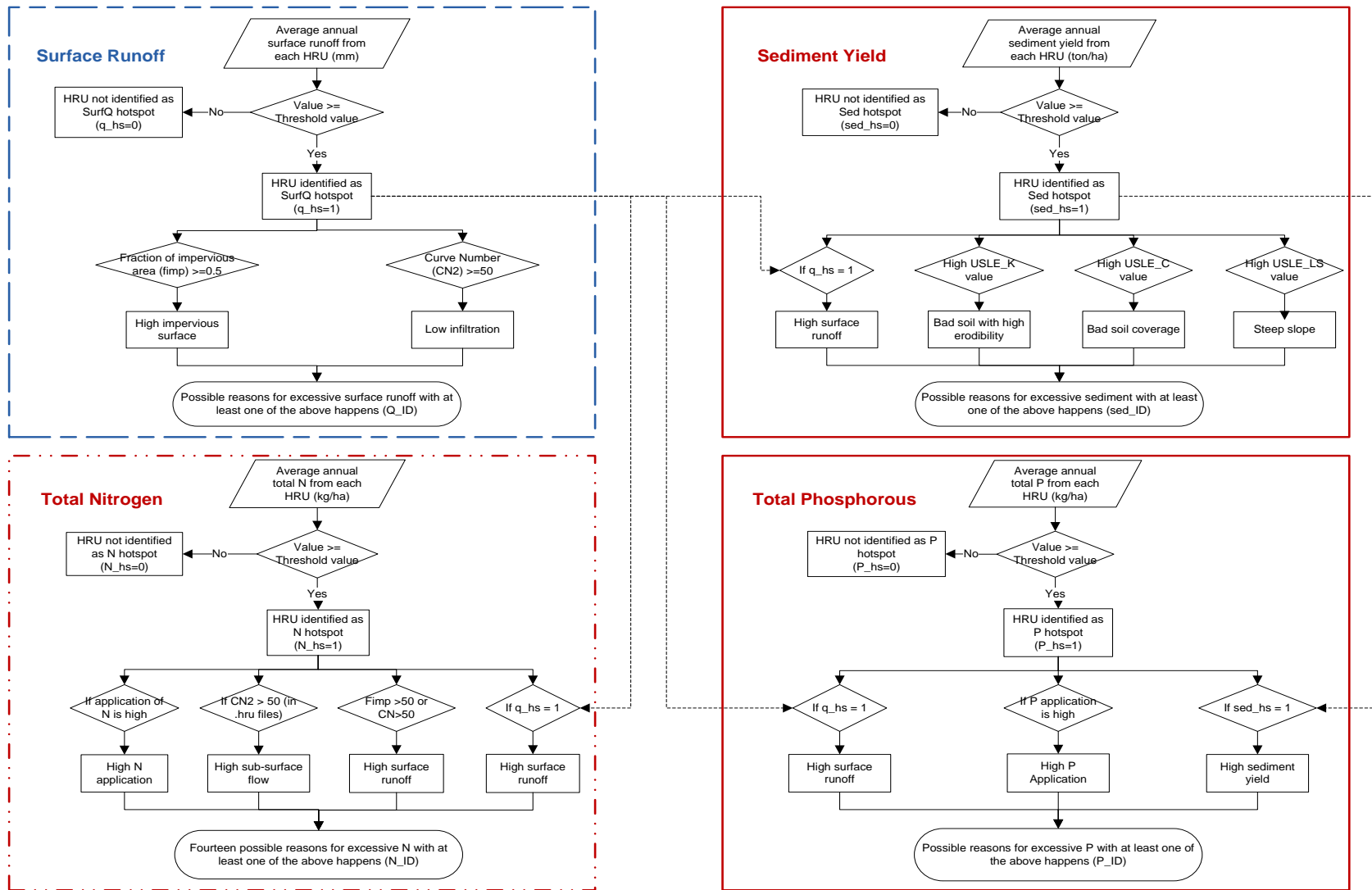
Figure 3-2 DES Flow Chart

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Each BMP has its own primary function (Section 3.2.1). Pervious pavement is designed to reduce surface runoff, vegetated filter strips are used to reduce sediments carried by overland flow. Therefore, proper BMPs should be assigned according to the type of hotspots identified earlier, whether it is a runoff hotspot or a sediment hotspot or a nutrients hotspot. At the same time, BMP implementation has geographical requirements and limitations. Rain gardens and pervious pavements should be avoided in steep slope areas. Infiltration trenches are not suitable in places where groundwater is the source of drinking water. Therefore, geographical features of each HRU should also be taken into account in BMP assignment. Because of these feasibility requirements, Expert System is a better option than optimization. The BMP assigning rules were developed in this research and are described in detail later.

One major goal for the Expert System developed in this study was to minimize the cost while maximizing the NPS reduction rate. The NPS reduction rates (%) for each of the four on-land variables, total area coverage (%) of the recommended BMPs, and the total cost ($) of implementing the BMPs are the three major factors in decision making related to stormwater management and NPS control. Once a set of spatially distributed BMPs was determined by the PES, the costs for BMP installation were also estimated.

In urban areas, BMPs cannot be installed in people's backyard without residents' permission. Residents' preferences over certain BMPs and their willingness to adopt a BMP should be taken into account to promote the potential success of a BMP allocation plan produced by the DDSS. The research plan intended to incorporate an adoption model developed and proposed by collaborator in the Department of Landscape Architecture and the Department of Environmental Science and Technology. The survey work and analysis,

however, were not completed in time to be incorporated into this study. Thus, a simplified conceptual approach to resident preference (RP) was developed. Due to the modular structure of the PES, the RP model can be replaced when improved empirical and theoretical treatment are available.

A BMP cost-estimation model includes two components: fixed cost of human resources (proportional to the BMP coverage area); and BMP installation costs (determined by the type and number of BMP recommended) and RP. Generally speaking, a higher RP indicates a higher BMP adoption rate, and consequently, less governmental efforts/budget needed. Once a set of BMPs were recommended by the DDSS, the total coverage area of the target hotspots (in another word the area of HRUs) was used to calculate the fixed cost. BMP installation costs, which represent the amount needed for incentive programs, include the basic total BMP cost (BC) and an adjustment factor to indicate residents' preferences (K_{RP}). The proposed cost estimation is described in detail in a later text.

The basic PES procedures are shown in the Fig. 3-3. The whole DDSS was coded in MATLAB. Once spatially distributed BMPs are selected by the PES, the BMPs would be implemented virtually in the SWAT models of the two study watersheds to quantify their effectiveness and cost (Section 3.2).
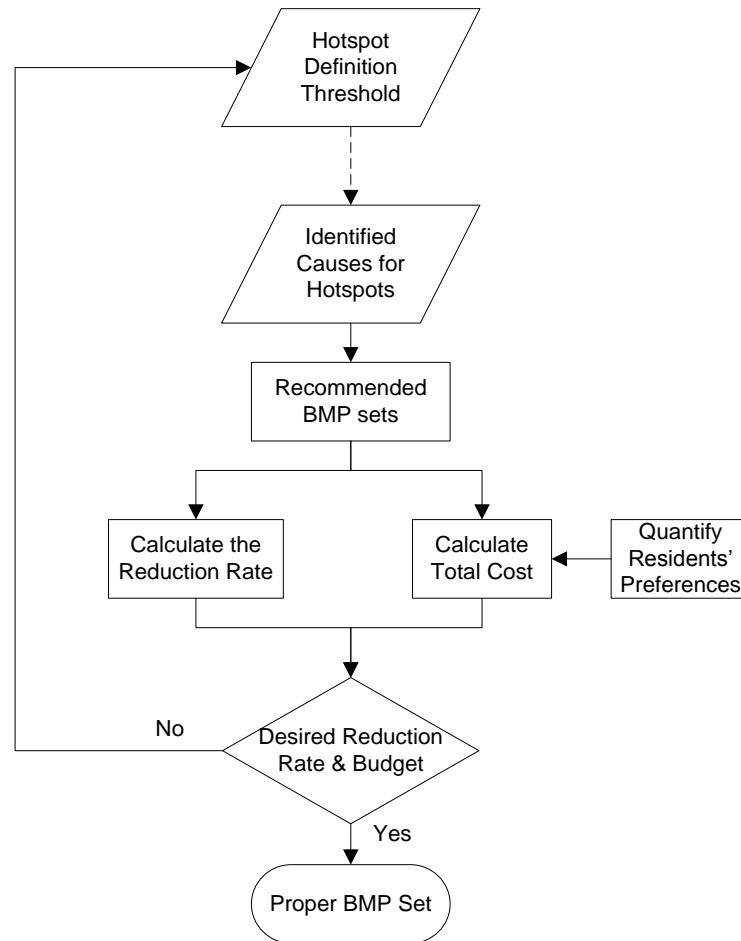
Figure 3-3 PES Flow Chart

3.4 Incorporating Future Climate Conditions

Research has been carried out on the sensitivity of large-scale BMP and LID BMP under changing climate (Section 2.5.2). However, the analysis has been focused on the effectiveness of climate change on individual BMPs, rather than its effects on effectiveness of overall stormwater management plans. Therefore, in this research, the effects of future climate condition on combined effectiveness of BMPs and on the overall management plans were analyzed.

According to IPCC Special Report of Emission Scenarios 4 (IPCC, 2007), global warming may result in higher average temperature and more precipitation in general. At the same time, more extreme temperature and precipitation events are expected, resulting in more severe drought and flood. These changes would increase the possibility of channel erosion and surface soil loss. The effectiveness of certain BMPs, which work through rainwater storage, would be lowered as a consequence. Vegetation growth can also be affected by climate change. Increase in temperature and precipitation may promote plant growth, resulting in faster growing lawn and higher fertilizer demand for a fairly good growth. This may affect the nutrients yield within a watershed.

3.4.1   Different Future Climate Projections

The IPCC 2007 Assessment Report 4 (AR4) was selected for the climate change analysis in this research. Three future climate projections, Scenarios A1B, A2, and B1 (Section 2.5.1), were applied in the SWAT model to represent the changes in temperature and precipitation. In each scenario, changes in two different periods were analyzed: a 10-yr future climate prediction (climate condition at 2020) and a 100-yr future climate prediction (climate condition at 2100). The ten-year projection was used to represent a moderate climate change condition. The 100-year projection was used to represent a more severe climate change condition. Altogether, 6 different future climate scenarios were analyzed in this research, with three moderate scenarios (A1B, A2, and B1) and three severe scenarios (SA1B, SA2, and SB1). The following three figures were retrieved from the IPCC AR4. Fig. 3-4 shows the predicted changes in surface air temperature under

different emission scenarios. Fig. 3-5 shows changes in both temperature (ºC) and precipitation (%). Fig. 3-6 shows the increase in precipitation intensity represented by the increase in standard deviation. Scenario B1 represents the smallest climate change and scenario A2 represents the most dramatic change.
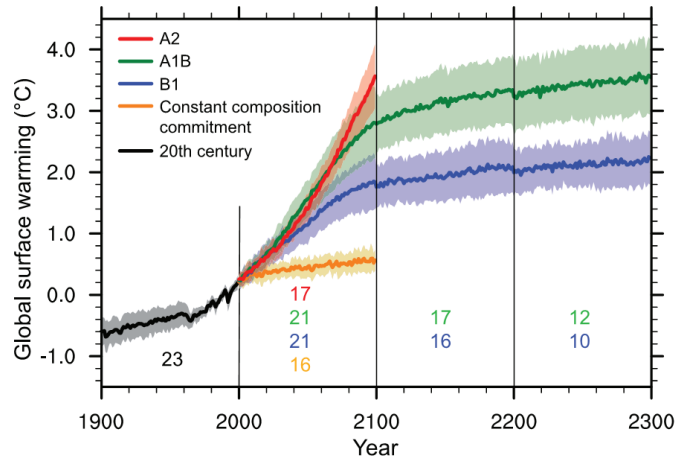
Figure 3-4 Global Surface Warming (IPCC AR4)
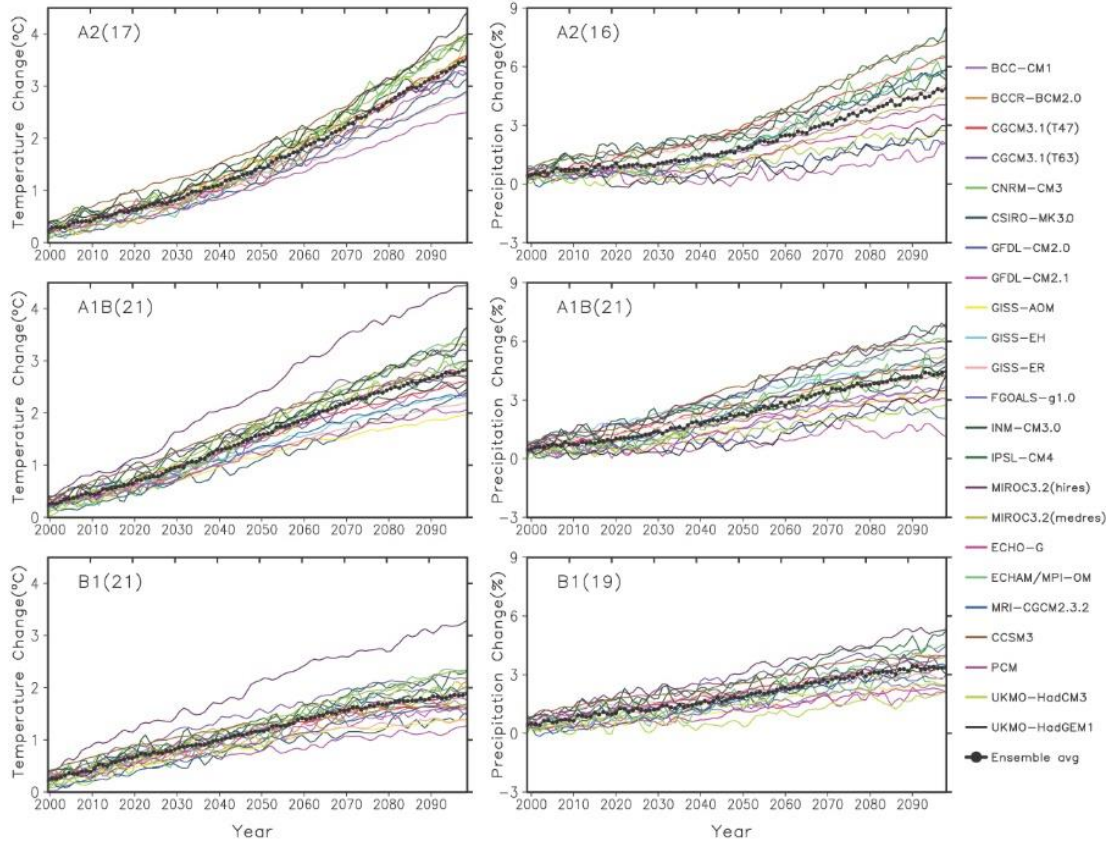
Figure 3-5 Temperature and Precipitation Change (IPCC AR4)
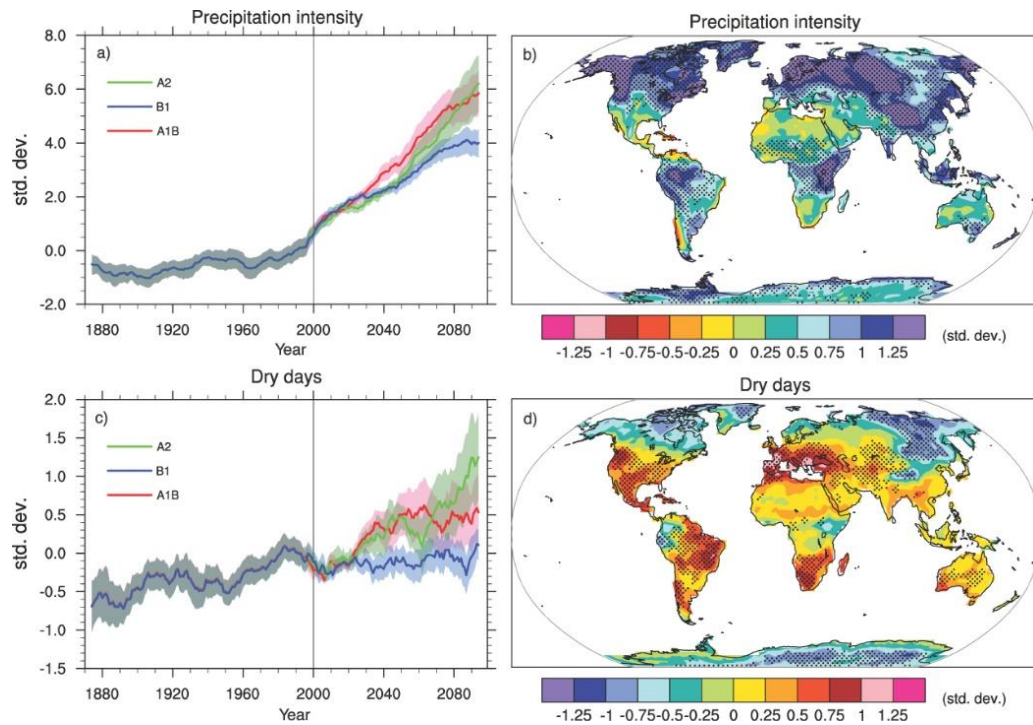
Figure 3-6 Changes in Precipitation Intensity (IPCC AR4)

In the three moderate future climate scenarios (10-year outlook), global surface temperature is expected to increase by approximately 0.33 ºC. The differences within the three scenarios are quite small in the first 10-yr prediction. As for precipitation, a 2-4% of increase in precipitation amount is expected in each of the moderate climate scenarios. The severity of temperature and precipitation are expected to increase as well. The standard deviation of precipitation is expected to increase by 1.5 for precipitation in all three scenarios in the first 10 years. No IPCC prediction was available for extreme temperatures, so a 5% of increase in standard deviation was assumed for temperature in the first 10 years for all three scenarios. Table 3-17 lists the expected increase in mean and standard deviation of temperature and precipitation for the three moderate change scenarios.

Table 3-17 Global Temperature and Precipitation Change in 10 year (Moderate Scenarios)

Scenario	Temp. increase in 10 years (ºC)	Increase in extreme temp. (%)	Prep. increase in 10 years (%)	Increase in extreme prep.(mm)
A2	0.32	5	0.4	1.5
A1B	0.345	5	0.3	1.5
B1	0.33	5	0.2	1.5

Expected increases in precipitation, temperature, precipitation extremes, and temperature extremes in the severe scenarios (100-year outlook) are listed in Table 3-18. Global surface temperature are expected to increase by 3.6, 2.8, and 1.8 ºC. A 3-4.6% of increase in precipitation amount is expected in the next 100 years. The severity of temperature and precipitation is expected to increase as well. The standard deviation of precipitation is expected to increase by 4-6 for precipitation in all three scenarios in the 100 years. A 20% increase in standard deviation was assumed for temperature in the severe scenarios.

Table 3-18 Global Temperature and Precipitation Change in 100 year (Severe Scenarios)

Scenario	Temp. increase in 100 years (ºC)	Increase in extreme temp. (%)	Prep. increase in 100 years (%)	Increase in extreme prep. (mm)
SA2	3.6	20	4.6	6.3
SA1B	2.8	20	4.1	5.8
SB1	1.8	20	3.0	4.0

In order to assess the effects of climate change, different future climate scenarios were represented in terms of a percentage change or a fixed amount of change in the monthly statistics for each weather station. The change values in the six scenarios were incorporated into the weather generation file in SWAT. The monthly statistics were used by SWAT weather generator to simulate site specific precipitation, temperature, and other weather related variables when no observation was available or when prediction was needed. The monthly statistics listed in the .wgn files include maximum/minimum air

temperature, the standard deviation of daily maximum/minimum air temperature, the average precipitation, the standard deviation of daily precipitation, the average humidity, the probability of a wet day, the probability of a wet day following a wet day, the average of wet day numbers, and the maximum rainfall depth for a 30-minute storm. In the future climate scenarios, maximum/minimum temperature were given a fixed amount of increase. Mean precipitation were given a corresponding percentage increase. Extreme climate events were represented in terms of standard deviation. The standard deviation of monthly temperature and precipitation were given corresponding increases. Higher standard deviations indicate more extreme events, thus indicating a more severe storm paten.

3.4.2   Analyzing the Effects of Climate Change

When developing water management and stormwater treatment plans, future climate change may affect the current planning. Two questions need to be answered in order to give proper management plan: 1) whether future climate conditions would affect the amount and location of simulated NPS pollutants, and eventually affect the hotspot identification and recommended BMPs; and 2) if a stormwater management plan has been made and the BMPs are installed (or partially installed) in the watershed already, will the future climate conditions affect the effectiveness of these BMPs? To answer these two questions, two sets of analyses were carried out in this research. Simulations and models used to answer the first question were named "ClimateScenario_hs" according to different climate condition. "_hs" indicated that the simulations were related to hotspots identification. "Climate Scenario _bmp" was used for the simulations carried out to answer

the second question. "_bmp" indicated that the simulations were related to existing BMPs or BMP plans. For all analyses and simulations carried out in this climate change analysis, no observed precipitation and temperature were available. Therefore, the Weather Generator utility in SWAT was used to simulate weather input data for the years from 2015 to 2025 based on specific weather statistics (Section 3.4.1).

In the first set of analyses (_hs analysis), one baseline simulation (WB_NC_hs) was carried out using the calibrated WB_SWAT_Pre model under current climate condition with no climate change. In this simulation, the SWAT model was required to carry out a 10-year simulation with simulated climate data based on the historical weather statistics. This simulation was needed in order to: 1) assess if there is any differences in hotspot identification between SWAT models using observed and simulated weather data; 2) determine if there are any differences in hotspot identification among different future climate scenarios. In addition to the baseline simulation, another 6 simulations were carried out using the six future climate scenario listed in the previous section. The models were named WB_A2_hs, WB _A1B_hs, WB _B1_hs, WB _SA2_hs, WB _SA1B_hs, and WB _SB1_hs. Analyses were carried out for the four on-land variables: surface runoff, sediment yield, total N yield, and total P yield, both in terms of per-area yield at the HRU level and total amount at the watershed level. The spatial distribution of the predicted hotspots was compared as well.

Similar analyses were carried out for the analysis of BMP effectiveness under different climate conditions (_bmp analysis). The difference between the two sets of analysis was that the baseline simulation (WB_NC_bmp) was carried out using the calibrated WB_SWAT_Post model with all recommended BMP modeled in SWAT driven

by model-generated weather data based on current statistics. Here again, in addition to the baseline simulation, another 6 simulations were carried out using the six future climate scenarios listed in the previous two sections. The models were named WB_A2_bmp, WB _A1B _ bmp, WB _B1_ bmp, WB _SA2_ bmp, WB _SA1B _ bmp, and WB _SB1_ bmp. The six models were based on the WB_SWAT_Post model where BMPs were already numerically implemented in the study area. The per-area yield and the total amount of the four on-land variables, and the spatial distribution of the hotspots were compared.

Chapter 4. Results and Discussion

4.1 SWAT Model Calibration

The results of hydrologic model development are presented in this sub-section. Watershed delineation is presented in section 4.1.1 as the result from SWAT model setup and a prerequisite for model calibration. The calibration and validation of the two SWAT models are presented in section 4.1.2.

4.1.1 Delineation of the Study Watersheds

Watershed delineation was performed in ArcSWAT. Stream network was first determined according to the Digital Elevation Model (DEM). The outlets of subbasins were then determined based on specific considerations for each watershed. Generally, subbasin outlets are located where tributaries join the main stem of the stream network, where a gauging station is build (available observations), and at the outlet of a pond, etc. Twenty-one sub-watersheds (subbasins) were delineated in the Watts Branch (WB) watershed, which included a total of 1832 HRUs (Fig. 4-1). The size of the HRUs defined in WB watershed ranges from 0.01 ha to 13.35 ha. The size of the subbasins ranges from 5.08 ha to 216 ha. The watershed outlet was the output of subbasin 3 (also reach 3). The USGS gauging station was located at the output of subbasin 9 (also reach 9).

Twenty sub-watersheds were defined in the Wilde Lake (WL) watershed, with a total of 1334 HRUs (Fig. 4-2). The size of the HRUs defined in WL watershed ranges from 0.0009 ha to 6.59 ha. The size of the subbasins ranges from 1.25 ha to 66.1 ha. The watershed outlet was the output of subbasin 20 (also reach 20). The USGS gauging station

was located at the output of subbasin 11 (also reach 11). It is important to model a reservoir in a single subbasin. Therefore, the outlets of subbasins 17 and 18 did not extend to the confluences.
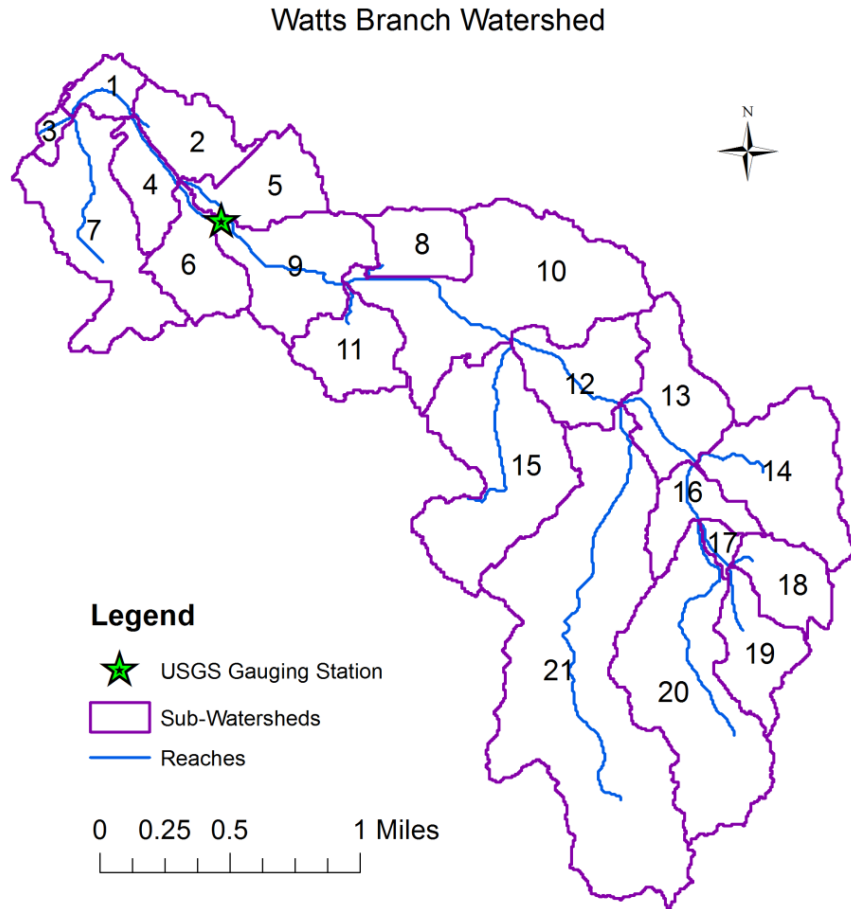
Figure 4-1 Watts Branch Watershed Delineation
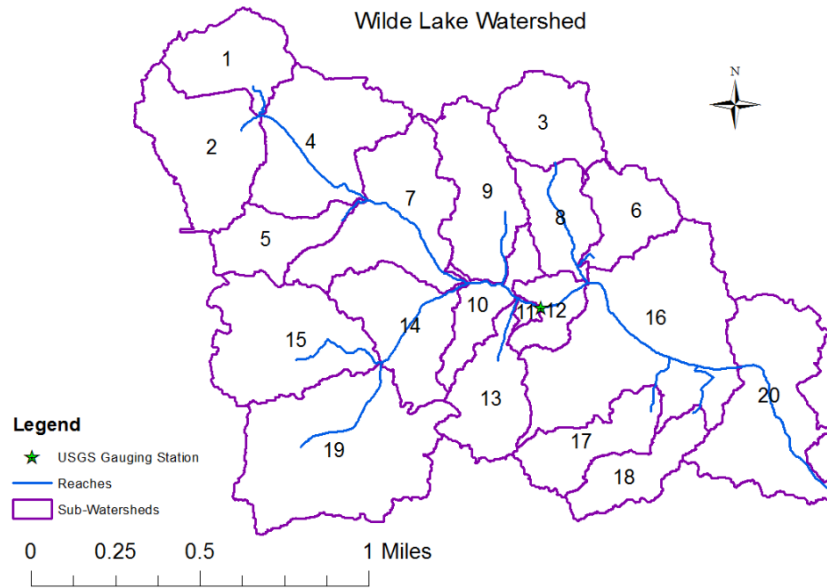
Figure 4-2 Wilde Lake Watershed Delineation

4.1.2 Model Calibration

4.1.2.1 Parameter sensitivity analysis

Sensitivity analysis was carried out to identify target parameters for model calibration (Section 3.1.2.1). SENSAN produced three output files. The first output file (ABSFLE) simply listed the desired model outputs, for example stream discharge, obtained from model simulations using different parameter sets. The second SENSAN output file (RELFLE) listed the relative differences between simulated values using alternative parameter set and the simulated values using the baseline parameter set (baseline simulation, Section 3.1.2.1). The values stored in RELFLE were relative differences, calculated as:

$$\frac{O_p - O_b}{O_b} \qquad\qquad Eq.\,4.1$$

where O_b represents the base-simulation, and O_p represents the value for a certain set of alternative parameter values.

The third output file (SENSFLE) provided model outcome "sensitivities" with respect to parameter variations from their base values. This output file includes the absolute sensitivity, which can be expresses as:

$$\frac{O_p - O_b}{P_p - P_b} \qquad Eq.\,4.2$$

where O_b and P_b are base-simulation and base-parameter set; O_p and P_p are the model outcome and parameter values pertaining to a particular model run.

Another sensitivity criterion is relative sensitivity, which was not directly available in any of the output files. The sensitivity values can be calculated directly from simulations using different parameter sets.

$$\frac{O_p - O_b}{P_p - P_b} \cdot \frac{P_b}{O_b} \qquad Eq.\,4.3$$

For each parameter of interest, there were 5 simulations (including one baseline simulation) and 4 sets of sensitivity results because of the 4 alternative parameter values. The sensitive evaluation criteria included absolute sensitivity and relative sensitivity. The criteria were calculated for mean annual stream discharge, sediment, and nutrients yield.

Table 4-1 Sensitivity of Stream Discharge to Selected Parameters

	Absolute Sens.	Relative Sens.
SL_P	$1.2 \cdot 10^{-5}$	$3.8 \cdot 10^{-9}$
K2	$-8.7 \cdot 10^{-6}$	$-7.2 \cdot 10^{-9}$
N1	$2.0 \cdot 10^{-4}$	$2.4 \cdot 10^{-7}$
NPERCO	$7.6 \cdot 10^{-5}$	$1.3 \cdot 10^{-6}$
K1	$-4.4 \cdot 10^{-3}$	$-3.7 \cdot 10^{-6}$
SURLAG	$-2.4 \cdot 10^{-5}$	$7.8 \cdot 10^{-6}$
N2	$-4.5 \cdot 10^{-2}$	$-5.2 \cdot 10^{-5}$
EPCO	$-9.2 \cdot 10^{-4}$	$-7.7 \cdot 10^{-5}$
CANMX	$9.2 \cdot 10^{-4}$	$8.0 \cdot 10^{-5}$
SMFMX	$4.0 \cdot 10^{-4}$	$1.5 \cdot 10^{-4}$
BIOMIX	$-1.5 \cdot 10^{-2}$	$-4.7 \cdot 10^{-4}$
DELAY	$9.3 \cdot 10^{-4}$	$2.4 \cdot 10^{-3}$
SMFMN	$-1.0 \cdot 10^{-2}$	$-3.9 \cdot 10^{-3}$
ALPHA_BF	2.6	$1.0 \cdot 10^{-2}$
GW_REVEP	-6.9	$-1.1 \cdot 10^{-3}$
ESCO	18.8	2.7
CN2	1.0	0.4

Table 4-2 Sensitivity of Sediment Yield to Selected Parameters

	Absolute	Relative
K1	-4.1	$-7.0 \cdot 10^{-5}$
EPCO	0.1	$1.7 \cdot 10^{-4}$
NPERCO	-0.95	$-3.2 \cdot 10^{-4}$
SURLAG	0.14	$9.4 \cdot 10^{-4}$
N1	-47.5	$-1.1 \cdot 10^{-3}$
CANMX	1.5	$2.7 \cdot 10^{-3}$
BIOMIX	6.9	$4.3 \cdot 10^{-3}$
SMFMX	-0.69	$-5.2 \cdot 10^{-3}$
SMFMN	-40.5	-0.3
PRF	1.4	0.1
CN2	$8.2 \cdot 10^{-3}$	0.2
ESCO	677.2	1.1

Table 4-3 A Summary of the Influential Parameters

Parameter	Meaning	Flow	Sediment	Nutrients
CN2	Curve Number	√	√	√
SMFMN	Snow melt factor	√	√	
ESCO	Soil evaporation compensation factors	√	√	√
NPERCO	Nitrogen percolation coefficient			√
N1	Manning's n value for tributary channels		√	
N2	Manning's n value for main channel	√		
BIOMIX	Biological mixing efficiency	√	√	√
USLE_P	USLE support practice factor		√	√
ALPHA_BF	Base flow recession factor	√		√
REVEP	groundwater re-evaporation time	√		√

Based on the sensitivity analysis result, critical parameters selected for model calibration included those controlling evapotranspiration and soil water behavior (EPCO, ESCO, CANMX, BIOMIX), roughness coefficients for overland and channel flow (N1, N2, OV_N, CN2), the groundwater recession parameters (ALPHA_BF, REVEP), sediment yield (PRF, ADJPKR, CH_K1, CH_K2), and nutrients losses (NUPDIS, PUPDIS, NPERCO, PHOSKD, PSP).

Nineteen parameters were selected for model calibration, which was automatically done by using the model calibration tool Parameter ESTimation (PEST) (Wang, 2013). Note that the total number of parameters used for calibration was greater than 19. Sub-parameters were used to take into account the spatial variation of some watershed characteristics, as is shown in column 5, Table 4-4. Each of the sub-parameters was calibrated separately. Altogether, 81 parameters were calibrated in the WB_SWAT model and 78 in the WL_SWAT model.

Table 4-4 Parameters Being Calibrated

Model Input	Meaning	Value Ranges	Grouping Method	Sub-parameter No. in WB	Sub-parameter No. in WL
ALPHA_BF	Coefficient in groundwater recession	0.0 - 0.1	Soil type[1]	11	10
CANMX	Maximum canopy interception	0 - 100	Two values – crop and forest	2	2
CH_N1	Manning's "n" for tributary channels	0.01 - 0.5	Soil type	5	5
CH_N2	Manning's "n" for main channels	0.01 - 0.5	Soil type	3	2
EPCO	Adjustment factor for plant uptake of water by evapotranspiration	0 - 6	N/A	1	1
ESCO	Adjustment factor for evaporation from soil	0 - 1	Soil type	11	10
CH_K1	Channel erodibility of the soil layer	0.001-500	Soil type	5	5
CH_K2	Channel cover factor	0.001-500	Soil type	3	2
NPERCO	Nitrogen percolation coefficient	0.001-1	N/A	1	1
ADJPKR	Peak rate adjustment factor for sediment routing in the subbasin	1-10	N/A	1	1
PRF	Peak rate adjustment factor for sediment routing	1-10	N/A	1	1
NUPDIS	Nitrogen percolation coefficient	0.001-100	N/A	1	1
PUPDIS	Phosphorus percolation coefficient	0.001-100	N/A	1	1
PHOSKD	Phosphorus partitioning coefficient	0.001-1000	N/A	1	1
PSP	Phosphorus sorption coefficient	0.001-1	N/A	1	1
BIOMIX	Biological mixing efficiency	0.001-1	Two values – crop and forest	2	2
REVEP	groundwater re-evaporation time	0.001-1	Soil type	11	10
OV_N	Overland Roughness Coefficients	0.01 - 0.5	Soil type	7	5
CN2	Curve number antecedent moisture condition II	±20% 49-98	Original Default Values	13	17

Please note that division of groundwater parameters were based on the soil types in all soil layers. The division of surface soil related parameters was determined by the soil types in the top soil layer.

4.1.2.2 Calibration and Validation Results for WB

Daily stream discharge observations were obtained from the USGS gauging station located in the Watts Branch for model calibration (Section 3.1.2.2). Several daily (event-based) samples of sediments, total N, and total P were obtained from the District Department of Environment (DDOE). The model calibration period was from water year 2002 to 2008, excluding a 2-year spin-up period. The model was validated from water year 2009 to 2012. The statistics including Nash-Sutcliffe Coefficient (NSE), correlation coefficient (r), and relative bias (e/y) for daily stream discharge were recorded in Table 4-5 in both the calibration and the validation periods.

Table 4-5 Statistics of Daily Stream Discharge in WB

	Calibration 2002-2009	Validation 2009-2012
NSE	0.67	0.66
r	0.85	0.83
Relative Bias	-19.5%	-21.5%

The *NSE* in both the calibration and validation periods were greater than 0.65. For calibration over daily stream discharge, the values indicated a relatively good model performance. The correlation coefficients *r* showed a good linear relationship between the simulations and the observations. Relative biases were at about -20% in both periods. Although it is possible to reduce the bias of the discharge simulation by decreasing evapotranspiration in the watershed, the model was not un-biased because sediments and

nutrients simulation were also calibrated in the model. Manually adjusting parameters to increase discharge may lead to unreasonable simulation in other constituents, therefore, the 20% bias was accepted for this study. As expected, statistics in the validation period were slightly worse than those obtained in the calibration period. Generally speaking, the statistics suggested a good calibrated model in terms of daily stream discharge. Fig. 4-3 shows the comparison of hydrographs between SWAT and USGS observations for daily stream discharge in the calibration period and Fig. 4-4 in the validation period.
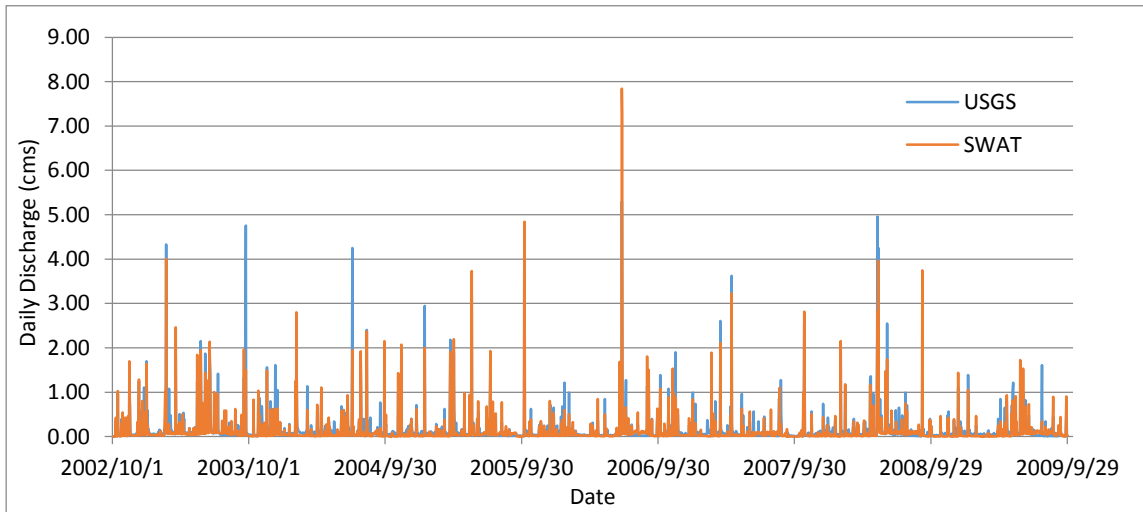

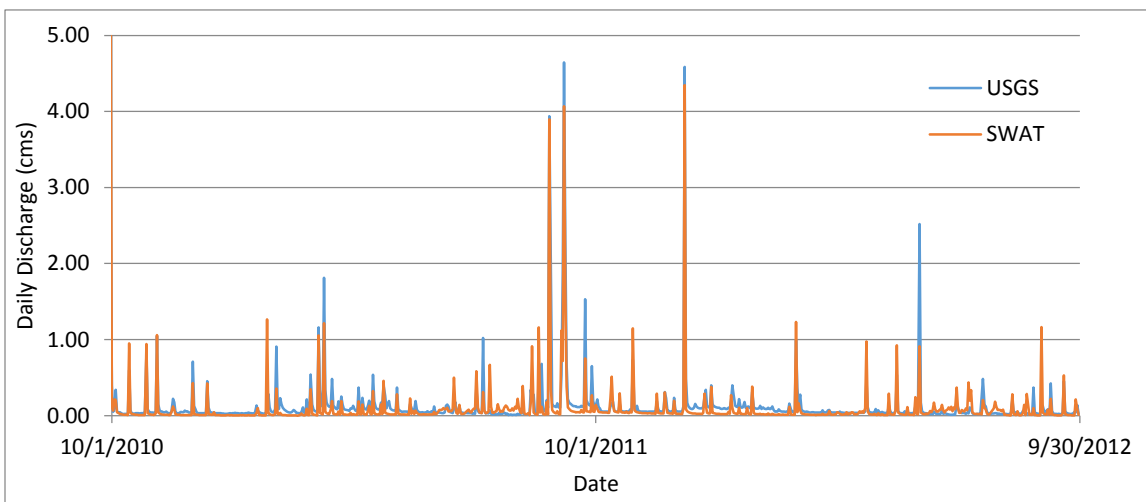Figure 4-3 Daily Stream Discharge in WB_SWAT_Pre and USGS (Calibration)

Figure 4-4 Daily Stream Discharge in WB_SWAT_Pre and USGS (Validation)

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The sediment and nutrients samples were only available in the calibration period. Eight years of daily in-stream suspended solid and nutrients (over 2100 data points for each constituent) were simulated, but there were only approximately 10 observations for each constituent in the whole calibration period. Therefore, no sediment/nutrients statistics were calculated in the calibration period nor in the validation period. Although the nutrients and sediment data was limited, these data were crucial for bringing the magnitude of the simulations to a reasonable level. Sediment yield simulated in an un-calibrated SWAT model, those simulated in the calibrated model, and the event-based observations are shown in Fig. 4-5. Sediment yield simulated in the calibrated model and the observations use the primary y-axis (left), and those simulated in the un-calibrated model use the secondary one (right). The timing of the calibrated and the un-calibrated models matched well. This is because sediment yield is generally related to precipitation event. The SWAT model showed a consistent watershed response to the precipitation events in both the calibrated and un-calibrated models. In the un-calibrated WB_SWAT model, the maximum daily suspended solid simulated at the gauging station reached 3300 tons. The maximum sediment yield in the calibrated model was 65 tons, which is more reasonable according to Watts Branch Subwatershed Action Plan (400 tons/yr) (2012). It is obvious that the model calibration would still benefit from the limited event-based data. The magnitude of total annual sediment yield had been brought down by 2. This calibration result was partially achieved through reducing the channel erodibility factors (CH_K1). Adjusting parameters related to surface runoff generation (such as curve number) also helped in reducing surface runoff, and consequently reducing overland sediment yield.
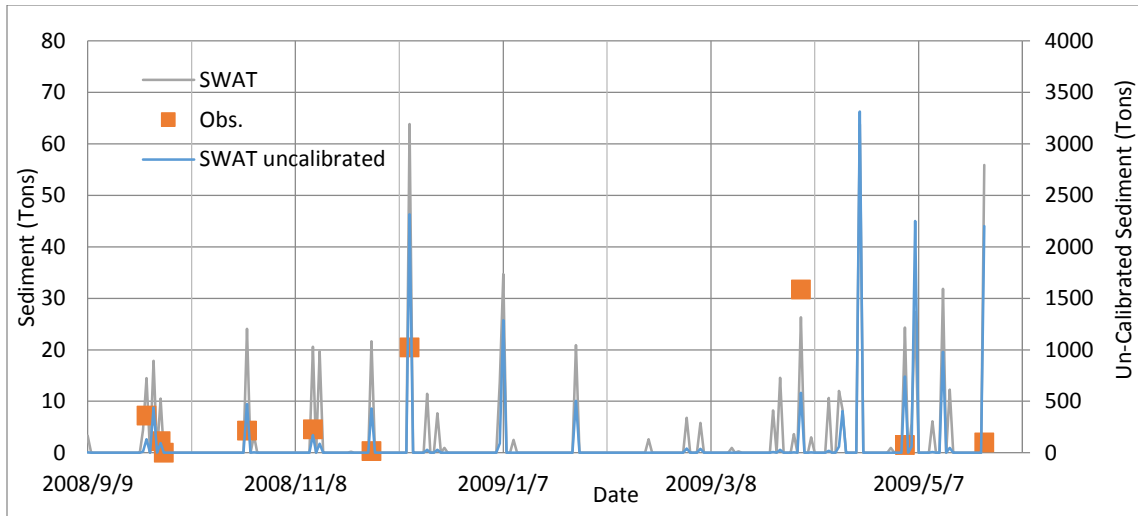
Figure 4-5 Daily Sediment Yield in Un-calibrated WB_SWAT model,
Calibrated WB_SWAT_Pre model, and Observations

The simulated daily values and the observed event-based values of total nitrogen and total phosphorus are plotted in Fig. 4-6 and Fig. 4-7. Previous research has shown that SWAT was less capable of accurately simulating daily nutrients (Bracmort et al. 2006; Gitau et al., 2008; O'Donnell et al., 2008; Zhang & Zhang, 2011; Lam et al., 2011; Liu et al., 2013). In this research, the calibrated WB_SWAT (WB_SWAT_Pre) was able to simulate the nutrients in the reasonable magnitude. The model can be considered a fair one.
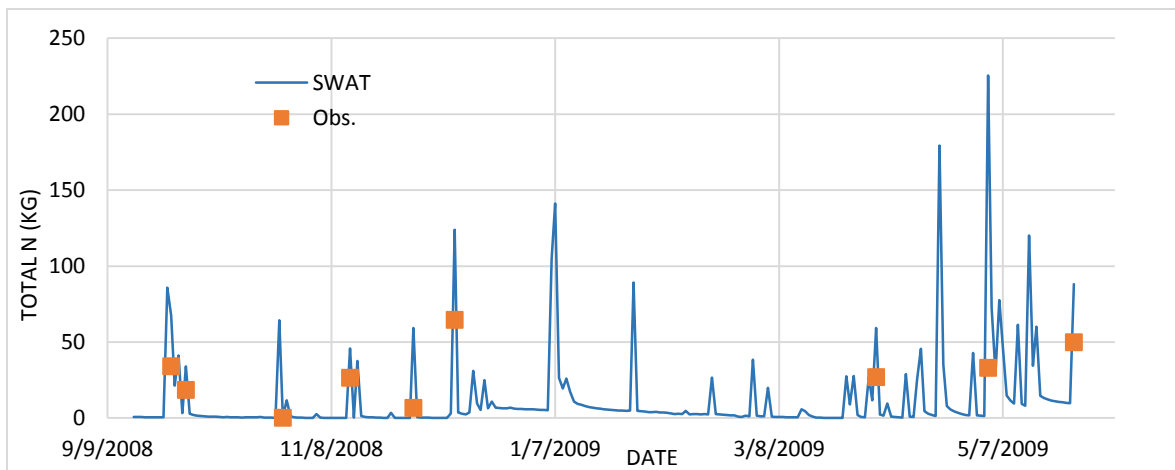
Figure 4-6 Daily Total N in the Calibrated WB_SWAT_Pre and Observations
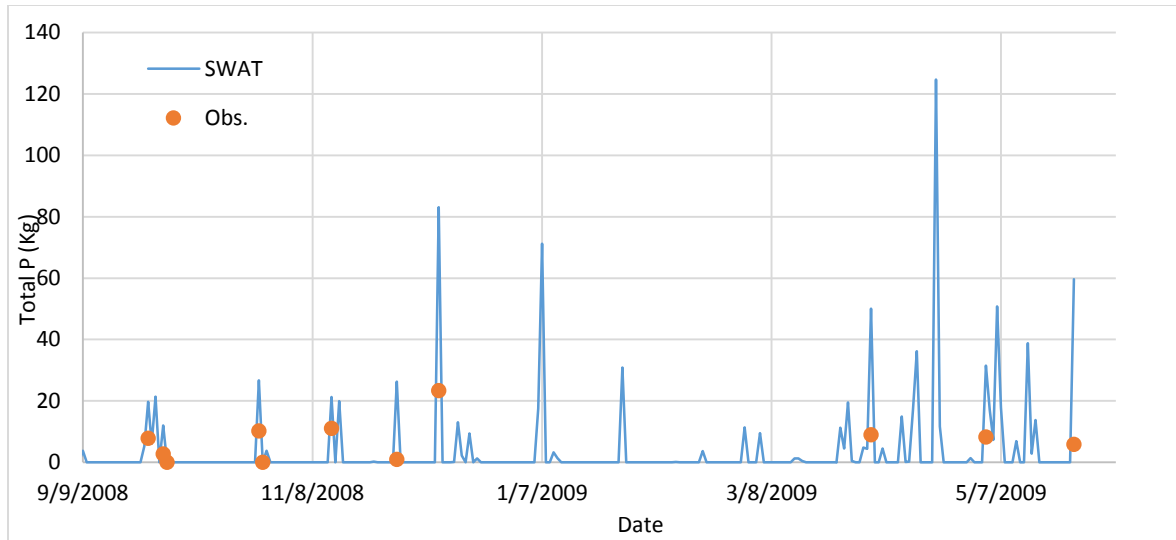
Figure 4-7 Daily Total P in the Calibrated WB_SWAT_Pre and Observations

4.1.2.3 Calibration and Validation Results for WL

As stated earlier, the USGS gauging station located at the Little Patuxent River Tributary above Wilde Lake at Columbia was not functioning until Oct. 1, 2012. However, the water quality data were obtained from 2008 to 2011. Therefore, water years from 2002 to 2011 were selected for model calibration. The SWAT model was calibrated over 20-30 observations for each of the four in-stream variables: daily discharge, suspended solid, total N, and total P observed in streams. Water years from Oct. 1, 2012 to Sept. 30, 2014 were selected for model validation. Correspondent weather data in the validation period were also obtained from the national climate data center.

Because of the paucity of the available observation data, simulated values were plotted against the observations in the calibration period. Similar magnitude was the only evaluation criteria. The following four plots (Figs. 4-8 to 4-11) show the in stream discharge, suspended solid, total N, and total P. A linear regression line was drawn in each figure. In the figures, simulation using the calibrate WL_SWAT model (WL_SWAT_Pre)

model did not match the observations well. One reason is that the observations were event-average but the simulations were daily average. The observations were sampled whenever there was a precipitation event, which generally last only for a few hours. Therefore, it is reasonable that the average hourly discharge during a storm event is greater than the average daily discharge. As for sediment and nutrients, both over-estimation and under-estimation were observed. The simulations and the observations were at least being in the same order of magnitude.
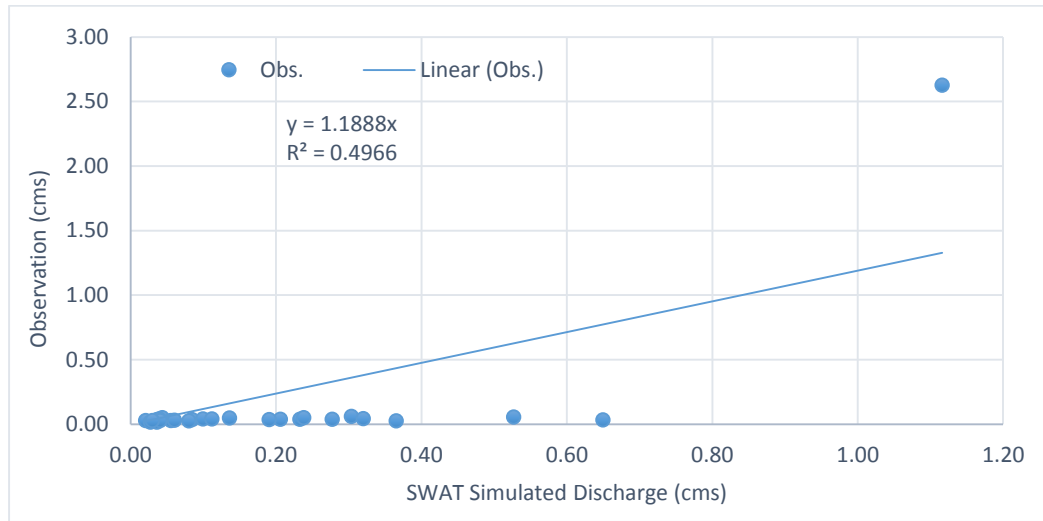
Figure 4-8 Daily Discharge in the Calibrated WL_SWAT_Pre and Event Observation
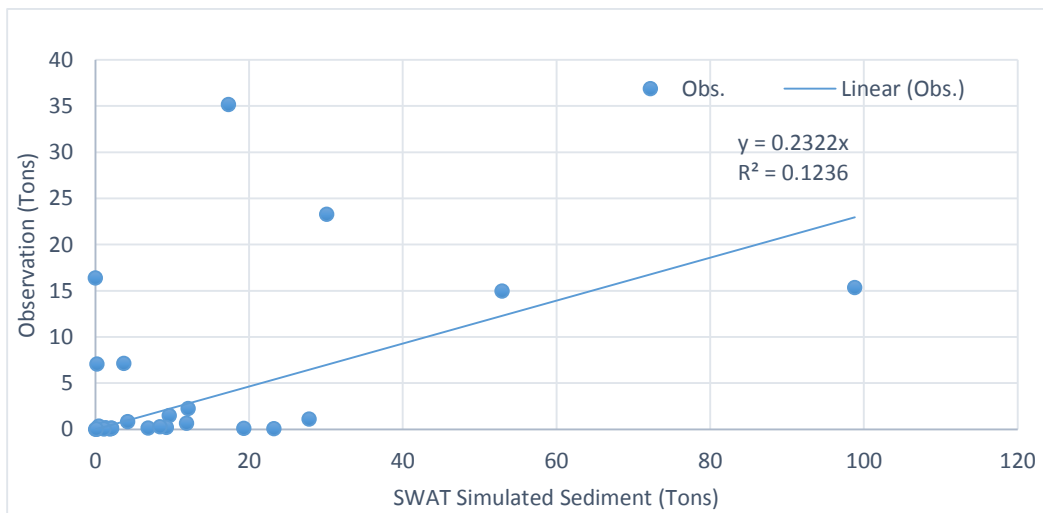
Figure 4-9 Daily Sediment Yield in the Calibrated WL_SWAT_Pre and Event Observation
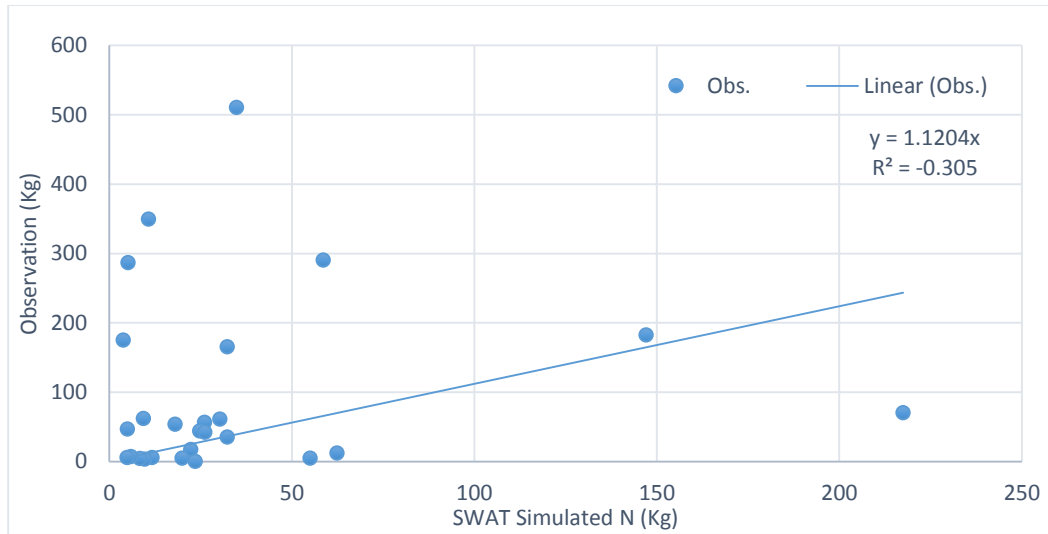
Figure 4-10 Daily Total N in the Calibrated WL_SWAT_Pre and Event Observation
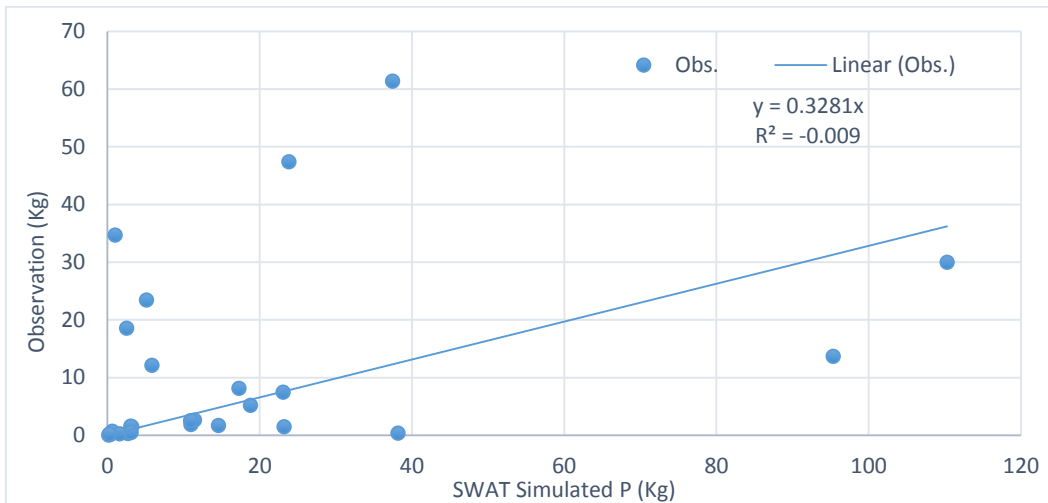
Figure 4-11 Daily Total P in the Calibrated WL_SWAT_Pre and Event Observation

In the validation period, daily stream discharge simulations were compared with the observations. For the 2-year period, the *NSE* was over 0.8, *r* was 0.9, and the relative bias was only -3% (Table 4-6). This indicated a good model performance, at least in terms of stream discharge. The hydrograph is shown in Fig. 4-12.

Table 4-6 Statistics of Daily Stream Discharge in WL

	Validation 2009-2012
NSE	0.8032
r	0.9008
Relative Bias	-0.0340
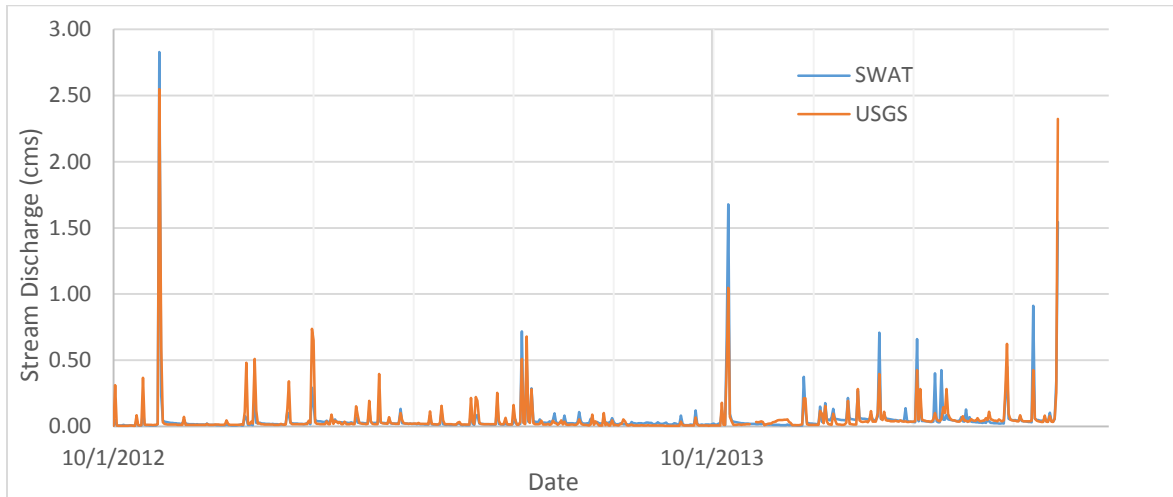
Figure 4-12 Daily Stream Discharge in the Calibrated WL_SWAT_Pre and USGS (Validation)

4.2   BMP modeling results

In this subsection, values of SWAT parameters that have been selected to represent the candidate BMPs are determined. The BMP expressions are also validated through modeling the BMPs in randomly selected hotspot HRUs.

4.2.1   Urban LID BMP Representation in SWAT

Sensitivity analysis of the parameters selected for BMP modeling was carried out in the one-at-a-time way (Section 3.2.2). The sensitivity analysis was based on the uncalibrated WB_SWAT model. Sensitivities of the selected SWAT parameters were calculated on the four variables at watershed level, namely the average annual surface

runoff (mm), sediment loading (tons/ha), total N (kg/ha), and total P (kg/ha). The four variables examined here are different from either the 4 in-stream variables or the 4 on-land variables. The 4 in-stream variables (Section 4.1.2.3) were total watershed yield represented in unit of mass/day. The 4 on-land variables were HRU level (generated in each HRU, Section 3.3.1) yield represented in unit of mass/area. The four variables examined in this section were total watershed yield represented in unit of mass/area, which were calculated by total amount of watershed yield divided by the total watershed area. Fig. 4-13 to Fig. 4-20 show the relationship between changes in one parameter values and changes in SWAT variable values. Y-axis indicates the percentage change of the four variables. X-axis shows the absolute change (FILTERW) or relative change (all other parameters) of the parameters. Whether an absolute change or a relative change was used depends on the initial value and characteristics of the parameters (Section 3.2.2).

Increases in AWC (available water capacity for plants) generally resulted in decreases in all four variables. AWC is related to lateral flow simulation and evapotranspiration (ET) of plants. AWC value is used by SWAT to determine the daily curve number value, which consequently determine the surface runoff generation. Higher AWC means more water available for plants. For a given plant type, the wilting point is fixed, and more available water means higher field capacity (water content retained in soil) and more voids in soil particles. Increase AWC would result in higher soil water content and less water yield in general. No obvious trend was observed when continuously increase the AWC value. When the AWC was increased to 120%, all four variables exhibited the highest reduction rate. When AWC continued to increase to 180% of the original value, the reduction rate decreased and maintained in that level for all four variables. The possible

reason for this decrease-increase-maintain phenomenon might be ET. When vegetation is involved, complexity in the hydrological process increases. Vegetation growth and the correspondent actual ET can be affect by AWC in a non-linear way, thus resulting a non-linear reduction in the variables. The least sensitive variables were sediment and phosphorus. This is because generation of sediments and a large portion of P (attached to sediments) only occurs in the first few inches of the soil layer. The change in AWC may not significantly change the simulated amount of these two parameters. However, decreased surface runoff caused by increases in field capacity and ET may still reduce the sediment and P generation. The most sensitive variable to AWC was total Nitrogen. It is highly possible that increased AWC promote the vegetation growth, which increased the N consumption. In summary, a 100% increase in AWC values led to less than 10% decrease in Q, Sed, N, and P.
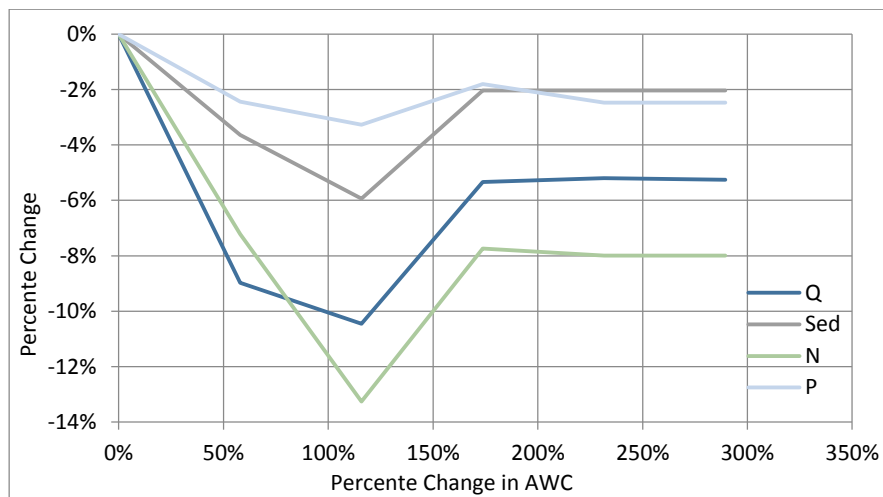
Figure 4-13 Model Sensitivity to AWC

Increases in CANMX resulted in linear decreases in most of the constituents. CANMX is the maximum amount of water that can be trapped by the canopy when the canopy is fully developed. CANMX determines the daily canopy, which is used to

determine the amount of rainfall captured by canopy and the amount of rainfall available for surface runoff. Generally, an increase in the maximum canopy results in decrease surface runoff. A possible explanation for the linear relationship between increase in CANMX and decreases in other variables is that CANMX determines the amount of rainwater that can reach the soil surface and eventually appear in streams. Water being held on the canopy evaporates back into the atmosphere directly without further involvement in the terrestrial water cycle. The effect of higher CANMX is similar to that of less precipitation, which is the driving force for all on-land and in-stream hydrology. Total P was not sensitive to CANMX. Total N and surface runoff were the most sensitive. The reduction rate of sediment remained at about 3%-4% when CANMX was increased by 500%. Higher CANMX can decrease surface runoff and sediment yield when it rains. However, the effect is still limited depending on the precipitation amount, intensity, and soil types. Also, suspended solid in stream not only include the sediment generated on land, but also include channel erosion. The total amount of sediments is not simply determined by on-land generation of sediment, thus CANMX may not be strictly linearly related total sediment yield in a watershed.
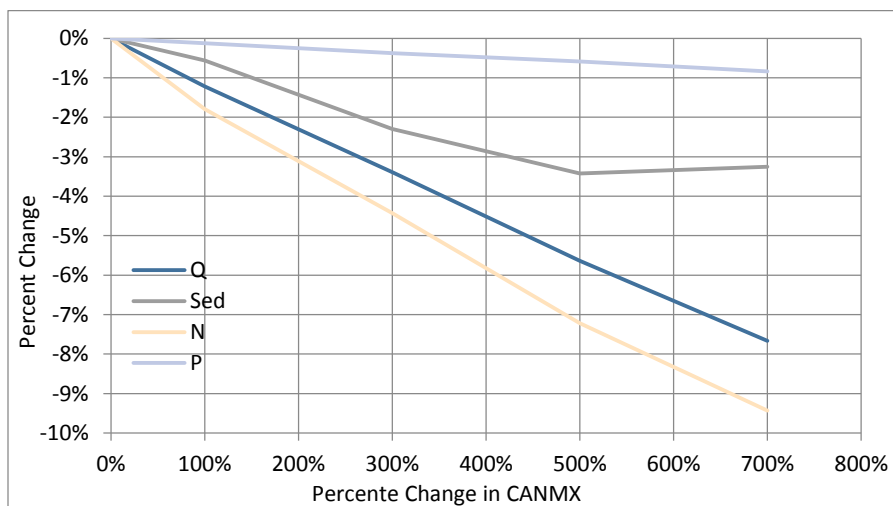
Figure 4-14 Model Sensitivity to CANMX

Change of Curve Numbers (CN2) led to two changing patens. Changes in surface runoff, sediments, and total P were positively related to the change in curve numbers. The lower the curve numbers, the less surface runoff and sediments were simulated. The reduction rates in Q and Sed were relatively high and were linearly related to the reduction in CN2. This is reasonable because CN2 was used to determine the partitions of rainwater arrival into infiltration and direct runoff as is used in the SCS equations (Eq. 3.2 and Eq. 3.3). CN2 is also used in SWAT to determine the effective soil conductivity, which is essential for simulating infiltration and lateral flow. Generally, higher surface runoff and less infiltration is expected for high CN2. However, changes in total N showed an opposite correlation: decreases in CN2 caused increases in N. This is because total N includes organic N, NO3 in surface runoff, NO3 in lateral flow, and NO3 in groundwater flow. Although there was a significant decrease in surface runoff, a greater increase in groundwater was simulated consequently. Soluble N is modeled as proportional to water flows in different soil layers. Therefore, as long as the total amount of water contributing streams increases, more N would be simulated. Generally speaking, CN2 is a influential parameter.
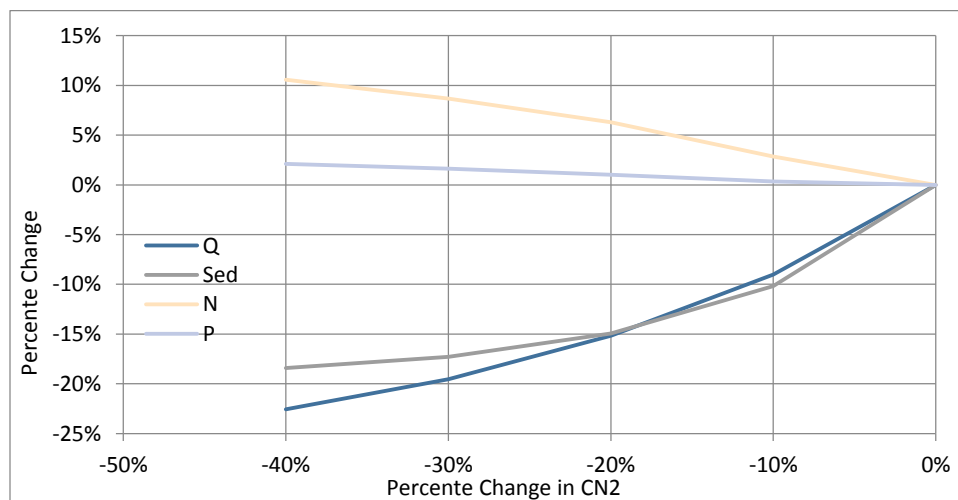
Figure 4-15 Model Sensitivity to CN2

The effects of filter strip width were quite obvious and were consistent with how SWAT treats this parameter (Fig. 4-16). Increasing the filter strip width had no effect on surface runoff generation, but resulted in linearly decreased sediment, N, and P. In SWAT, the parameter FILTERW is used to calculate the trapping coefficient for sediment, N, and P, but not for surface runoff. And practically, vegetated filter strips are designed to decrease sediments through filtration. Therefore, it is reasonable that no effects on surface runoff were observed, especially the average annual surface runoff. The assumption used in SWAT agreed with the reductions observed in existing vegetated filter strips (Section 3.2.1). Sediment loading was quite sensitive to FILTERW. A 1-meter filter strip would decrease over 35% of total sediments contribute into the streams. Trapping coefficient of nutrients are generally proportional to that of sediment. This is why the reduction curves are almost parallel to one another. Another fact that needs to be paid attention to is that NO3 in lateral flow and groundwater flow would only be reduced when FILTERW is greater than 2.5 meter in SWAT (Neitsch, 2005).
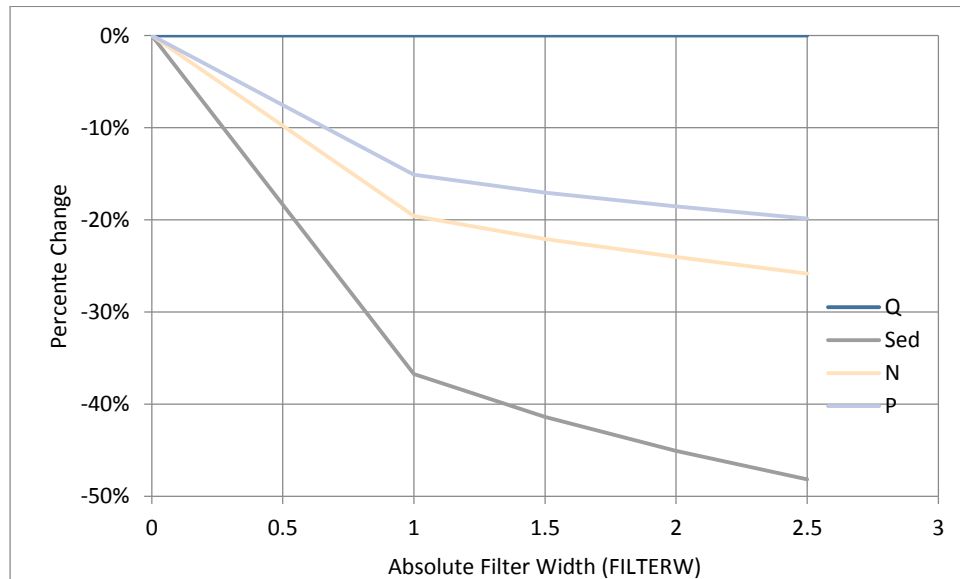
Figure 4-16 Model Sensitivity to FILTERW

Increases in Ksat (hydrologic conductivity at saturation) resulted in small, almost linear decreases in surface runoff, sediment yield, and total P yield (Fig. 4-17). Increase Ksat increases effective hydrologic conductivity which controls the amount of infiltration. This is why decreases were observed for surface runoff. Sediment yield decreased because of the decreased surface runoff, total phosphorus decreased consequently due to sediment attachment. Slight increase in total N was observed as Ksat changed. The reason is similar to the one stated earlier for CN2: groundwater increase. Generally, none of the water related variables was sensitive to Ksat. A 100% increase in the Ksat values can only result in 1.5% reduction in surface Q at most.
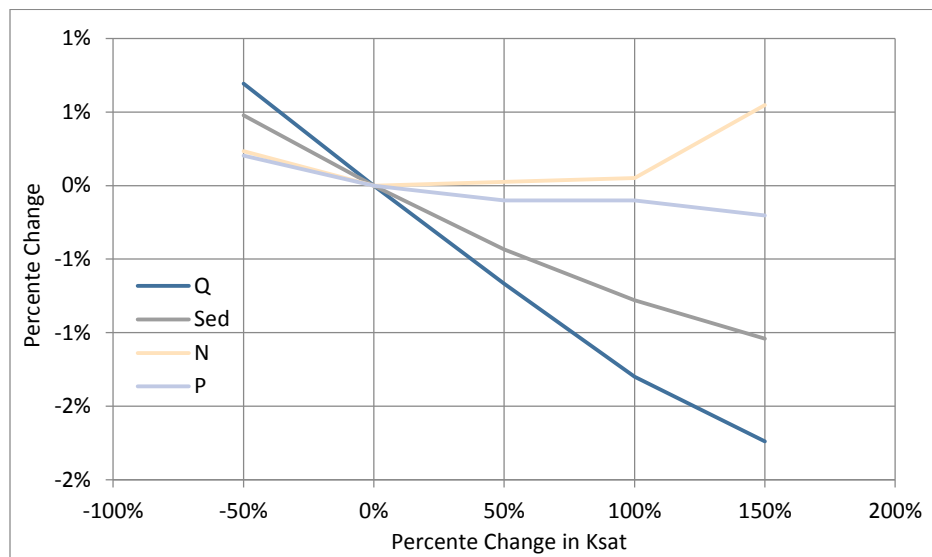
Figure 4-17 Model Sensitivity to Ksat

The SWAT model is generally not sensitive to OV_N (overland roughness coefficients), especially for the annual yield of the four variables (Fig. 4-18). OV_N is used to calculate time of concentration for overland flow. Therefore, peak runoff is more sensitive to this parameter than is total runoff volume. For a given storm (in terms of volume), higher peak runoff will cause more erosion and result in more sediment yield. This is why increase OV_N did not affect the total amount of surface runoff but showed a

linearly decrease in sediment yield. Note that the reduction in sediment was only 1.3%
when OV_N was increase by 100%. Although the overall reduction rate was small,
adjusting this parameter to simulate certain BMPs would provide a better representation to
the real world and, of course, decrease peak flow which would also affect channel erosion.
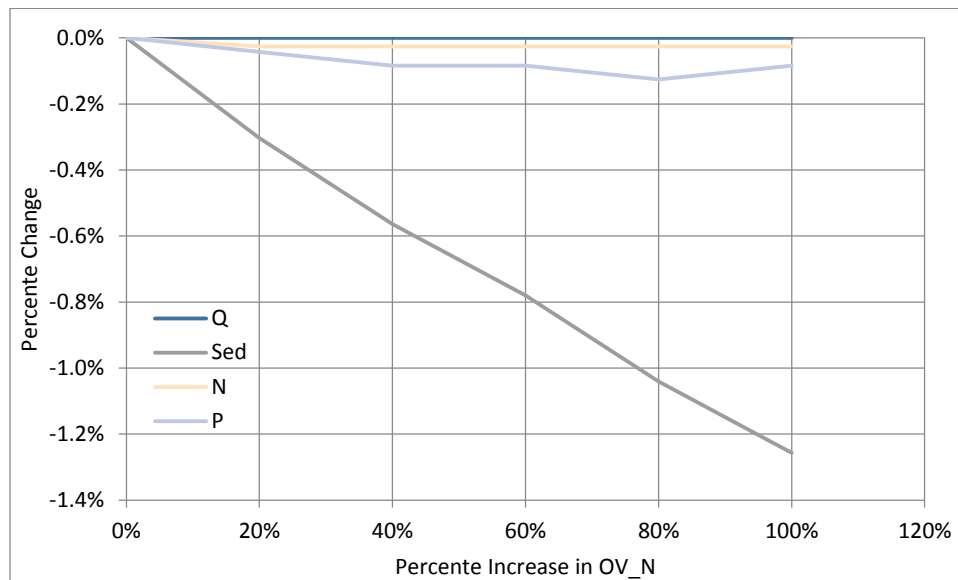
Figure 4-18 Model Sensitivity to OV_N

SWAT showed the expected response to increases of USLE_K (Modified Universal
Soil Loss Equation K Factor representing soil erodibility) (Fig. 4-19). According to Eq. 3.4
(Section 3.3.2), sediment simulation in SWAT is linearly related to USLE_K factor. As
one of the controlling variable for sediment simulation, increase in USLE_K substantially
increased sediment yield (Fig. 4-19). The reason why 50% of increase in USLE_K did not
result in a 50% increase in sediments is probably because USLE_K is only linearly related
to on-land sediment yield. In stream channel erosion is not controlled by the MUSLE.
Assuming that 50% of the in-stream sediment yield is due to channel erosion and 50% to
overland erosion, reducing the overland component by half would reduce the total by only
25% of total in-stream sediment. As for surface runoff, total N, and total P, slight increases

were observed as USLE_K increased. A 100% increase in USLE_K resulted in less than 10% of increases in these variables. Though negligible, changes in total N and total P were still linearly related to changes in USLE_K.
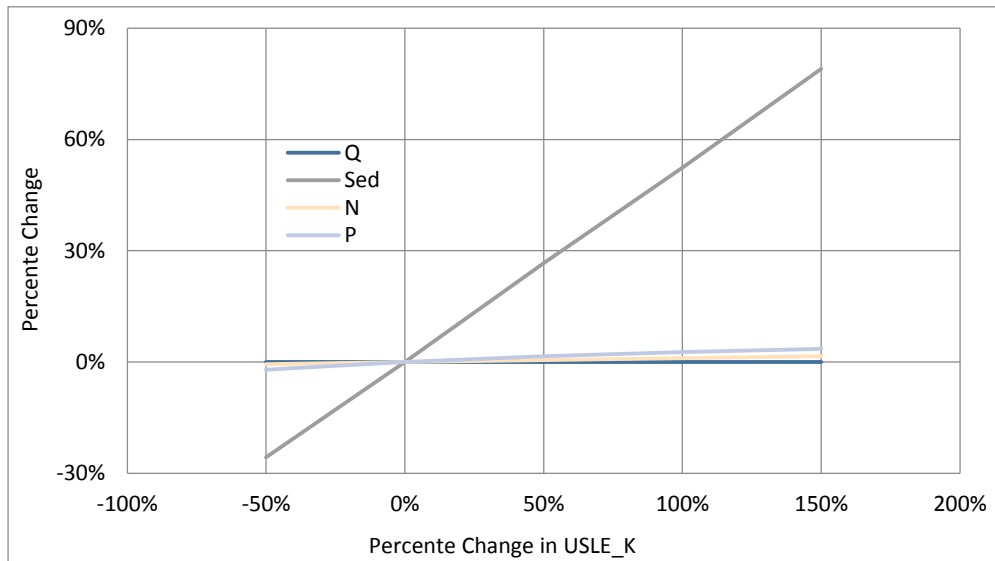
Figure 4-19 Model Sensitivity to USLE_K

FIMP (percentage of impervious surface) is a parameter directly determined by Urban Landuse Type. FIMP for each urban landuse is fixed and cannot be changed without affecting other parameters. Therefore, in order to change FIMP, the Urban Landuse ID in the .mgt SWAT input file need to be changed. The new urban landuse ID is selected according to the desired reduction in FIMP. A 100% reduction was achieved via changing the urban landuses into a non-urban one. Because FIMP is only available to urban landuses, all parameters in non-urban ones were remained the same. Therefore, the reductions were only observed in urban area. Though partly adjusted, surface runoff and sediment yields were still sensitive to changes in FIMP. When all urban areas were modeled as non-urban with zero percent of impervious area, almost 70-80% of surface Q and Sediments were reduced. Total N and P were less sensitive, but a constant 10% of decrease was still observed. Generally, FIMP is an influential parameter to SWAT simulations.
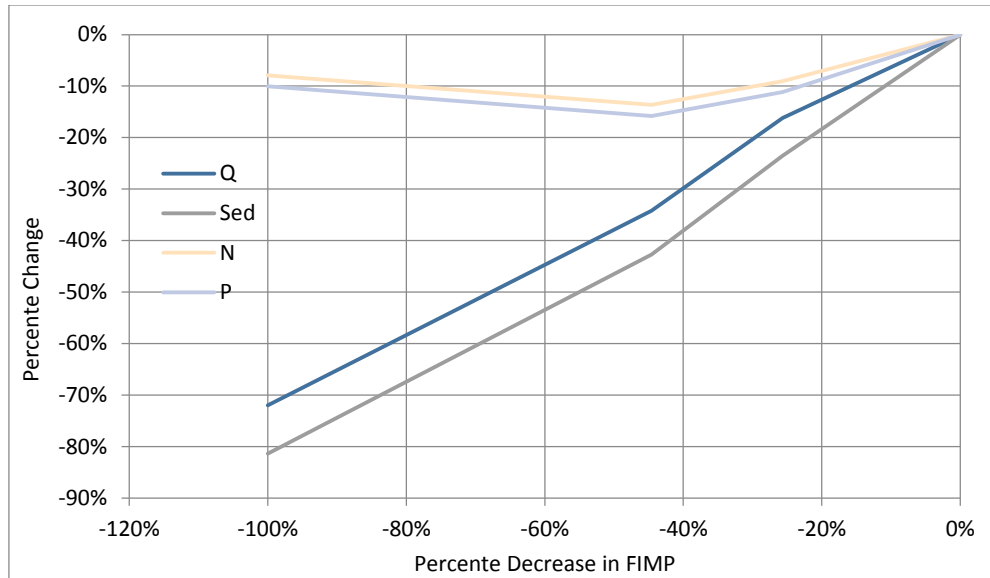
Figure 4-20 Model Sensitivity to FIMP

This sensitivity analysis provided insight into how each BMP related parameters are used in the SWAT model and how they affect the model simulation in terms of surface runoff, sediment loading, and nutrient yields. A BMP was modeled by adjusting one or more of these parameters, and present the combined effect of the changes in the variables. By comparing Fig. 4-13to Fig. 4-20 with the observed reduction rate (Table 3-16, Section 3.2.3), the parameter-change rules for each urban BMP were determined (Table 4-7). Note that some parameter may not have significant effects on reducing surface Q or any other constituents. However, including the parameters in BMP modeling is good for representing some of the physical features of the BMP. Parameters such as overland roughness coefficients OV_N may not affect the total volume of surface runoff generation in a whole year, but it may affect the time of concentration and affect the peak flow during a storm events.

Table 4-7 Parameter Representation of BMPs

BMP Codes[1]	Name	AWC	CN2	CANMX	FILTERW	OV_N	KSAT	USLE_K	FIMP	mgt.
100	Pervious pavement		↓20%			↑100%	↑100%		↓60-80%	
200	Filter strip			↑50%	4 m					
300	Rain barrel			↑15mm						
400	Green roof		↓20%	↑8mm		↑100%			↓20-40%	
500	Native landscaping	↑100%		↑100%	1 m	↑50%				mgt_500[2]
600	Rain garden	↑100%	↓30%	↑12mm	1 m		↑100%	↓50%	↓20-40%	
700	Fertilizer reduction									mgt_700[2]
800	Infiltration trench		↓30%	↑2mm			↑900%		↓20-40%	

1. BMP Codes are index used in MATLAB coding. They do not have physical meaning.

2. mgt_500 and mgt_700 are specific scheduled management operation, which include several parameters. Discussed in detail below.

To model pervious pavement, the fraction of impervious area needs to be reduced by about 70% by changing the urban land ID in order to reduce surface runoff. The industrial urban landuse (Urban ID = 6) which has 84% of impervious area is replaced by a mid-low density urban residential landuse (Urban ID = 3) with 20% impervious area. The high density urban residential landuse (Urban ID = 6) with 60% of impervious area is replaced by an urban residential with mid-low density (Urban ID = 4) with 12% impervious area. No exact reduction in FIMP is achievable because of the fixed FIMP values. Therefore, reduction ranges are provided in Table 4-7. Ksat is doubled and CN2 was set to 80% of the original values to allow for more infiltration. Overland roughness coefficients are also doubled based on the notion that pervious pavement can slow the surface runoff down.

According to SCS Recommended VFS Width (Fig. 3-1, Section 3.2.3), a filter strip needs to be at least 4m to be effective. Therefore, the filter width is given a value of 4m.

Filter strips are dense vegetation, which also increase interception. Therefore, the maximum canopy capacity is also increased by 50% to increase the amount of water being captured on the leaf area.

Rain barrels have fixed volume for rainwater storage. Therefore, a fixed increment of maximum canopy was provided. The average rain barrel holds about 55 gallons (0.227 cm^3) of water. Average roof area is estimated to be 150 ft^2 (14m^2). Therefore, the amount of rain that can be captured is about 14.7mm. Therefore, a 15 mm of canopy is added to the original CANMX.

Green roof transform the impervious roof top into a vegetated pervious area. Therefore, the percentage of impervious area in the HRU would decrease. More rainwater would be captured by vegetation. The roughness of coefficient for the roof area is decreased, resulting in a roughness decrease in impervious area in general.

Rain gardens decrease surface runoff through a depression area where rainwater can be hold. Therefore CANMX is increased. Vegetation in the garden creates a natural filter strip. Though less effective, more sediment can be trapped in the rain garden. The pounded water would be more available for transpiration. AWC is doubled accordingly. Decrease of CN2 and increase of Ksat can allow for more infiltrate. The soil used for the rain garden can be modified into a less erodible soil for sediment control. FIMP is also decreased to achieve the runoff reduction target of rain gardens.

Infiltration trench promotes groundwater recharge. Therefore, both CN2 and Ksat were adjusted for a higher effective hydraulic conductivity. FIMP and CANMX are adjusted to increase runoff reduction for infiltration trench. The modeling of native

landscaping also includes a modification of scheduled management operations. Native landscaping usually convert traditional lawn into low-maintenance native plants. The native plants would act as a natural filter strip, increasing interception, and allowing for more transpiration. The most important feature of native plants is that they do not need as much irrigation and fertilizers as the lawn. Therefore, the total amount of irrigation and total amount of fertilizer are reduced by 90% in the model. The irrigation and fertilizer efficiency were also increased slightly. Different areas have different native plants. Therefore, the type of plants in the operation management should be changed. Originally, the plant type in residential areas is BERM (Bermuda grass), which usually used for modeling lawn. The plant type was changed into Little Blue Grass, which is one of the native plants in Maryland. The SWAT plant database has limited options. New plant type can be added into the database according to specific need. These changes are made in the .mgt file.

To model reduced fertilizer usage, operation management should be changed. Slow-release fertilizers are always a better choice than the fast-release ones. These fertilizers would remain effective in the ground for a longer time and slowly release the nutrients needed by plants. Therefore, the modeled nutrients application each time can be reduced. The total maximum amount applied can also be changed. In this study, the total amount and the amount applied each time were reduced to ½ of the original values. The type of fertilizer applied can also be changed if necessary. Changes are made in the .mgt file.

4.2.2 BMP modeling Validation

As discussed in Section 2.6.2, the land phase processes and constituents yields were of concern in this study. Therefore, simulated on-land variable values were used for validation of BMP modeling. On-land variables are stored in SWAT's output.hru file, including surface runoff (mm), sediment yield (Ton/ha), total N (Kg/ha), and total P (Kg/ha) contribute to streams from each HRU. The annual values of the four on-land variables were averaged throughout the study period respectively (calculation see Section 3.3.1).

Results obtained from the calibrated WB_SWAT_Pre model were used as the pre-BMP scenario. Table 4-8 shows the basic statistics of the per-area yield of the four variables at HRU level. Different HRUs have different sizes due to the definition of HRU: a unique combination of landuse, soil type, and land slope, not spatially contiguous (Neitsch, et al. 2002). Large values observed in the per-area yield do not necessarily mean large total amount (in weight). On average, each of the 1832 HRUs (all HRUs in the WB_SWAT) generated approximately 308 mm of surface runoff, 4.6 ton/ha of sediment, 8.2 Kg/ha of N, and 3 kg/ha of P, per year (Table 4-8). The whole watershed generated 351,642 m3 of surface runoff, 1681 Tons of sediments, 8350 Kg of N, and 2363 Kg of P annual in the land phase of the SWAT model (Row 2, Table 4-10).

Table 4-8 Average annual variable values for HRU in the pre-BMP scenario in WB

Pre_BMP	Surf Q (mm)	Sed. (Ton/Ha)	N (Kg/Ha)	P (Kg/Ha)
MAX	795.59	59.37	73.73	30.40
MIN	0.09	0.00	0.76	0.00
AVE	307.65	4.57	8.18	3.08
SD	173.06	7.84	7.51	4.02

The BMPs were modeled on HRU level, which means only one type of BMP was modeled in an HRU. Eight candidate BMP types (Section 3.2.1), were modeled in the post BMP scenario. Each type of BMP was modeled in 50 randomly chosen selected from the identified hotspot HRUs. Altogether, about 20% of HRUs (in number) within the Watts Branch watershed were modeled with a selected type of BMP. Though randomly assigned, the selection process was not strictly random because the BMPs were still assigned to HRUs where relatively large amount of surface runoff, sediments, or nutrients were generated. The model with BMP implemented was defined as Post-BMP scenario. Another SWAT run was carried out in the post-BMP scenario. On average each HRU generated approximately 273 mm of surface runoff, 2.9 tons/ha of sediment, 7 Kg/ha of N, and 2 kg/ha of P annually (Table 4-9). On average, the whole watershed generated 335,424 m3 of surface runoff, 1474 tons of sediments, 8104 Kg of N, and 2176 Kg of P annual in the land phase of the SWAT model (Row 5, Table 4-10).

Table 4-9 Table Average annual variable values for HRU in the post-BMP scenario in WB

Post_BMP	Surf Q (mm)	Sed. (Ton/Ha)	N (Kg/Ha)	P (Kg/Ha)
MAX	586.00	33.75	58.55	12.50
MIN	0.09	0.00	0.76	0.00
AVE	273.34	2.89	7.08	2.07
SD	128.60	3.72	5.02	2.01

On HRU level, the maximum annual yields of all four variables were reduced significantly, with 25-30% reduction in runoff and N, 50-60% reduction in sediment and P. The mean annual yield were also reduced, with 10% reduction in runoff, 35% in sediment, 13% in N, and 30% in P. Reduction in standard deviation was also observed, which was resulted from a reduction in extreme values.

Besides comparison between the per-area yields at HRU level, reductions regarding the total watershed yield (in weight) were compared. The term "coverage area" is used in this research and in this document to represent the total area of HRUs to which BMPs were assigned. It also refers to the total area that is under control by stormwater BMP. Consequently, the total amount of the constituents generated in all these HRUs is referred as targeted constituents (in weight). In this post-BMP scenario, the 400 HRUs that were modeled with BMPs account for about 9% of total watershed area. The total amount of constituents generated in these 400 HRUs accounted for 15% of surface runoff, 25% of sediment yield, 12% of total nitrogen, and 20% total phosphorus in the pre-BMP scenario (Row 4, Table 4-10). In other words, the BMPs were prescribed to target on 15% of runoff, 25% of sediment, 12% of N, and 20% of P in weight. In the post BMP scenario, the reductions in total weight were solely caused by the reductions in the 400 HRUs due to implementation of BMPs. This is reasonable because no change should be expected in HRUs which were not assigned a BMP and whose parameters were not changed at all. The reduction rates at the whole watershed level were 5%, 12%, 3%, and 8% respectively (row 8 of Table 4-10). For the area covered by BMPs (the 400 HRUs), reductions rates were 31%, 50%, 24%, and 41% for the four on-land variables (row 9 of Table 4-10). The differences in the reduction rates are easily understood because the rest of the watershed was not changed and not being treated by the BMPs.

Table 4-10 Average annual variable values in Candidate HRUs and in the Whole Watershed

	Area	Surf_Q (m3)	Total Sed (Ton)	Total N (Kg)	Total P (Kg)
Pre_BMP	Watershed	351,642	1,681	8,350	2,363
	BMP Covered	52,325	420	1,029	462
	Target Percentage	15%	25%	12%	20%
Post_BMP	Watershed	335,424	1,474	8104	2,176
	BMP Covered	36,108	212	783	274
	Target Percentage	11%	14%	10%	13%
Reduction	Watershed	-5%	-12%	-3%	-8%
	BMP Covered	-31%	-50%	-24%	-41%

In the post BMP scenario, the average reduction rates of the four variables in each type of BMP were calculated individually (Table 4-11). Nitrogen in surface runoff (Surf N) is of particular interest because the majority of the observed N reduction rates were based on N in surface runoff or effluent of the BMPs. A small reduction rate in total N does not mean the BMP is improperly modeled. N is modeled as proportional to flow in SWAT. The reduced N in surface runoff was mainly caused by reduced surface runoff. For some infiltration type of BMPs, decreased surface runoff means more lateral flow and groundwater. Therefore, as long as the total amount of flow does not change, the total N contributing to streams would remain constant. Comparing Table 4-11 with Table 3-16 (Section 3.2.3), of the 4 BMPs with available observed reduction rates, pervious pavement, green roofs, and vegetated filter strip show acceptable modeled reduction rate. Native landscaping reduced 13% of surface runoff, 61% of N and 38% of P, just as expected. Native plants needs less irrigation and nutrients, and consequently generated less sediments. Fertilizer reduction reduced over half of all N and 20% of P. Surface runoff and sediments were slightly changed. The difference observed in reduction rates between N and P is partially related to the type of fertilizer used. In this study, the most common 10-10-10 fertilizer, which keeps the weights of N/P equal to 100/44, was selected. The reduction

rates between the two variables showed agreement with this 100/44 ratio. Other factors such as the plant type, the atmospheric deposition rate, and the soil chemistry would also lead to different reduction rate in N and P. The reduction rates of P in all BMPs were usually highly related to the reduction rates of total sediments. This is due to low mobility and the high adhesiveness to soil of P. The modeled reduction rates for infiltration trench were lower than the observed ones. But the reduction rates agree with the actual reduction rate observed in real world projects. Generally speaking, the modeled effectiveness of the BMPs are reasonable and acceptable. Therefore, the parameter adjustments proposed in Table 4-7 were used in the remainder of the study to simulate BMPs in the watershed models.

This section needs to demonstrate that your selected parameter adjustments correctly simulate the effects of BMPs, compared to reported observations.

Table 4-11 Table Average annual variable values for HRU in the post-BMP scenario

BMP	Reduction Rate				
	Surface Q	Sediments	Total N	Total P	Surf N
Pervious Pavement	-73%	-89%	-52%	-90%	-65%
Filter Strip	0%	-56%	-40%	-55%	-55%
Rain Barrel	-17%	-16%	-12%	-14%	-7%
Green Roof	-43%	-59%	-9%	-62%	-50%
Native Landscaping	-13%	-36%	-61%	-38%	-57%
Rain Garden	-43%	-75%	-29%	-78%	-53%
Fertilizers Reduction	-3%	2%	-53%	-20%	-47%
Infiltration Trench	-21%	-27%	-17%	-31%	-19%

4.3   DDSS Results

The primary goal of this Diagnostic Decision Support System is to find physically suitable BMPs for the entire watershed with diverse landuses and soil types. Limited

budget has always been a challenge in making stormwater management and NPS control plans. Therefore, priority should be given to areas that pose the highest threat to the overall water quality in a watershed. Those high threat areas -- called NPS hotspots -- should be identified before any plans are made. By doing so, the management plan can be executed with minimum input (budget, human resources) while getting the maximum output (NPS reduction).

4.3.1 Hotspot Identification

4.3.1.1 Hotspots Identified in Watts Branch Watershed

The simulation results from the calibrated WB_SWAT_Pre model were used for hotspot identification. The average annual per-area yield of surface runoff (SurfQ), sediment yield (Sed), total nitrogen (N), and total phosphorus (P) were imported into GIS maps for visualization. The HRUs were ranked by annual per-area yield of NPS and classified into five categories by HRU count (Figs. 4-22 to 4-25), which also indicated of severity of the NPS problem. Color red indicates the highest yield and the highest threat; color green indicates the least yield and the least threat. Each category, represented by different colors, includes the same number of HRUs. Because HRUs had different sizes, as how the concept of HRU is defined by SWAT, same number of HRU does not mean a same size of area, thus resulting in an un-even distribution of colored area. Category red indicates the areas where the highest rate of surface runoff, sediments, or nutrients was simulated in the watershed. The red area was the hotspots identified in the watershed for each of the variable of interest. The annual per-area yield of the constituents, instead of the

total yield in weight, was used as the indicator of hotspots because of the cost-effective concern.

In the Watts Branch watershed, surface runoff generation was almost evenly distributed in the whole watershed. The majority of the hotspots (SurfQ_hs) were observed in the northern part (downstream area). The northern 2/3 of the watershed contributed large amount of surface runoff into the Watts Branch. In the upstream area, surface runoff generation was the lowest (Fig. 4-22). Comparing the Surface Runoff Hotspots Map (Fig. 4-22) with the Satellite Image Map (Fig. 4-21), a clear correlation between urban landuses and surface runoff generation is observed. The places with more forest and vegetation coverage tend to generate less surface runoff, as is observed in the southern part of the watershed and a green spot south of the highway. Highway, parking lot, and bare land generate the highest amount of surface runoff, followed by residential area with various densities. The highest amount of simulated annual surface runoff was 800 mm, and the lowest was 0.09 mm (legend in Fig. 4-22). The lower four categories each showed a range of approximately 100 mm. The hotspots category (red) showed a range of 460 to 800mm, which is almost 3 times of the other ranges. Because each category had the same number of HRUs, the differences in range indicated that extreme runoff generation was only observed in a small number of HRUs.

Sediment yield hotspots (Sed_hs) were much less observable (Fig. 4-23) compared to the SurfQ_hs. Although bearing the same number of HRUs, the total area of the sediment hotspots was much smaller than that of the runoff hotspots because of the variation in HRU sizes. The small hotspots coverage area indicated that the most sediment was generated in a relatively small area with extremely high concentration. 80% of HRUs in Watts Branch

watershed were simulated to have less than 7 tons/ha/yr of sediment yield. Sediment yield in the remaining 20% of HRUs was as high as 60 tons/ha/yr. The range of sediment yield in each category differed from 0.06 to 54 tons/ha/yr. Compared to the ranges observed in the SurfQ_hs, the variation in the range of Sed_hs indicated that sediments were less uniformly distributed in the watershed. This result agrees with other research finding (Lemunyon and Gilbert, 1993; Sharpley et al., 2003; Sivertun & Prange, 2003; Heathwaite et al., 2005; Page et al., 2005; Scanlon et al., 2005; Sadegh-Zadeh et al., 2007; Buczko and Kuchenbuch, 2007; Srinivasan & McDowell, 2007; Frey et al., 2009).

A large amount of total Nitrogen generation was observed in the DC portion of the watershed (Fig. 4-24). Fertilizer from lawn in residential area is a main contributor to the total amount of N yield. The sources of N in the rest of the Watts Branch watershed included atmospheric deposition, precipitation, and nitrogen in soil. High level of surface runoff in this area is another reason. Higher surface runoff tends to wash away a larger amount of fertilizer in a storm event. Hotspots location for total N are correlated to the surface runoff hotspots location to some degree. Generally, in areas with high surface runoff generation, simulated N generation was also high (in category red and orange). The N hotspots tend to have both high surface runoff and a residential landuse type.

The distribution of total P hotspots was closely related to sediment hotpots (Fig. 4-25), partly because of the low mobility and P attachment to sediments. Fertilizer modeled in the watershed also contains P. Therefore, a relatively high P (orange category) simulation was observed throughout the residential area. A clear dividing line is observed in the P_hs map. This is the boundary between the District of Columbia and Prince George's County (PG), Maryland. The SSURGO data were retrieved on a county basis.

DC and PG uses different soil names and categories in the soil survey. Therefore, the same type of soil on both sides of the border was identified as different soil types in the ArcSWAT model, resulting in different HRUs and the dividing line. Ideally, the two soil survey data should be merged, and the same type of soil should be given a unique name. Since the naming of the soils are so different and it is extremely hard to merge the two sets, the names and types of soil in the two area were kept the same as the original data. Moreover, having one type of soil divided into two would not cause any technical modeling problems. The changes would be an increased number of HRUs in the subbasins where the dividing line is located. Parameters for model calibration would also increase, which is generally not a concern nowadays because of modern computers with better computational power.
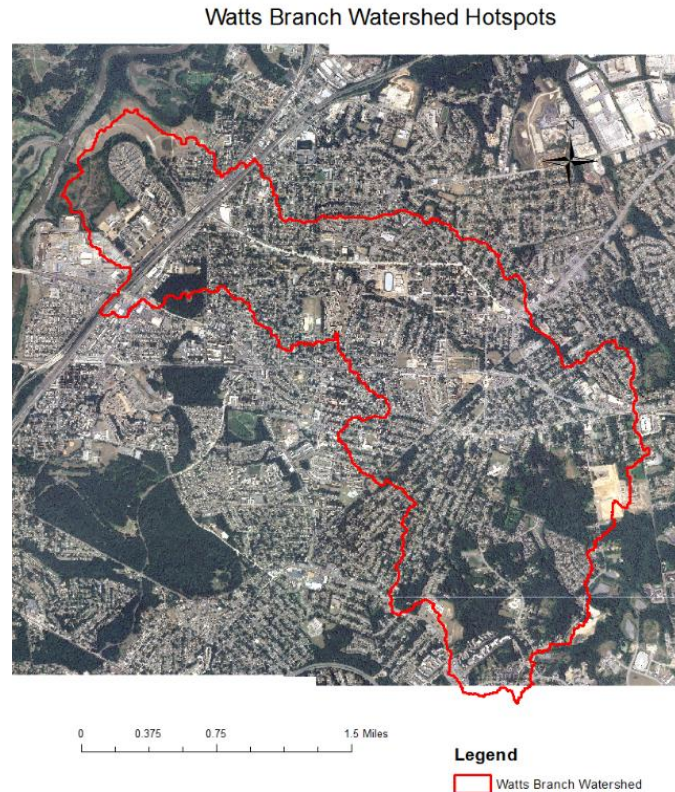
Figure 4-21 Satellite Image of Watts Branch Watershed

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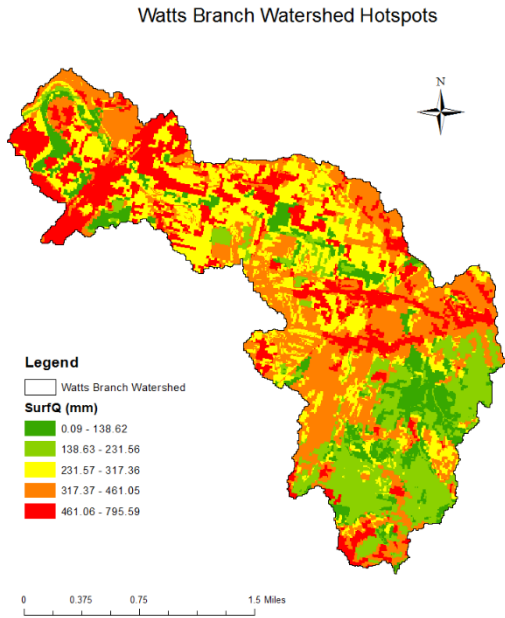
Figure 4-22 Surface Runoff Hotspot in Watts Branch Watershed
HRUs are ranked by runoff depth, and divided into 5 categories by count.
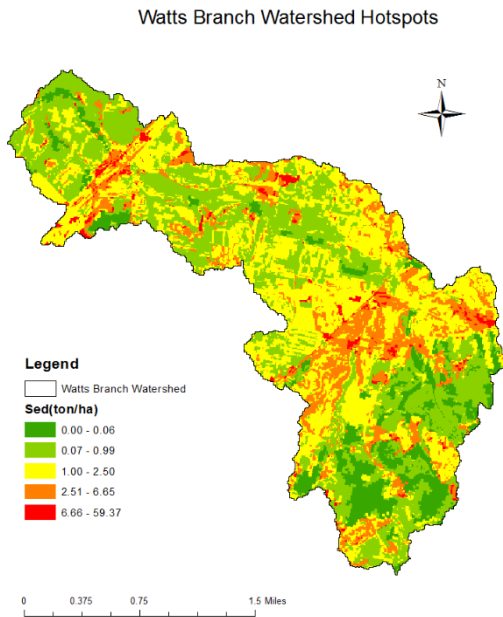
Figure 4-23 Sediment Hotspots in Watts Branch Watershed
HRUs are ranked by sediment yield (tons/ha), and divided into 5 categories by count.
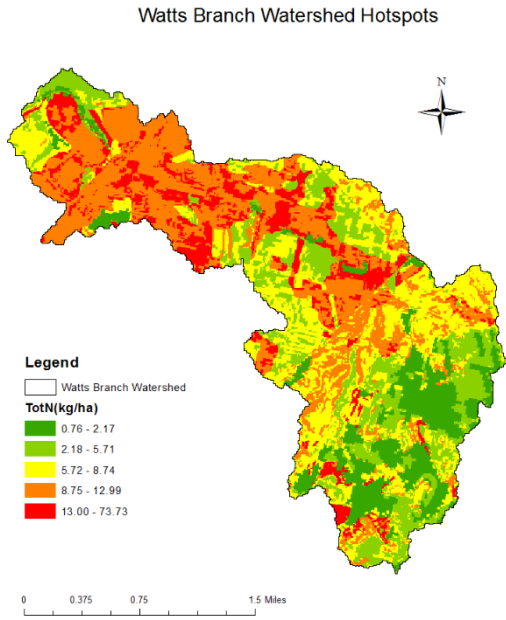
Figure 4-24 Nitrogen Hotspots in Watts Branch Watershed
HRUs are ranked by N yield (kg/ha), and divided into 5 categories by count.
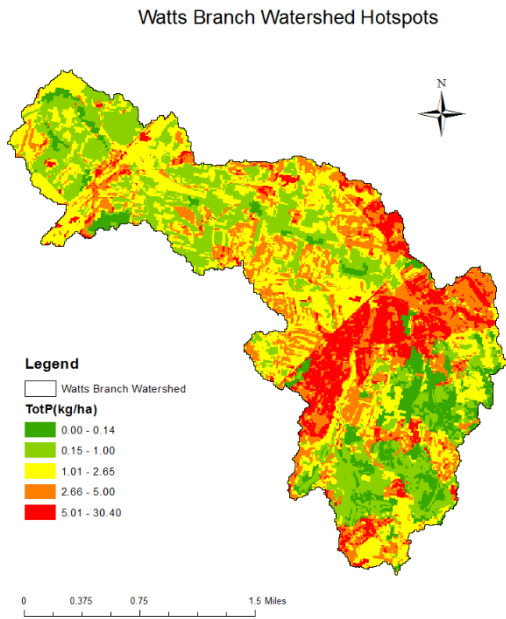
Figure 4-25 Phosphorus Hotspots in Watts Branch Watershed
HRUs are ranked by P yield (kg/ha), and divided into 5 categories by count.

Besides the range of the data sets and the spatial distribution of the hotspots, analysis was also carried out to examine how hotspot definition threshold would affect the total BMP coverage area and the total amount of NPS pollutant treated. In Figs. 4-26 to 4-29, the X-axis is the HRU numbers in percentage. A 10% means 10% of HRUs that generate the highest amount of per-area NPS pollutants. Y-axis shows the percentage of watershed area covered and percentage of total NPS weight treated. Assuming that the top 20% HRUs were chosen as hotspots, about 20% of total watershed area would be covered to treat 30% of total amount of surface runoff. Sediment hotspots would cover 3% of total watershed area and treat 20% of total sediments. N hotspots would cover 18% of total area with 32% of total N being targeted. P hotspots would cover 5% of total area and treating 20% of total P. If the top 40% HRU were chosen as hotspots, about 50% of total watershed area would be targeted to treat 70% of total amount of surface runoff; 15% of coverage area targeting 50% of total sediments; 35% of watershed area targeting 60% of total N; and 22% of coverage area targeting 55% of total P. These four figures better illustrate that surface runoff was more evenly distributed in this urban watershed. Sediments and nutrients were more likely to be localized in smaller area. The four figures also provide useful information for decisions regarding how many hotspots should be identified in terms of coverage area and targeting NPS.

One thing that needs to be noted is that hotspots for surface runoff are not necessarily the hotspots for sediment or nutrients. The hotspots identified for different variables were based on the yield of that specific variable. Therefore, the 20% of HRU identified as SurfQ_hs may not be the same 20% of HRU identified as Sed_hs. This is why the total

coverage area for all four sets of hotspots within a watershed is greater than the coverage

area of each variable alone (Table 4-16, Section 4.3.2.3).
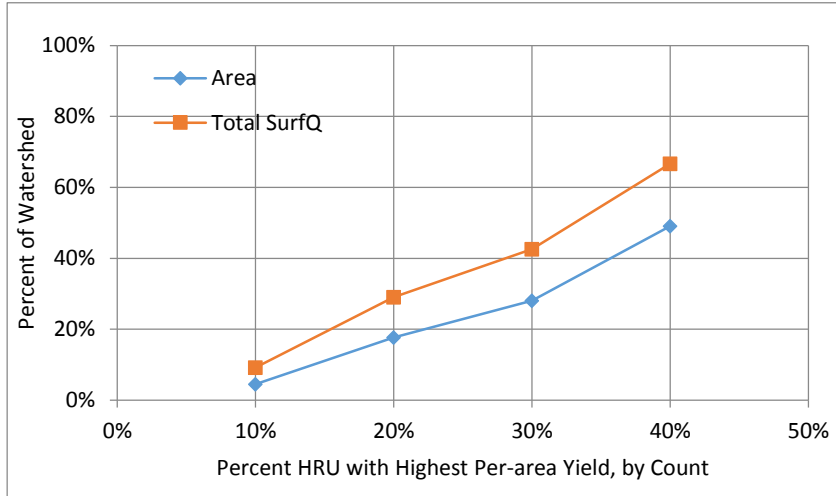
Figure 4-26 Coverage Area and Treating Amount vs. Hotspots Thresholds
Per-area yield of surface runoff in Watts Branch Watershed
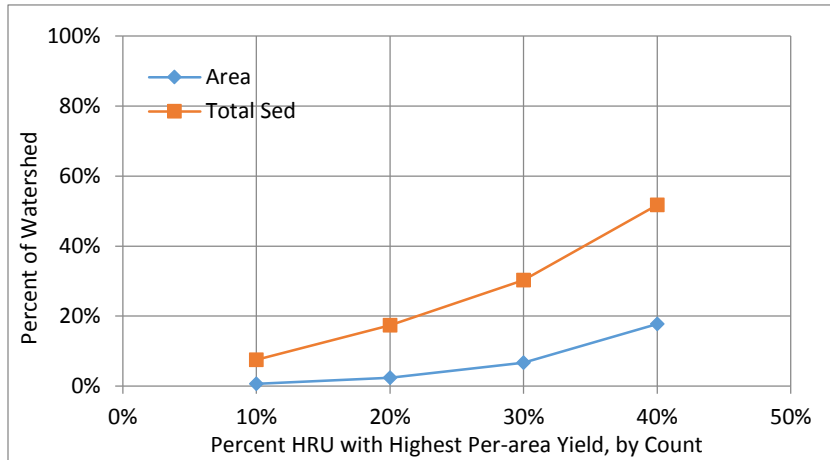
Figure 4-27 Coverage Area and Treating Amount vs. Hotspots Thresholds
Per-area yield of Sediment in Watts Branch Watershed
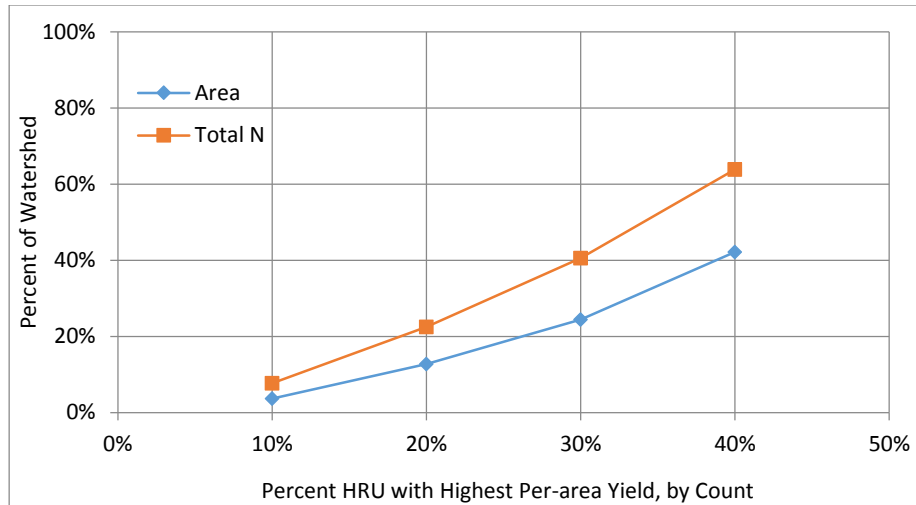
Figure 4-28 Coverage Area and Treating Amount vs. Hotspots Thresholds
Per-area yield of N in Watts Branch Watershed
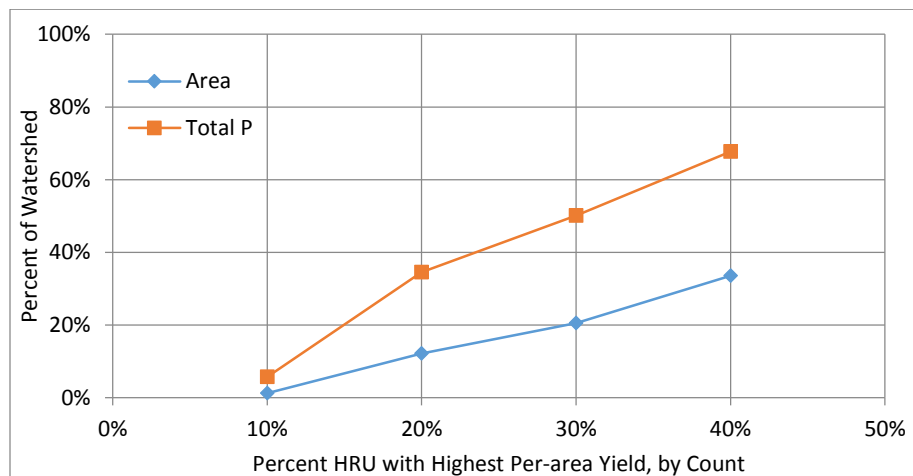
Figure 4-29 Coverage Area and Treating Amount vs. Hotspots Thresholds
Per-area yield of P in Watts Branch Watershed

As stated earlier, per-area amount were used as the indicator for hotspots rather than the total amount of yield in each HRU. The reason for doing so can be better illustrated through Figs. 4-30 to 4-33. These four figures show similar analysis as discussed above, showing the total coverage area and total targeted weight in percentage, with the exception that the hotspots were identified using the total amount. When identifying hotspots using the total HRU yield, targeting 10% of HRUs that generate the greatest NPS pollutant

amount would require an approximately 50% of total watershed area be covered with BMPs. At the same time, the total amounts being treated were similar to those being treated by BMPs applied to 40% of HRUs identified on the per-area yield basis.
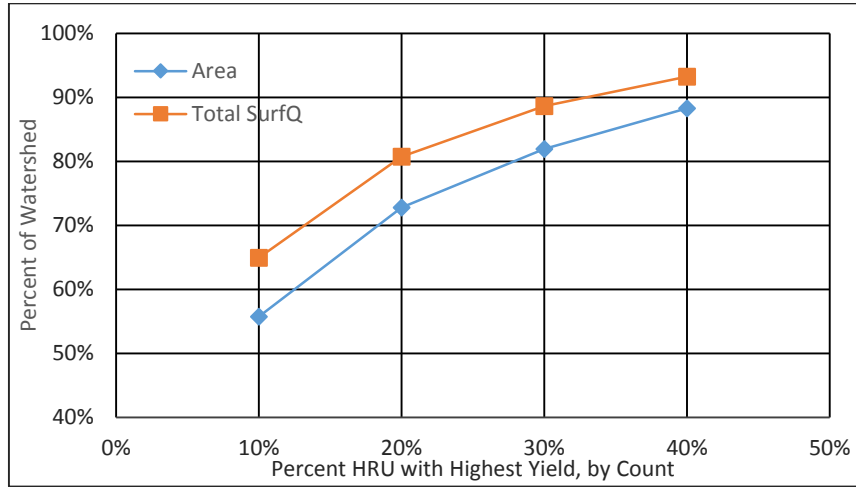
Figure 4-30 Coverage Area and Treating Amount vs. Hotspots Thresholds
Total yield of surface runoff in Watts Branch Watershed
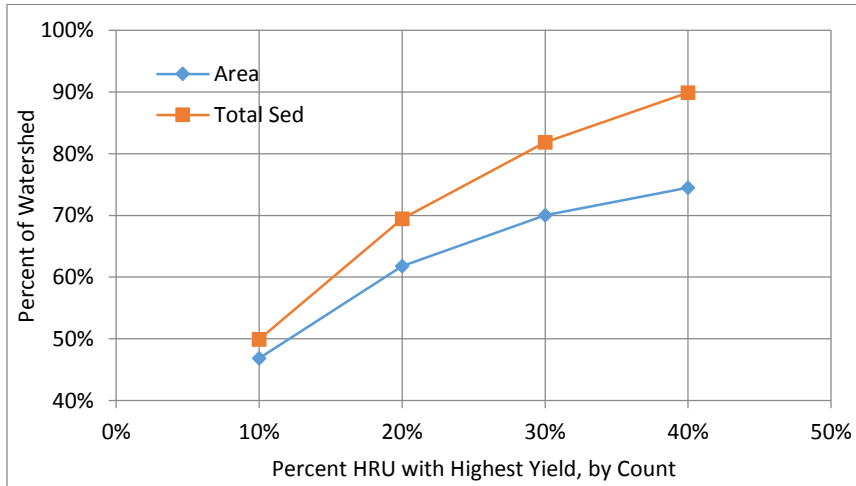
Figure 4-31 Coverage Area and Treating Amount vs. Hotspots Thresholds
Total yield of sediment in Watts Branch Watershed
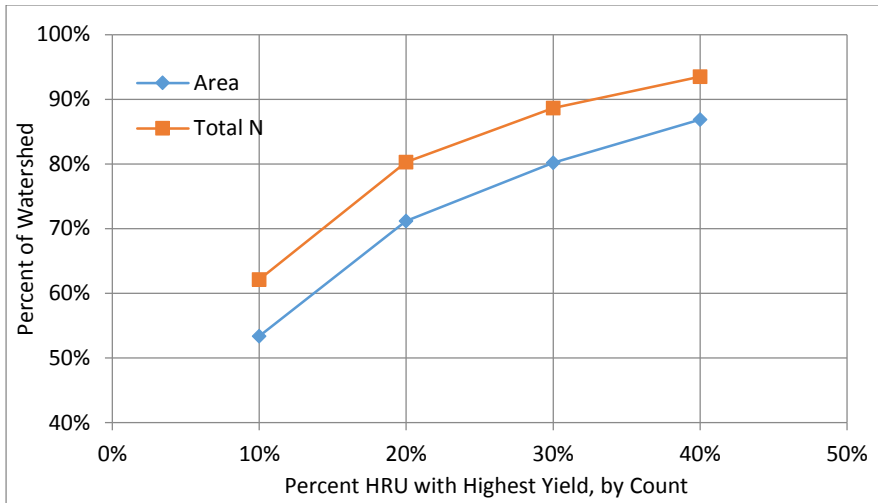
Figure 4-32 Coverage Area and Treating Amount vs. Hotspots Thresholds
Total yield of N in Watts Branch Watershed
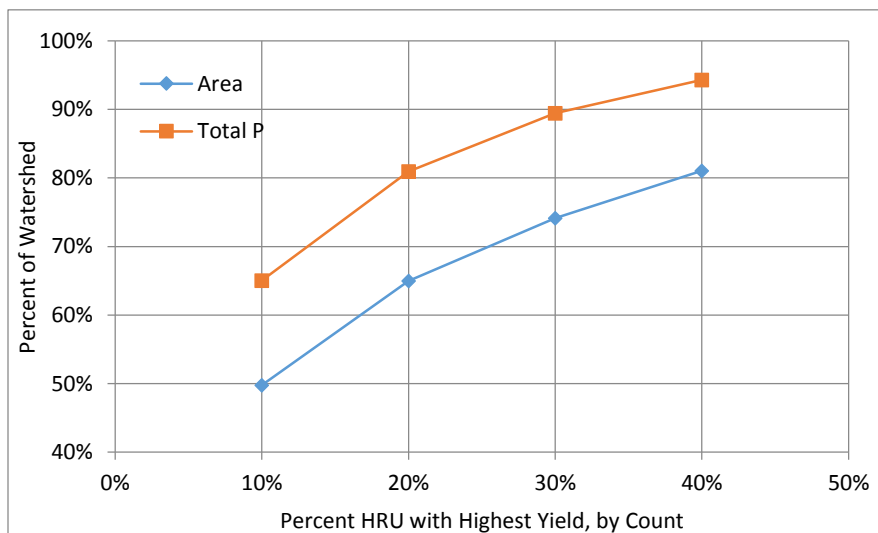
Figure 4-33 Coverage Area and Treating Amount vs. Hotspots Thresholds
Total yield of P in Watts Branch Watershed

4.3.1.2   Hotspot Identification in the Wilde Lake Watershed

Hotspots in the Wilde Lake watershed were identified using the same procedure as used in the Watts Branch watershed. The HRUs were ranked by annual per-area yield of NPS and classified into five categories by HRU count. Color red indicates the highest yield and the highest threat; color green indicates the least yield and the least threat. Each

category, represented by different colors, includes the same number of HRUs. In the Wilde Lake watershed, surface runoff hotspots (Fig. 4-35) were located at the southern part of the watershed where highway and high density urban residential area are observed (Fig. 4-34). Low runoff area overlapped the non-urban landuses as shown in the satellite image. The residential area in the northern part also show high runoff yields. Category red indicated a surface runoff generation from 400 to 700 mm per year in the hotspots. A large range from 0 to 200 mm in category green is also observed because of the relatively large open water area of the Wilde Lake. Compared to the Watts Branch watershed, the highest runoff generation at HRU level in Wilde Lake watershed was about 100mm less. The two watersheds are located within a distance of 30 miles. The annual precipitation and air temperature are approximately the same in the two areas. One possible reason for this discrepancy in surface runoff is that Watts Branch watershed is more urbanized and Wilde Lake has a flatter terrain. Also, the soil property in the two watersheds may differ. Wilde Lake tend to have more permeable soil, which allows for more infiltration and produces less stormwater runoff.

The sediment hotspots in the Wilde Lake watershed were mainly located in the northwestern and the southern parts of the watershed (Fig. 4-36). The annual sediment yield in the hotspots ranges from 6 ton to 175 tons per hectare per year. The maximum sediment yield in an HRU was 3 times the amount generated in Watts Branch. One possible reason is that the top soil layer in Wilde Lake is more erodible: the mean soil erodibility factor USLE_K is 0.22 in WB and 0.30 in WL. Moreover, lack of observation data in the WL watershed might have resulted in less reliable model calibration results, which is another explanation for the discrepancy.

The nitrogen hotspots were located in the southeastern highway area and the northwestern Cedar Lane Park (Fig. 4-37). The highway area is also identified as surface runoff hotspots, therefore, high level of nitrogen is expected in this region. The Cedar Lane Park has several soccer fields and baseball fields. Maintenance of the fields requires large amount of fertilizer, which is known to be a main source of N in urban/suburban watershed. The N hotspots are also scattered in the urban residential area where fertilizer is also required in large amount to maintain the lawn. Nitrogen generation in Wilde Lake is higher than that in Watts Branch in general. One possible reason is that residential area with lower urban density tend to have more pervious surface, most of which is contributed to lawn. Less lawn area requires less fertilizer application, which in turn increases the amount of fertilizer being washed away in storm events. Also in the Wilde Lake watershed, there are more recreational area and sports fields which require more nutrients for maintenance. There are also other landuse types such as hay and crops, contribute large amount of nutrients, but were not observed in the Watts Branch watershed.

Phosphorus hotspots in the area were highly related to sediment yields (Fig. 4-38). Generally speaking, if the HRU is identified as a sediment hotspot, it is also identified with high P yield (category orange or red). The amount of P is also closely related to fertilizer. The fertilizer being modeled in the study is the most common 10-10-10 among which N, P, and K account for 10% of the total fertilizer weight, respectively. Therefore, high amount of P were simulated in urban residential area. A higher P yield in the watershed as compared to that in the WB share the same reason as is explained for higher N yields. One may also notice that the P hotspots are more spread out in the whole watershed while the P hotspots in WB watershed tend to localize in the central part of the watershed. This is

mainly because of the landuse difference between the two watersheds. The landuse in WB is quite unique because of the district division line. Landuse within DC (lower WB) area are high and medium density residential landuses. The downstream part of WB within PG County are dominated by low-density residential houses, while the upstream area is forest. The regional landuse differences caused the P hotspots distribution in the Watts Branch watershed. However, in the Wilde Lake region, residential landuses with high, medium, and low density were evenly distributed along the stream within the watershed.
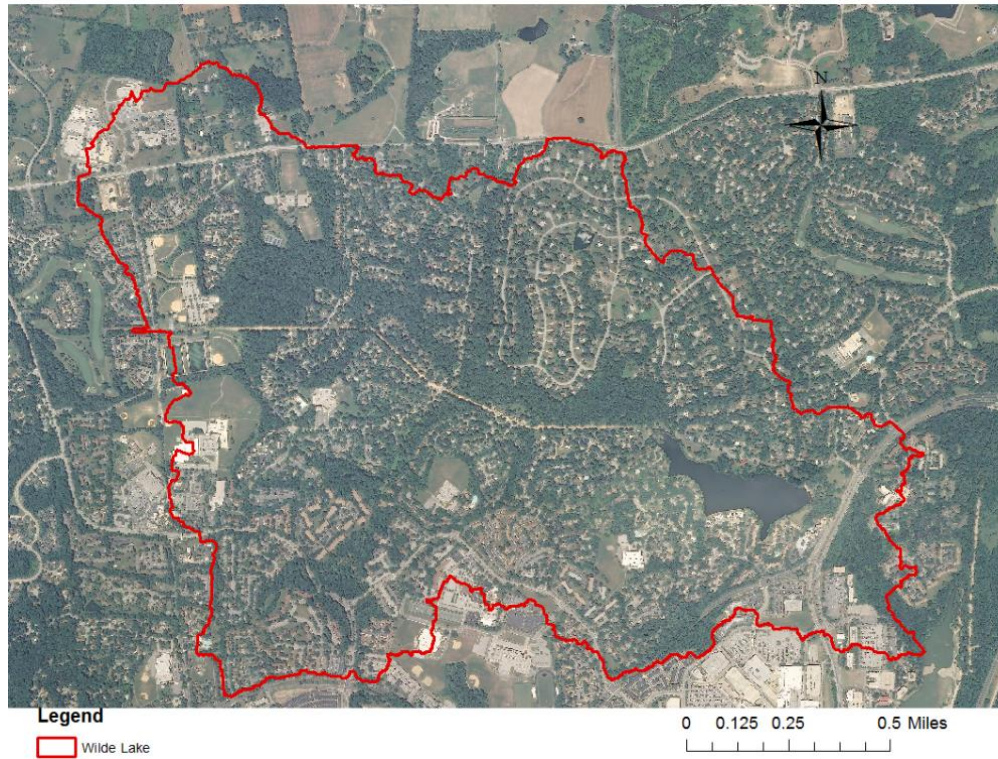
Figure 4-34 Satellite Image of the Wilde Lake Watershed
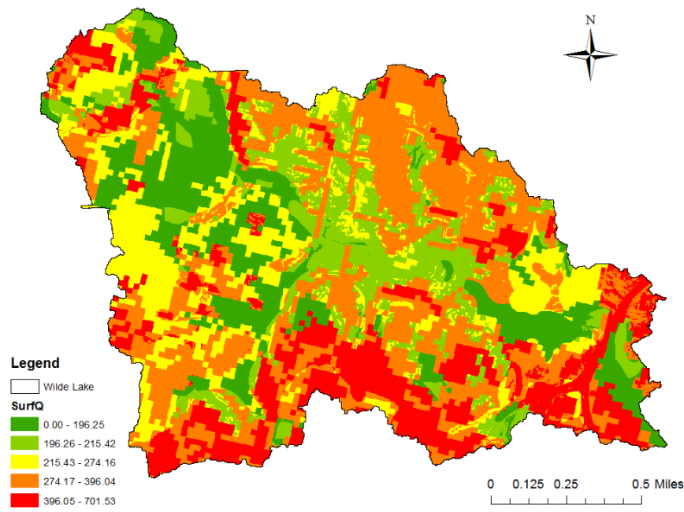
Figure 4-35 Surface Runoff Hotspots in Wilde Lake Watershed
HRUs are ranked by runoff depth (mm), and divided into 5 categories by count.
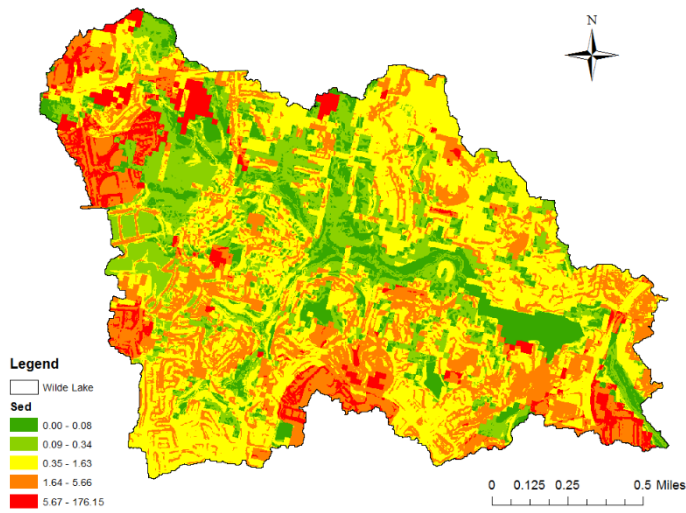
Figure 4-36 Sediment Yield Hotspots in Wilde Lake Watershed
HRUs are ranked by sediment yield (tons/ha), and divided into 5 categories by count.
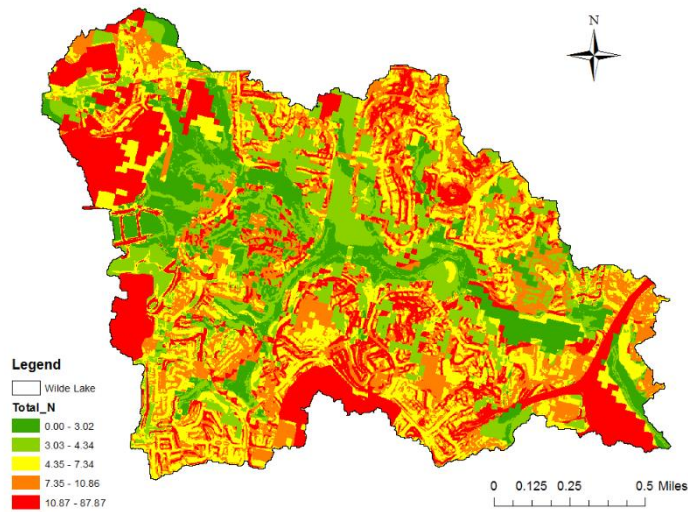
Figure 4-37 Nitrogen Hotspots in Wilde Lake Watershed
HRUs are ranked by N yield (kg/ha), and divided into 5 categories by count.
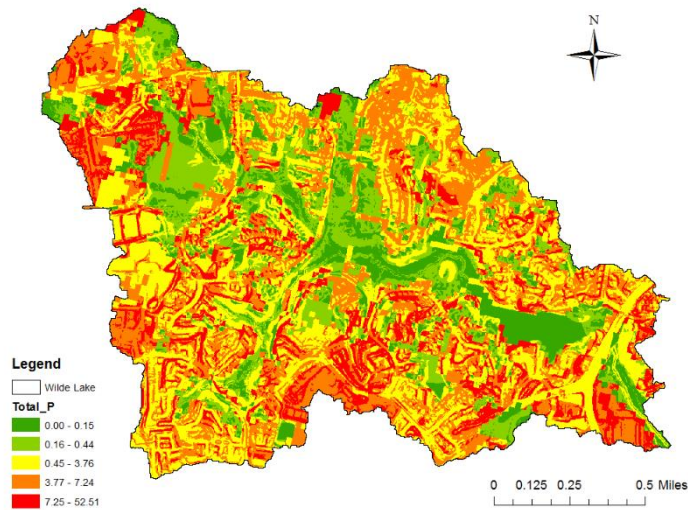
Figure 4-38 Phosphorus Hotspots in Wilde Lake Watershed
HRUs are ranked by P yield (kg/ha), and divided into 5 categories by count.

Similar to Watts Branch, the area/weight analysis was also carried out for the Wilde

Lake watershed. The relationship between HRU definition with total covered area and total

treated amount for surface runoff in WL is similar to that shown in WB. At a 20% HRU

level (of 1344 HRUs in total), 20% of total watershed area is covered with 30% total runoff

being treated. At a 40% HRU level, 50% of area is covered with 65% total runoff being treated. Although more distributed in the watershed, sediment hotspots are still concentrated in a small area. The top 20% of HRU account for only 8% of total watershed area while targeting 50% of sediments; the top 40% of HRU account for 30% of area while targeting over 80% of sediment. The weight/area ratio for Nitrogen is much higher than that in WB. Top 20% of HRUs, which takes 20% of watershed area, were simulated to have generated over 70% of total Nitrogen. 80% of total P was generated within the top 40% of HRUs which only account for 40% of total watershed area. Figs. 4-39 to 4-42 indicated that the suburban watershed of Wilde Lake perform somehow more similar to an agricultural watershed. A large number of research have demonstrated that hotspots were identified in a small confined area in an agricultural watershed (Sharpley & Rekolainen, 1997; Pionke et al., 2000; Gburek et al., 2002; Agnew et al., 2006; Walter et al., 2009). Compared to the weight/area ratio of the hotspots identified in WB, the hotspots in WL were more limited in small regions with extremely high yields.
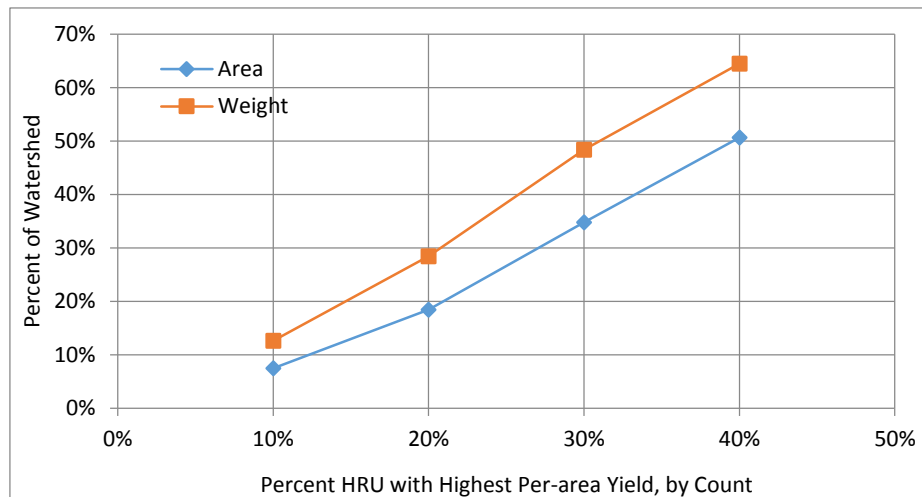
Figure 4-39 Coverage Area and Treating Amount vs. Hotspots Thresholds
Per-area yield of surface runoff in Wilde Lake Watershed
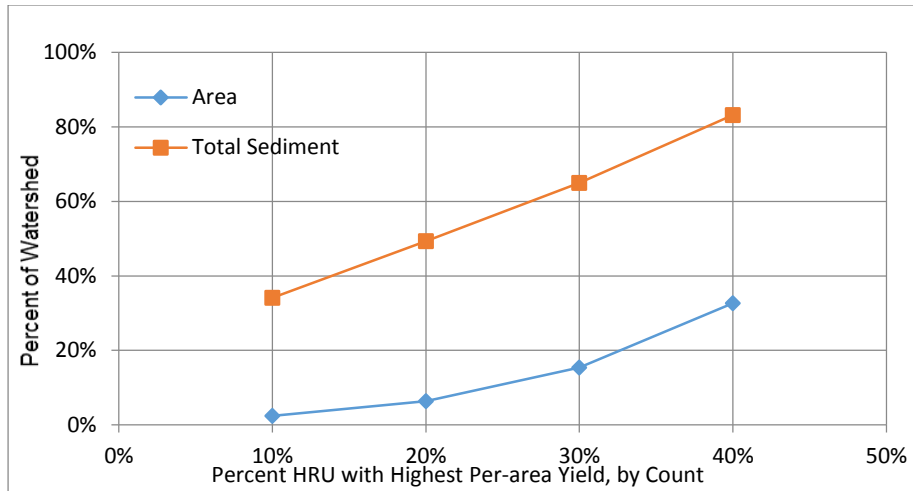
Figure 4-40 Coverage Area and Treating Amount vs. Hotspots Thresholds
Per-area yield of sediment in Wilde Lake Watershed
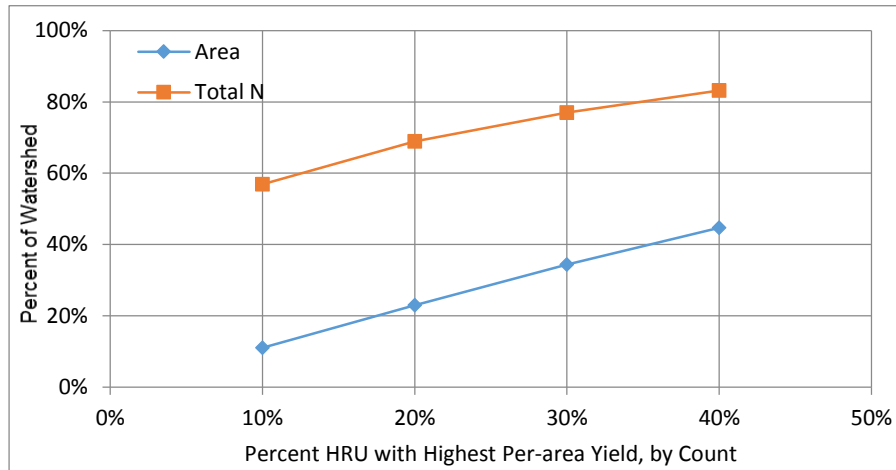
Figure 4-41 Coverage Area and Treating Amount vs. Hotspots Thresholds
Per-area yield of N in Wilde Lake Watershed
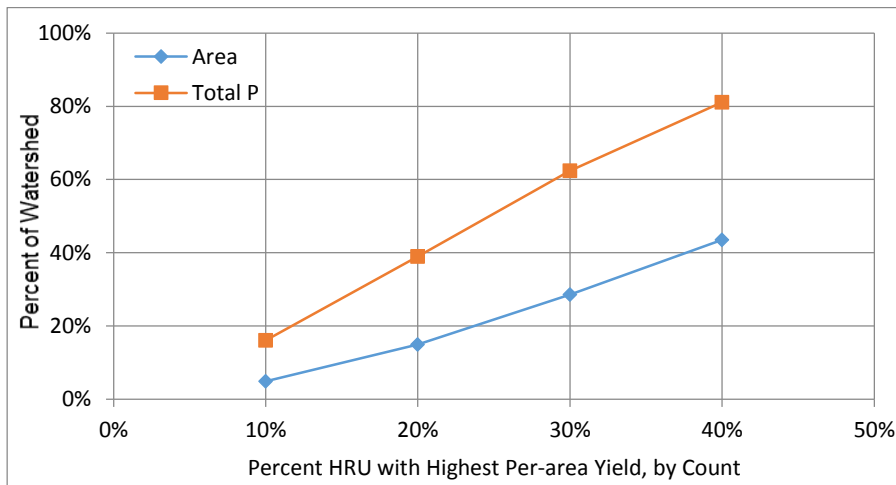
Figure 4-42 Coverage Area and Treating Amount vs. Hotspots Thresholds
Per-area yield of P in Wilde Lake Watershed

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Similar analysis regarding hotspots identified based on the total amount, as is mentioned above for WB, was carried also carried out in the Wilde Lake watershed. Fig. 4-43 to Fig. 4-46 show the total targeting area and total treating weight in percentage, whereas the hotspots were identified using the total amount. Similar conclusion can be made that per-area yield is a better indicator for hotspot identification. For all four variables of interest, a 40% of HRUs that contribute the highest amount (in total weight) generally account for 80% of total watershed area and generate over 90% of the constituents.
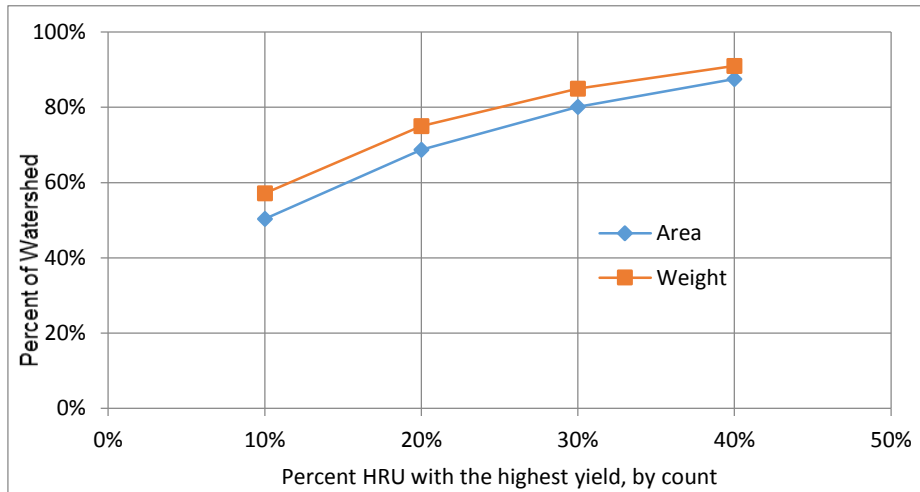
Figure 4-43 Coverage Area and Treating Amount vs. Hotspots Thresholds
Total yield of surface runoff in Wilde Lake Watershed
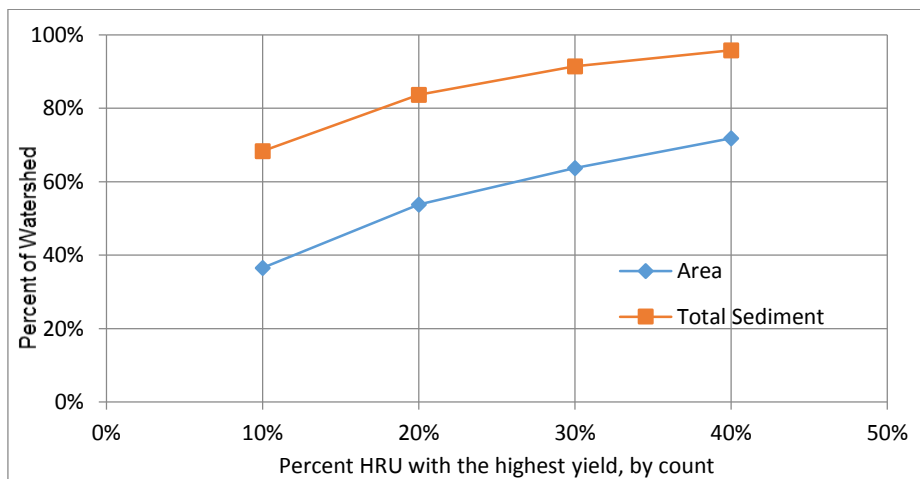
Figure 4-44 Coverage Area and Treating Amount vs. Hotspots Thresholds
Total yield of sediment in Wilde Lake Watershed
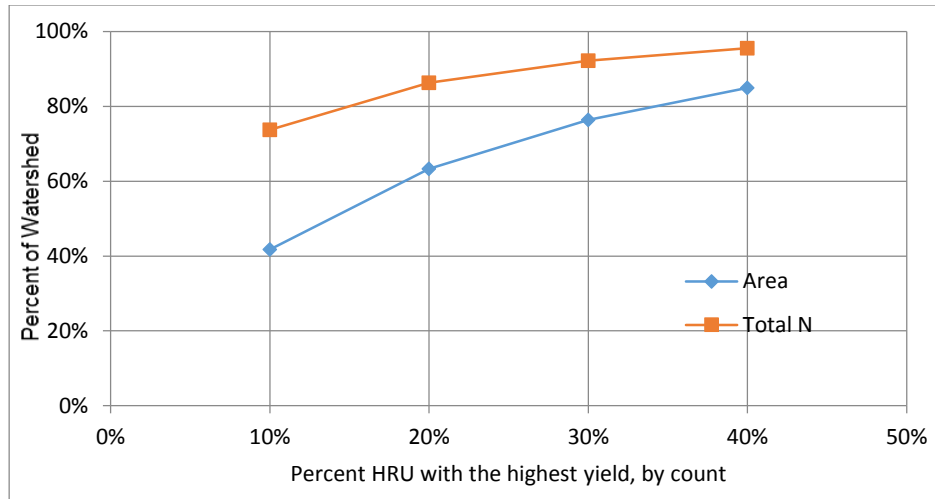
Figure 4-45 Coverage Area and Treating Amount vs. Hotspots Thresholds
Total yield of N in Wilde Lake Watershed
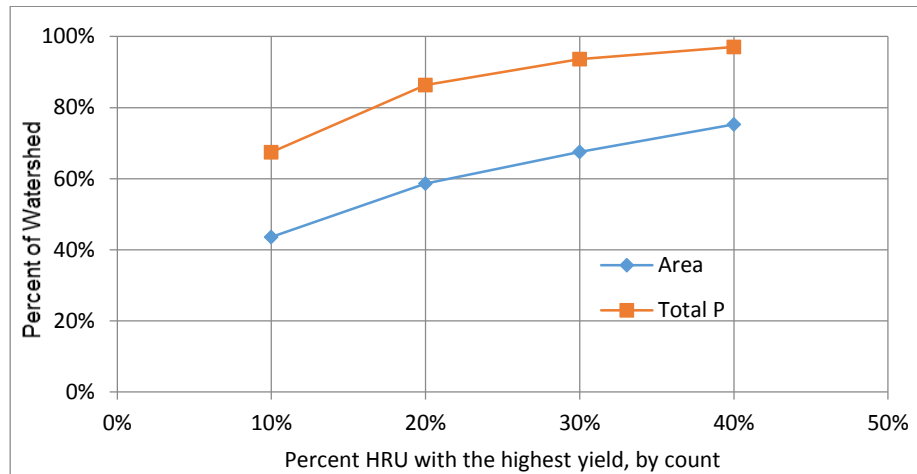
Figure 4-46 Coverage Area and Treating Amount vs. Hotspots Thresholds
Total yield of P in Wilde Lake Watershed

4.3.2　Spatially Distributed BMP Assignment

The hotspots for surface runoff, sediment, and nutrients generation in the watershed have been identified. The next step is to propose appropriate BMPs to address these sources. This section describes how each type of BMP is recommend to specific HRUs, how total cost is estimated, and the final prescribed BMPs to the two study watersheds.

4.3.2.1   Prescriptive Expert System: BMP assigning rules

A Diagnostic Decision Support System (DDSS) is different from other DSS in a way that the diagnosis is based on physical condition and feasibility of an LID BMP rather than the effectiveness of the BMPs alone. For example, pervious pavement, with proper design, can reduce surface runoff by 80% to 100%. However, this type of BMP is not recommended in areas with steep slope. Applying PP in such areas would reduce the effectiveness of the BMP. If the planner insists in building PP, additional cost would be expected in association with proper grading. Therefore, certain BMP selection rules were applied to the DDSS in order to get a series of BMPs that are feasible and cost-effective in the study area. For simplicity, the names of the candidate BMPs are represented by acronyms and index numbers (Table 4-12). The recommendations are provided based on the expert system that has been coded into the DDSS.

Table 4-12 Acronym and Index Number of BMPs

BMP Name	Acronym	Index No.
Pervious Pavement	PP	100
Vegetated Filter Strips	VFS	200
Rain Barrel	RB	300
Green Roof	GR	400
Native Landscaping	NL	500
Rain Garden	RG	600
Fertilizer Reduction	FR	700
Infiltration Trench	IT	800
Vegetated Filter Strips + Fertilizer Reduction	VFS + IT	207
Rain Barrel + Native Landscaping	RB + NL	503

For surface runoff hotspots, candidate BMPs include: 100 (PP), 300 (RB), 400 (GR), 600 (RG), and 800 (IT). Surface runoff hotspots are mainly observed in urban industrial landuse and high density urban residential areas. A small number of HRUs with medium

density urban residential area were identified as hotspots because of high curve number. Some general rules include:

- BMP100 is recommended in area where slope is less than 5%.

- BMP600 is not recommended in area where land slope is greater than 20%.

- BMP400 is not recommended in single houses residential area because of non-flat roof top.

- BMP800 is not recommended in areas with high sediment yield and high land slope (greater than 10%).

- BMP300 is the cheapest option for rainwater harvesting.

Table 4-13 NLCD Landuse Explanation

NLCD ID	SWAT	ID[1]	FIMP[2]	Explanation
21	URLD	4	0.12	Developed, Open Space - areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.
22	URMD	2	0.38	Developed, Low Intensity - areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 49% percent of total cover. These areas most commonly include single-family housing units.
23	URHD	1	0.60	Developed, Medium Intensity – areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50% to 79% of the total cover. These areas most commonly include single-family housing units.
24	UIDU	6	0.84	Developed High Intensity -highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80% to 100% of the total cover.

Note: 1 is the urban landuse type ID number (URBID) used by SWAT; 2 is the percentage of impervious area (fimp) correspond to the specific urban landuse.

Table 4-13 shows how National Land Cover Database defines each land cover and how SWAT model translate the information into a model. The explanations are useful for understanding some of the assigning rules.

If an HRU is modeled as urban industrial landuse (URBID =6), the area usually includes apartment complexes, row houses, and commercial/industrial. The impervious surfaces in this landuse account for 80% to 100% of the total cover. BMP100 is assigned to area with slope less than 5%. BMP400 is a good option for slope greater than 20% (roof area). Rain gardens are recommended for industrial area with a slope between 5% and 20%.

If the HRU is high residential area (URBID =1), it is usually covered by single-family housing units. The 60% of impervious area can be divided into roof top (30%), drive way (15%), and main road (15%). BMP400 can only treat the 30% impervious area (the roof) and is not recommended in non-flat roof top. BMP100 can only treat 15% of impervious area if applied because it is not applicable for main roads. Both BMP600 and BMP800 can treat runoff from both rooftop and the drive way (45%). Therefore, BMP800 is recommended to area with slope smaller than 10%, BMP600 for areas with slope greater than 10%.

Mid-density urban residential area (URBID =2) is usually covered by single-family housing units, which include roof top (15% of area), drive way (7.5%), and road (15%). BMP600 and BMP800 are still good options in terms of percentage impervious area covered. However, runoff in these area is generally not high (not considered as hotspot), and relatively large pervious area generally indicates a larger lawn area where more irrigation is generally needed. Therefore, rain barrel can be a good option which can

decrease peak runoff and save the rainwater for lawn irrigation in a later time. Non-urban landuse (URBID=0) is generally not identified as hotspot for runoff generation. The detailed assigning rule for surface runoff BMPs is listed in Fig. 4-47.
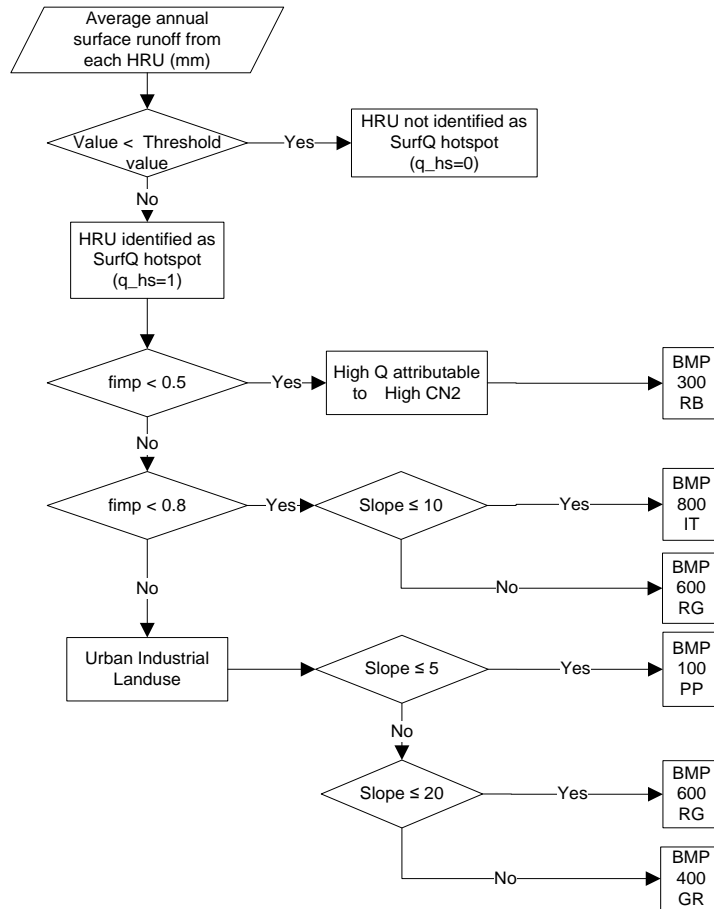
Figure 4-47 Prescriptive Expert System for Surface Runoff Hotspots

For sediment yield hotspots, candidate BMPs include: 200, 500, and those recommended in surface runoff hotspots. Candidate BMPs for SurfQ_hs were considered because high sediment yield is usually related to high surface runoff and high peak discharge (Section 3.3.2). If high surface runoff is the only cause for high sediment yield, water quantity control would also result in sediment control. In this case, if a BMP has been assigned to deal with stormwater runoff previously, the same type of BMP is

recommended in the sediment hotspot. If the HRU is not identified as a runoff hotspot and is not assigned a BMP, then high surface runoff can be caused by high percentage of impervious area (fimp > 50%) or high curve number (CN2 > 50). BMP600 or BMP800 are recommended in HRUs with high impervious area (URBID = 6, 1, usually URBID = 6 are already assigned a BMP). The assigning rule is similar to the one that is used in runoff control for mid-density residential area. Since in this condition slope is not a concern (high Q be the only cause) and BMP800 is sensitive to sediment clogging, a safe recommendation should be BMP600. When high surface runoff is caused by high CN2 and low FIMP (URBID = 2, 4), sediments are likely to be generated from the permeable area (lawn area) in such landuse. A good way to control runoff in such condition is to decrease the amount of water entering the lawn area. Therefore, BMP300 is recommended. BMP 600 is recommended for hotspots with higher percentage of impervious area (fimp>0.5, high flow) and erodible soil (USLE_K > 0.25), where the erodible soil only accounts for less than 40% of the surface area. BMP500 is recommended in hotspots with fimp<0.5 (high flow) and erodible soil, because the erodible soil accounts for over 60% of the surface area. In a steep-slope situation, BMP200 is not recommended. If no BMP is recommended as a control method for surface runoff previously, BMP600 is recommended for area with over 50% impervious area (fimp>0.5), BMP 503 for fimp < 0.5. BMP500 is recommended for all other reasons related to steep land slope. If non-urban area has sediment issue, or unknown reason is related to high sediment yield, then BMP200 will be assigned to the hotspots. The detailed assigning rule for sediment BMPs is listed in Fig. 4-48.
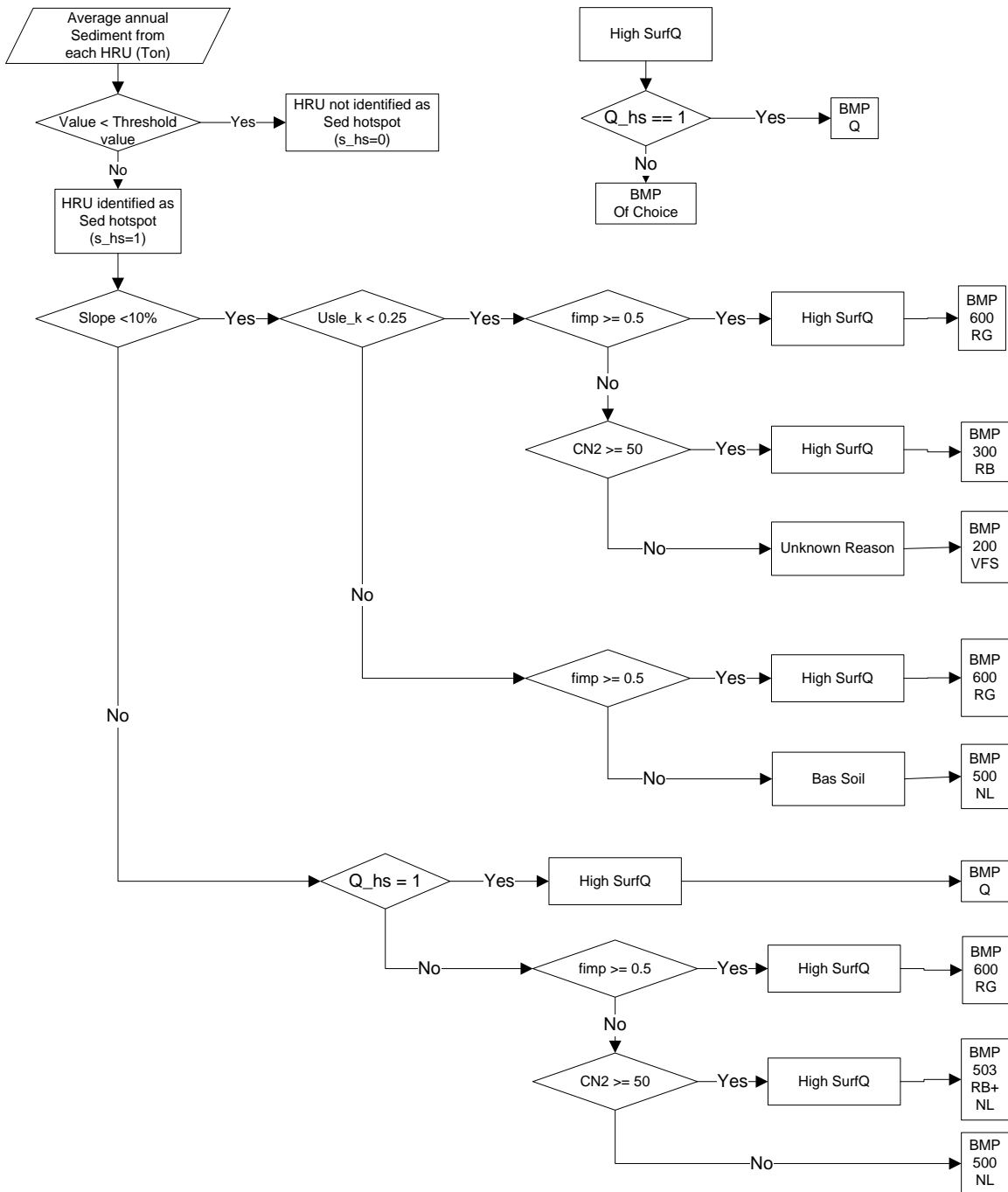
Figure 4-48 Prescriptive Expert System for Sediment Hotspots

A few words about high runoff generation is presented here. It is highly possible that some high runoff area were not identified as hotspots. As stated earlier, the number of HRUs which were defined as hotspots is somehow a subjective decision. Some high runoff

yield HRUs may not be hotspots based on the 20% HRU rule. However, the same area can be identified as a hotpot on the 30% HRU rule. Therefore, even if SurfQ_hs was not identified, the HRU may have a high surface runoff yield but less than those currently selected as hotspots.

Candidate BMPs for Nitrogen control include: 500, 700 and candidate BMPs assigned to SurfQ_hs. As discussed in Section 3.3.2, besides large amount of N sources, high nitrogen contribution into the streams is because of high flow, either surface runoff, or sub-surface flow (lateral flow and groundwater flow). If the HRU has already been identified as a surface runoff hotspot, controlling surface runoff can control N. In this situation, CN2 is usually high (based on the previous analysis on surface runoff hotspots), which somehow prevent infiltration and limits the N amount in groundwater. If CN2 is less than 50, high groundwater flow and high N contribution though groundwater are possible. In order to prevent infiltration, BMP600 is recommended to replace any BMP800 that has been assigned as a runoff control BMP. Even if a HRU is not defined as a SurfQ hotspot, high percentage of impervious area (FIMP >0.5) and high curve number (CN2>50) may also cause relatively high surface runoff, thus BMP600 or BMP800 is recommended according to land slope. Both high surface runoff and high sub-surface flow are possible when FIMP is greater than 0.5 and CN2 is less than 50, BMP600 is recommended in this situation. When FIMP is less than 0.5 and CN2 is less than 50, high base flow is the only reason for high N contribution to the streams. Therefore, BMP500 is recommended for mid/low density residential area and BMP700 for agricultural area (FIMP = 0). When flow is not a concern (FIMP <0.5 and CN2>50), high N concentration in soil or high N application is the reason for high N yield. BMP500 or BMP700 is recommended in this

situation according to landuse type: 500 for residential landuses and 700 for non-urban area. The detailed assigning rule for N BMPs is listed in Fig. 4-49.

Candidate BMPs for phosphorus control include: 500, 700, and candidate BMPs for SurfQ_hs and Sed_hs. The BMP assigned for runoff control is used to control P if high surface runoff is the only cause for high P yield. The BMP assigned for sediment control is used to control P if high sediment yield is the only cause for high P yield. In situation when both high runoff and high sediment yield contribute to high P yield, sediment BMPs are recommended because surface runoff has already been taken into account in sediment BMP selection. If high P yield is caused neither by runoff nor sediment, it is generally caused by high fertilizer application. BMP500 and BMP700 are recommended in this case according to landuses: 500 for residential landuses and 700 for non-urban area. The detailed assigning rule for P BMPs is listed in Fig. 4-50.
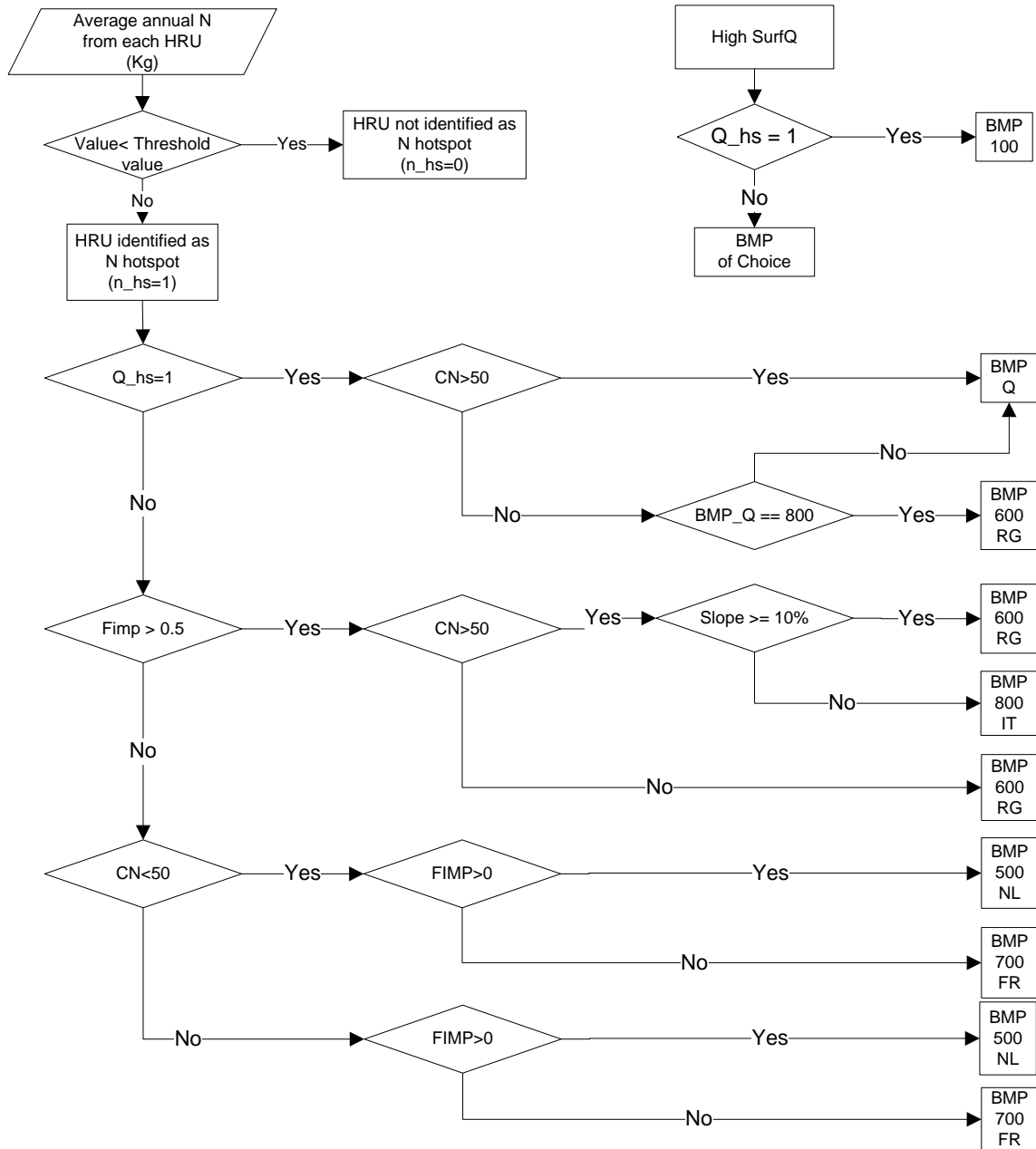
Figure 4-49 Prescriptive Expert System for Total N Hotspots
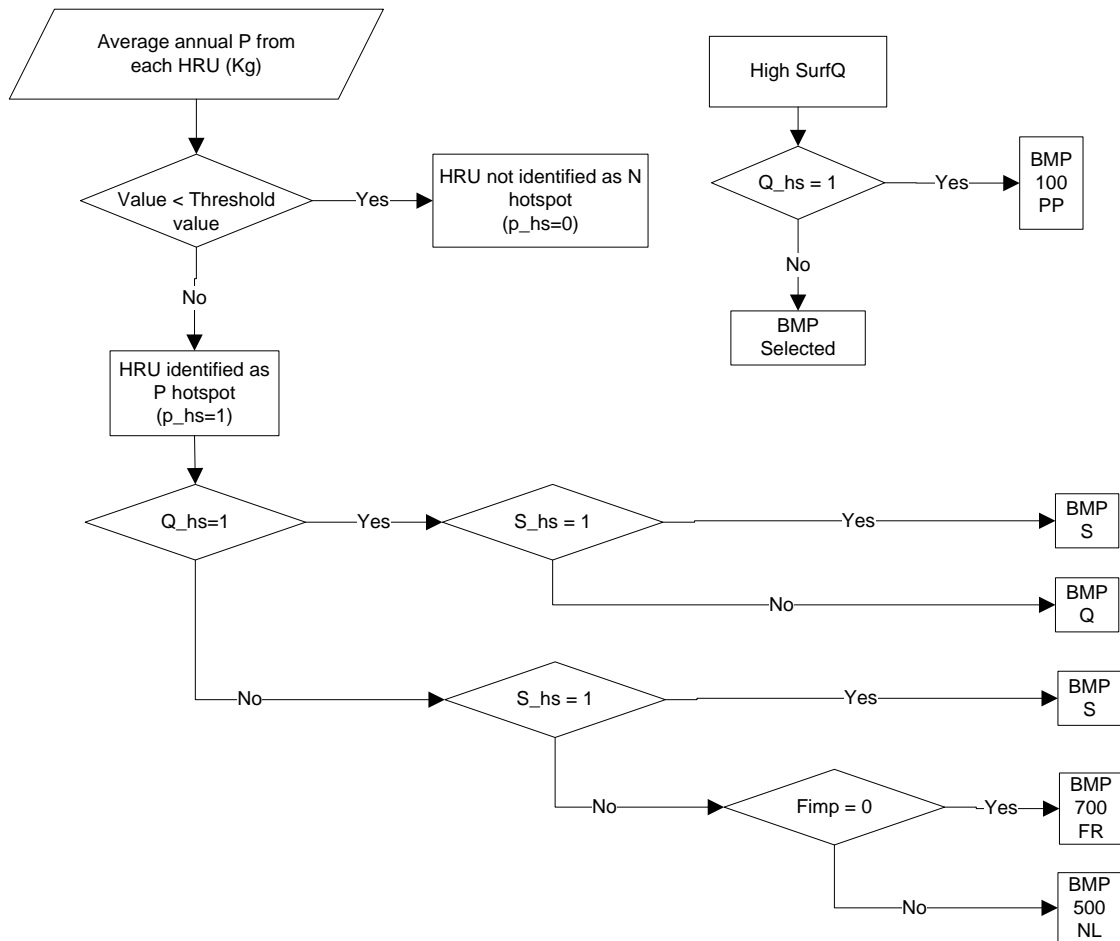
Figure 4-50 Prescriptive Expert System for Total P Hotspots

Different types of BMPs were recommended according to different types of hotspots: runoff hotspots, sediment hotspots, N hotspots, and P hotspots. However, as discussed in Section 4.3.1, hotspots for surface runoff are not necessarily the hotspots for sediment, hotspots for different constituents of concern may or may not overlap. Therefore, if hotspots-overlapping occurs, a proper mechanism is need to select a best BMP which can control all NPS pollutants of concern.

If the HRU is identified as a hotspot for only one of the four constituents, the BMP recommended for that specific type of pollutant is assigned to the HRU. If the HRU is identified as hotspot in more than one type of pollutants, the assignment rule is listed in the

figure below (Fig. 4-51). BMPs for different types of variables are named BMP_Q, BMP_S, BMP_N, and BMP_P for simplicity. This set of rules completes the BMP selection/assignment procedure. The procedure was programmed in MATLAB for automatic recommendation of BMPs.
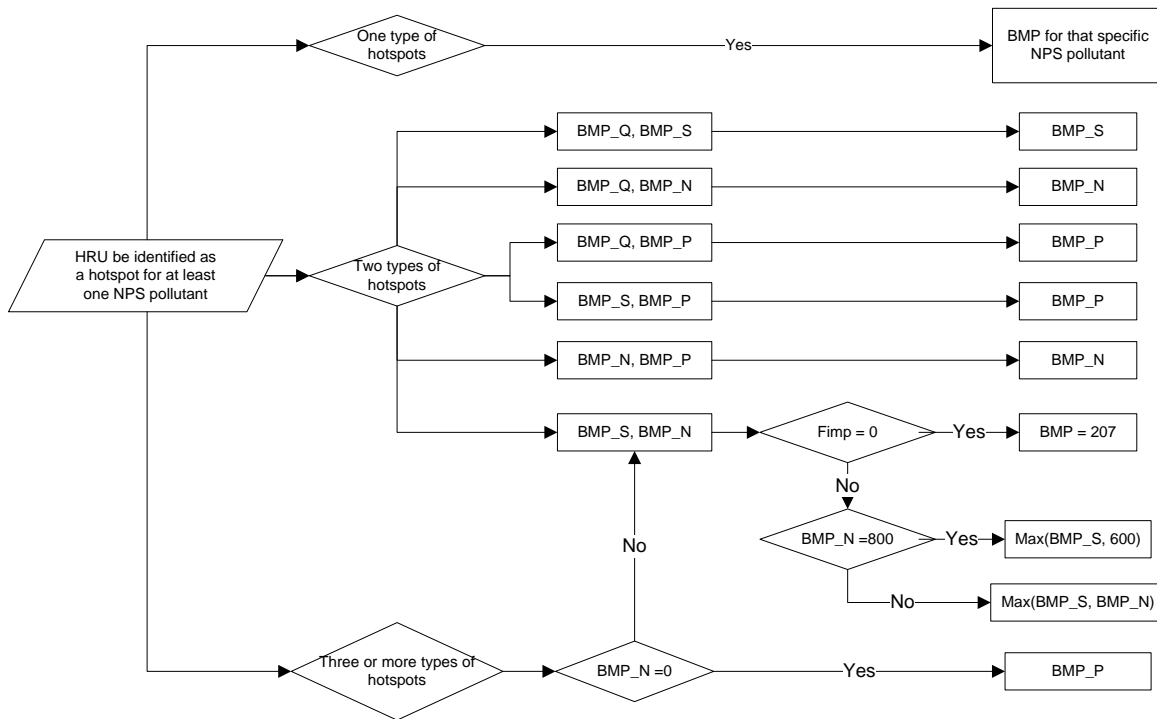
Figure 4-51 Final Determination of BMP Assignment

4.3.2.2 Cost Estimation in PES

Once a set of BMPs were recommended by the DDSS, the total coverage area of the target hotspots (in other words the area of HRUs) was used to calculate the fixed cost. BMP installation costs, which represent the amount needed for incentive programs, include the basic total BMP cost (BC) and an adjustment factor to indicate residents' preferences (K_{RP}). The Incentive Adjustment Factor K_{RP} is a function of the proposed adoption model and Residents' Preferences (RP). Due to limited time, an adoption model was not available. In

order to continue the research and demonstrate the basic concept of including PR in the decision making process, a simplified linear relationship between PR and K_{RP} was proposed.

$$TC = FC + IPC \qquad\qquad Eq.\,4.1$$

$$= f_a \cdot A + BC \cdot K_{RP} \qquad\qquad Eq.\,4.2$$

$$= f_a \cdot A + \sum_{i=1}^{N}(bc_i \cdot a_i) \cdot K_{RP} \qquad\qquad Eq.\,4.3$$

Where TC is the total cost, FC is the fixed cost, IPC is the incentive program cost, f_a is the fixed per-area cost, A is the total area of the targeted hotspots, BC is the total installation cost of BMP, bc_i is the cost of a BMP in a specific hotspot (HRU), a_i is the area of the hotspot (HRU), N is the total number of hotspots, K_{RP} is the Incentive Adjustment Factor, which can be expressed as:

$$K_{RP} = 1 - RP \qquad\qquad Eq.\,4.4$$

RP represents the likelihood of adopting a BMP. If the residents are extremely likely to install BMP, then RP = 100%, $K_{RP} = 0$, no incentive program is needed in this situation. If the residents are not likely to install BMP at all, then RP = 0%, $K_{RP} = 100\%$, government or any organizations initiating the plan are required to pay the full amount of BMP installation cost in order for the NPS reduction goal to be achieved or certain incentive programs need be proposed to increase the adoption rate. When incentive programs are involved, the total cost would be in a different form.

The estimated cost for each type of BMP was based on real-world BMP projects (Table 4-14). Again, the cost of one type of BMP may vary according to different design and different criteria. An average per-area cost was estimated based on the available data. The cost for each BMP can be easily adjusted in the MATLAB program when a more precise/specific cost estimation is available.

The fixed per-area cost of BMP installation was estimated to be $4,000/ha. The assumptions include: 1) cost of labor is 12/hr; 2) each house needs 1.5 hours of labor for inspection, consultancy, and documentation; 3) the area of a single family house is 5000 ft^2 (0.046452 ha) on average; 4) the per-area labor cost is $18/0.046452ha = $3600/ha; and 5) a $400 other cost.

The estimated cost for each BMP is listed in Table 4-15. Area factors were included because the BMPs were not supposed to be implemented throughout the HRUs (hotspots). For instance, one rain barrel was supposed to be installed in one single house family; native landscaping was supposed to be planted in the lawn area (about 75% of total single family house area).

$$f_a = \$4,000/ha$$

Table 4-14 General Costs of BMP Implementation

BMP	Cost	References
Pervious Pavement	$100 /square yard	ES (2006)
	Asphalt: 50c - $1 /ft^2 Grass/Gravel Pavers: $1.50 - $5.75 /ft^2 Porous Concrete: $2.00 - $6.50 /ft^2 Interlocking Concrete Paver Blocks: $5.00 - $10.00 /ft^2	Paver Search (2014) LID UDTW (2014)
	$7 - $15 /ft^2 10 foot by 20 foot single car driveway: $1,400 - $3,000 5,000 square foot parking lot: $3,500 - $7,500.	DER, PG County (2014)
Vegetated Filter Strip	30¢ per ft^2 for seed or 70¢ per ft^2 for sod $13,000 - $30,000 per acre for a filter strip	USEPA (2014e)
	$0 - $50,000 per acre	BWM (2006)
	$750 per acre (2006)	Yolo County RCD (2006)
	$13,000 - $30,000 per acre	Lake Superior Streams (2014)
	$5,000 per ha (1995)	FHWA (2014)
Rain Barrel	A single rain barrel, minus the downspout, in a residential area for use in small-scale irrigation and gardening purposes only $216	LID UDTW (2014)
Green Roof	$10 - $25 per square foot Annual maintenance costs for either type of roof may range from $0.75–$1.50 per square foot	USEPA (2014c)
	Extensive $10.00 - $30.00 per square foot Semi − intensive: $20.00 - $40.00 per square foot Intensive: $40.00 + per square foot	DC Greenworks (2014)
Native Landscaping	$3,500/acre	Pizzo et al. (2014)
	$3,400-$ 5,975/acre	USEPA (2014d)
	$3,100 - $10,300	Prairie Restorations, Inc. (2014)
Rain Garden	$3 - $20+ per sq. foot	ISWEP (2014)
	residential rain gardens: $3 - $4 per square foot Commercial and institutional site: $10 to $40 per square foot	LID UDTW (2014)
Fertilizer Reduction	Fast release fertilizer (10-10-10): $14 for 5000-sq ft., 3-4 week per application. =$ 84 /2500ft2/year Slow release fertilizer (10-10-10): $15 for 250-sq ft., 12 week per application. =$ 600 /2500ft2/year	Lowes (2014)
Infiltration Trench	$4 - $9 per cubic foot of storage provided (2003).	BWM (2006)
	6 feet * 4 feet (2,400 cubic feet): $8,000 - $19,000. 0.9 3 feet * 4 feet (1,200 cubic feet): $3,000 to $8,500. (1993)	USEPA (1999)

Table 4-15 Estimated BMP Cost

BMP	Cost ($/ft^2)	Cost ($/ha)	Area Factor
Pervious Pavement	6.32	680,630	1.0
Vegetated Filter Strip	0.50	53,820	0.25
Rain Barrel	0.043	4,650	1.0
Green Roof	23.75	2,556,429	0.25
Native Landscaping	0.11	12,263	0.75
Rain Garden	13.33	1,435,188	0.25
Fertilizer Reduction	0.2064	22,217	0.75
Infiltration Trench	25.79	2,776,192	0.1

4.3.2.3   Spatially assigning BMPs for the Watts Branch Watershed

Based on the rules applied to the PES in the previous section, a spatially distributed BMP series was recommended for the Watts Branch watershed. For each type of NPS pollutant of concern, the total coverage area and the total weight being treated agreed with the results shown in Section 4.3.1 when 20% of HRUs were chosen to be hotspots (row 2 and row 3 in Table 4-16). Because of the non-overlapping problem (first paragraph in Pg.111), the BMPs covering all types of NPS were prescribed in approximate 40% of watershed area, treating 50% of surface runoff, 63% of sediments, 55% of total Nitrogen, and 55% of total phosphorus (rows 4 and 5 in Table 4-16).

Table 4-16 Statistics of BMP Assigned in Watts Branch Watershed

	SurfQ	Sed	N	P
TA Individual	30.5%	17.4%	21.4%	34.5%
CA Individual	19.9%	2.4%	12.0%	12.1%
TA Total	49.4%	63.3%	55.0%	55.5%
CA Total	39.1%			

* TA: Treating Amount; CA: Coverage Area. Individual: calculated within the specific hotspot set;
   Total: calculated within the whole watershed.

The distribution of the BMPs, as determined automatically by the DDSS, was mapped in GIS (Fig. 4-52). In the Watts Branch watershed, Native Landscaping and Infiltration Trench were recommended the most in terms of coverage area, followed by Rain Barrels,

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Rain Gardens, and Pervious Pavement. Green Roof was not recommended in any of the hotspots. This is because there were no hotspots in the watershed with industrial urban landuse and slope greater than 20%. Compared Fig. 4-52 with Fig. 4-24, the distribution of IT matches the location of the runoff hotspots; and the distribution of NL matches the distribution of N hotspots and P hotspots. Although IT and NL were recommended in large area, it does not mean that they were recommended in more HRUs.

The total cost for installing the BMPs was estimated to be 532 million. According to different levels of residents' preferences, the total government cost ranges from $108,150,000 to $533,430,000 (Fig. 4-53) (Section 4.3.2.2). The figure indicates that social interaction can help reduce costs substantially.
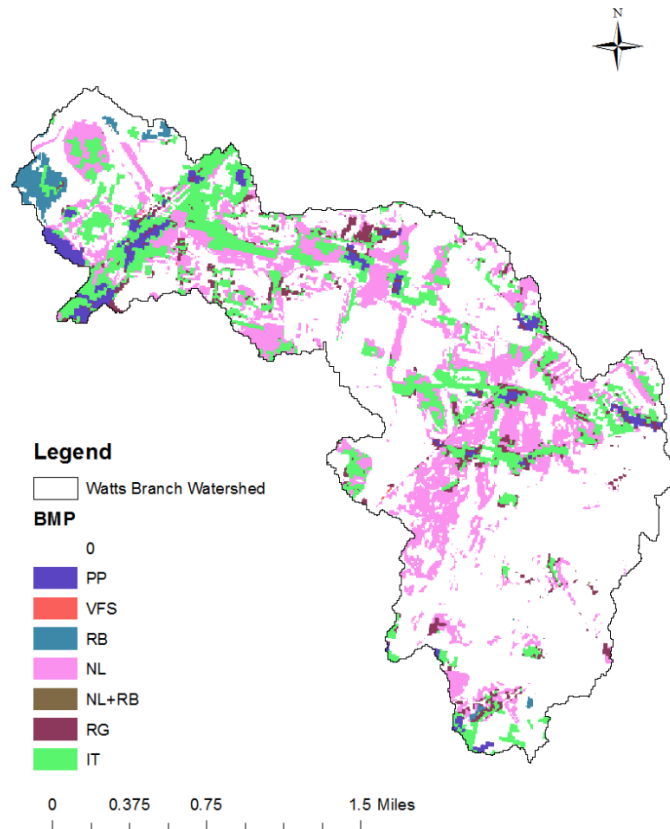
Figure 4-52 Spatially Assigned BMPs in Watts Branch Watershed
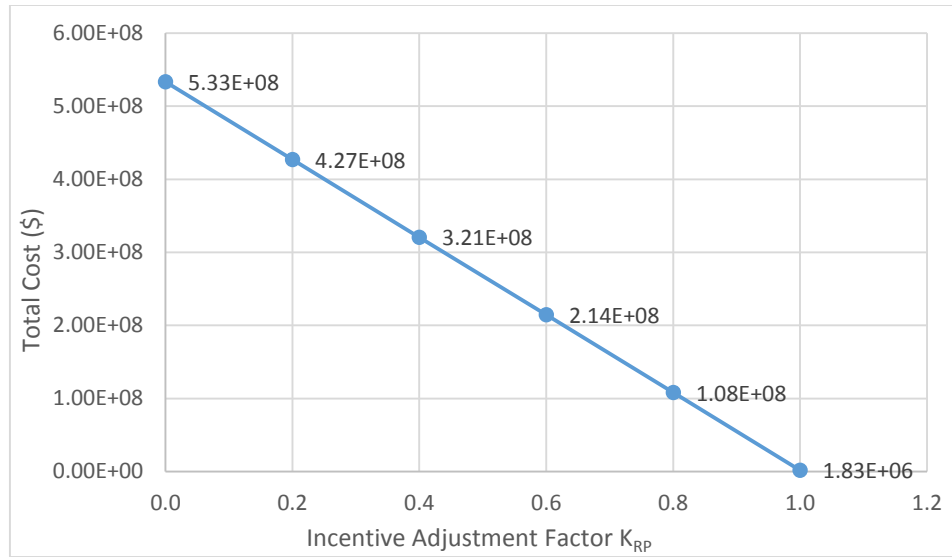
Figure 4-53 Estimated Total Cost of Applying the BMPs
as a Function of Residents' Preferences (WB)

The spatially distributed BMPs were modeled back into the WB_SWAT_Pre model using the parameter adjustments explained in Section 4.2. The new parameters were adjusted using batch DOS commands for speed processing. The new model with the BMPs incorporated was named WB_SWAT_Post. Two sets of comparisons were carried out between the pre and the post models. The first analysis compared the annual NPS pollutant yields (on-land) both in terms of per-area yield and total amount at the HRU level. The second set of analysis focused on the effected of BMP implementation on in-stream variables. In the first analysis, the highest annual per-area yield of surface runoff was 800mm, the lowest being 0.09mm in the WB_SWAT_Pre model. On average, the HRUs generated about 307mm of runoff each year with a standard deviation of 173mm. Sediment yield ranged from zero to 60 tons/ha, with an average yield of 4.5 tons/ha and a standard deviation of 8 tons/ha. Total Nitrogen yield ranged from 0.76 Kg/ha to 74 tons/ha, with an average yield of 8 tons/ha and a standard deviation of 7.5 kg/ha. An average of 3 Kg/ha of phosphorus, ranging from 0 to 30 kg/ha, was simulated in the WB_SWAT_Pre model with

a standard deviation of 4 kg/ha. The statistics show high skewed distributions for sediment, total N, and total P. This demonstrated the reason why the hotspot range for these three constituents are that large as indicated in the hotspot identification maps (Section 4.3.1).

When the BMPs were modeled in the WB_SWAT_Post model, the average annual per-area yields of runoff at HRU level was reduced by 18%, sediment yield by 54%, total N by 32%, and total P by 53%. The maximum per-are yield for sediment, N, and P were reduced to 1/3 of original values. The maximum runoff rate was reduced by 18%, which was close to the reduction rate for average runoff.

Table 4-17 Per-area Yield Statistics in the pre-BMP scenario in the Watts Branch watershed

WB_Pre	Q (mm)	Sed (Tons/ha)	N (Kg/ha)	P (Kg/ha)
MAX	795.59	59.37	73.73	30.40
MIN	0.09	0.00	0.76	0.00
AVE	307.65	4.57	8.18	3.08
SD	173.06	7.84	7.51	4.02

Table 4-18 Per-area Yield Statistics in the Post-BMP scenario in the Watts Branch watershed
BMP assigned by DDSS

WB_Post	Q (mm)	Sed (Tons/ha)	N (Kg/ha)	P (Kg/ha)
MAX	656.77	21.85	28.62	9.99
MIN	0.09	0.00	0.76	0.00
AVE	250.86	2.11	5.53	1.46
SD	113.85	2.68	4.19	1.39

In terms of total reduction amount, the total annual surface runoff generated was reduced by 17%, sediment by 38%, total Nitrogen by 18%, and total phosphorus by 37%, after the BMPs were modeled (Table 4-19). The statistics again demonstrated the correlation between surface runoff and Nitrogen yield, as well as the correlation between sediment and phosphorus yields.

Table 4-19 Reduction of Overland Runoff Volume and NPS Amount in the Watts Branch watershed BMP assigned by DDSS

	WB_Pre	WB_Post	Change Ratio
SurfQ (m3)	351641	300042	-17%
Sed (Tons)	1681.36	1034.43	-38%
N (Kg)	8350.00	6885.17	-18%
P (Kg)	2363.42	1496.56	-37%

Besides the on-land variables, in stream variables were also affected by BMP implementation (the second set of analysis). In the WB_Pre model, the statistics of the four in-stream variables were analyzed (Table 4-20). The variables include daily values of stream discharge (cms), total sediments (tons/day), and in-stream nutrients (kg/day) at the outlet of the watershed. The mean daily values for sediment, total N, and total P were reduced by 20% to 30%. However, the main daily stream discharge did not change at all. This is reasonable because the BMPs were used to control surface runoff volume and peak surface flow, while the stream discharge is a combined contribution from surface runoff, lateral flow, and groundwater flow. The candidate BMPs modeled in this study do not affect evapotranspiration (ET). Increased ET would be the only way to decrease total stream flow at the outlet given a fix amount of rainwater falling on the ground.

The maximum daily stream discharge in both the pre and the post model were resulted from a storm event on June, 25, 2006. A reduction in stream discharge on that particular day indicated that the BMPs were effective in reducing the surface runoff in storm events, thus reducing the flood risk. The total on-land sediment generation was reduce by 38% (Table 4-19) but the sediment reduction rate in stream were only 33%. The discrepancy lies in the in-stream sedimentation processes in the SWAT model. Surface runoff in the watershed has been reduced because of the installation of BMPs. Less stream discharge

generally means less tractor force which is the driving force for re-suspension. Suspended solid is more likely to settle down on stream beds in smaller discharge. Since phosphorus is highly attached to sediments. The discrepancy observed in total on-land P and in-stream P was also because of sedimentation.

Table 4-20 Comparison of Daily In-stream Variables at the Outlet of the Watts Branch watershed

Statistics	Discharge Q (cms)		Suspended Solid (Tons)		Total N (Kg)		Total P (Kg)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Mean	0.15	0.15	4.46	3.01	22.18	18.56	6.21	4.14
Max	9.64	8.60	353.90	253.30	560.40	368.50	654.30	403.20
Min	0.00	0.01	0.00	0.00	0.00	0.20	0.00	0.00
Std	0.47	0.41	19.61	13.48	41.43	30.12	27.31	18.15

In summary, the spatially distributed BMPs were effective in reducing surface runoff, on-land sediments, and on-land nutrients in the SWAT model. They were also effective in bringing down the sediment and nutrients in stream while maintaining the stream level, which is crucial for the health of aquatic life and achieving the Chesapeake Bay TMDL (USEPA, 2003) goal at the same time.

4.3.2.4   Randomly assigning BMPs for the Watts Branch Watershed

In order to test the effectiveness of the DDSS, another post BMP simulation WB_SWAT_R (R for Random) was carried out. In the WB_SWAT_R model, the BMPs were randomly assigned to the HRUs which generated the highest per-area yield of runoff, sediment, total N, and total P without considering feasibility, slope, and other geographical features. In the WB_SWAT_Post (also WB_SWAT_D, D for DDSS) model, about 800 HRUs were assigned one specific type of BMP. Therefore, in this random assignment

scenario, each of the eight candidate BMPs (Section 4.2) were randomly assigned to 100 HRUs. The WB_SWAT_R was rerun to simulate the hydrological processes in the watershed. The results were compared to those generated by the original WB_SWAT_Pre model and the DDSS assigned WB_SWAT_D model.

When the BMPs were modeled in the WB_SWAT_R model, the average annual per-area yields of runoff at HRU level was reduced by 20%, sediment yield by 50%, total N by 21%, and total P by 45% (Table 4-21). Compared to the BMPs assigned by the DDSS, the randomly assigned BMPs resulted in a slightly better reduction rate in surface runoff, slightly worse reduction rate in sediment and P yield, and significantly less reduction in N. The standard deviation of runoff and sediment in the R scenario are similar to the same statistics shown in the D scenario. However, the standard deviation of N and P were greater than those calculated in the D scenario (Table 4-18).

Table 4-21 Per-area Yield Statistics in post-BMP scenario in the Watts Branch watershed BMP assigned randomly

WB_SWAT_R	Q (mm)	Sed (Tons/ha)	N (Kg/ha)	P (Kg/ha)
MAX	549.07	21.34	62.53	7.88
MIN	0.09	0.00	0.76	0.00
AVE	246.78	2.29	6.46	1.69
SD	115.40	2.75	5.08	1.70

In terms of total reduction amount, the total annual surface runoff generated was reduced by 12%, sediment by 10%, total nitrogen by 11%, and total phosphorus by 16%, after the random BMPs were modeled. The reduction rates for the four constituents were smaller than those observed in the DDSS assigned BMPs at the watershed scale. Reduction in sediment and phosphorus were much lower than those in the DDSS scenario. The statistics again demonstrated the correlation between surface runoff and Nitrogen yield, as

well as the correlation between sediment and phosphorus yields. The results of this experiment indicate that a systematic, rule-based spatial assignment of BMPs is more effective than random BMP placement in reducing watershed scale outflow and constituent yield.

Table 4-22 Reduction of Runoff Volume and NPS Amount in the Watts Branch watershed BMP assigned randomly

	WB_pre	WB_SWAT_R	Change Ratio
SurfQ (m3)	351641.83	309846.61	-12%
Sed (Tons)	1681.36	1520.78	-10%
N (Kg)	8350.00	7451.92	-11%
P (Kg)	2363.42	1975.33	-16%

Similar to the analysis done in section 4.3.2.2, in stream variables including stream discharge, suspended solid, in-stream N and P simulated in the WB_SWAT_R model were compared to the WB_SWAT_Pre statistics. The average daily stream discharge was reduced by 8%. The mean daily values for sediment and total N were reduced by 10%. Total P were reduced by 17%. In the DDSS scenario, no change in stream discharge was observed. The 8% of decrease in this Random scenario may be result from green roof, the one BMP that was not recommended in any of the HRUs in Watts Branch watershed by the DDSS. Green roof prevents the rainwater collected on the rooftop from falling on the ground and entering the ground and surface water cycle, which decreases the amount of water entering the runoff/infiltration cycles. The results also indicated the effectiveness of using GR to reduce surface runoff. Water entering the green roof is removed as ET, causing a decrease in watershed runoff by surface and subsurface pathways.

Statistics	Discharge Q (cms)		Suspended Solid (Tons)		N (Kg)		P (Kg)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Mean	0.15	0.14	4.46	4.00	22.18	19.74	6.21	5.19
Max	9.64	8.85	353.90	284.3	560.4	474.5	654.3	529.6
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std	0.47	0.42	19.61	17.08	41.43	35.49	27.31	24.55

Statistics of the on-land variables and the in-stream variables all indicated that the BMPs assigned by DDSS perform better in terms of per-area rate and in total rate of sediment, N, and P. The 800 HRUs that were given randomly assigned BMPs account for 33% of the total watershed area, compared to 39% in the DDSS assigned scenario. Although the total cost for implementing the BMPs in the Random scenario was generally lower than in the DDSS scenario, the effectiveness and feasibility of the BMPs were not guaranteed. In summary, the DDSS performed well in assigning proper BMPs. It not only assigned BMPs that are feasible for specific geological features, but also provided better NPS pollutant reduction rates.
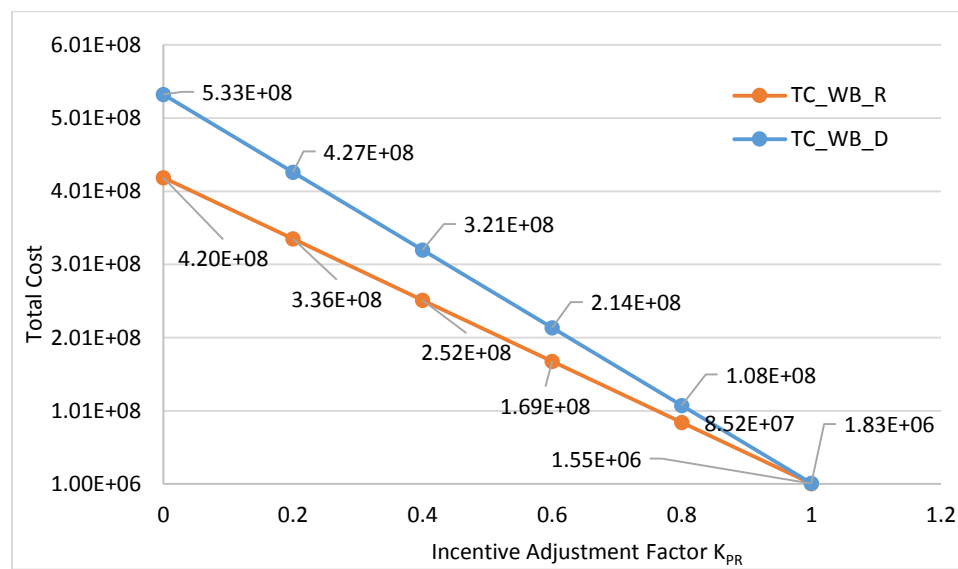
Figure 4-54 Comparison of Total Cost in the Watts Branch watershed
DDSS assigned BMPs (WB_SWAT_D) and randomly assigned BMPs (WB_SWAT_R)

4.3.2.5   Spatially assigning BMPs for Wilde Lake Watershed

Similar to the two BMP assigning scenarios simulated in Watts Branch watershed, a DDSS BMP assignment scenario and a random BMP assignment scenario were examined in the Wilde Lake watershed. The results of WL watershed were also compared to those of WB, in order to provide some insight about BMP assignment in urban and suburban watersheds.

A spatially distributed BMP series was recommended to the Wilde Lake watershed according to the DDSS assignment. For each type of NPS pollutant of concern, the total coverage area and the total weight being treated showed agreement with the results shown in Section 4.3.1 when 20% of HRU were chosen to be hotspots. Because of the non-overlapping problem, the BMPs were recommended in about 37% of watershed area, treating 47% of surface runoff, 85% of sediments, 77% of total Nitrogen, and 68% of total phosphorus.

Compared to Table 4-16 (Section 4.3.2.2), the hotspots identified in WL covered approximately the same percentage of watershed area and targeting similar amount of total surface runoff. The WL hotspots targeted at another 20% of total amount of sediment yield and total nitrogen yield, and another 10% of total phosphorus yield. The results agreed with the conclusion made in Section 4.3.1 that suburban area tend to have higher concentration of NPS pollutant in smaller area.

Table 4-24 Statistics of BMP Assigned in the Wilde Lake Watershed

	SurfQ	Sed	N	P
TA Individual	28.3%	49.1%	68.9%	38.5%
CA Individual	18.3%	6.3%	22.9%	14.7%
TA Total	47.4%	83.6%	76.8%	67.7%
CA Total	37.2%			

* TA: Treating Amount; CA: Coverage Area. Individual: calculated within the specific hotspot set; Total: calculated within the whole watershed.

The recommended BMPs were mapped in GIS (Fig. 4-55). For the Wilde Lake watershed, in terms of area coverage, Native Landscaping (NL) and Rain Barrel (RB) were recommended in most hotspots, followed by Vegetated Filter Strips (VFS), Fertilizer Reduction (FR), and Rain Gardens (RG). Green Roof, again, was not recommended in any of the hotspots. The reason for this is because no hotspot in the watershed was industrial urban land uses with a slope greater than 20%. Comparing Fig. 4-35 with Fig. 4-38, the distribution of NL matches the location of the nutrients (N and P) hotspots; the distribution of RB follows the distribution of surface runoff hotspots. Although RB and NL were recommended in large area, it does not mean that they were recommended in more HRUs. The total cost for installing the BMPs is 75.7 million USD. According to the simple model of residents' preferences, the total government cost ranges from $847,000 to $76,514,000 (Fig. 4-56).

Native Landscaping is the most recommended BMPs in both watersheds because of its effectiveness in reducing nutrients from the fertilizer applied to the lawn in residential landuse. Control methods for surface runoff are mainly IT in WB, and RB in WL. Fertilizer Reduction was not recommended in Watts Branch watershed because the hotspots for nutrients there were all urban landuses. Only non-urban area was assigned FR to control nutrients. Vegetated Filter Strips was also recommended to more HRUs in Wilde Lake, because of relatively flatter topography.
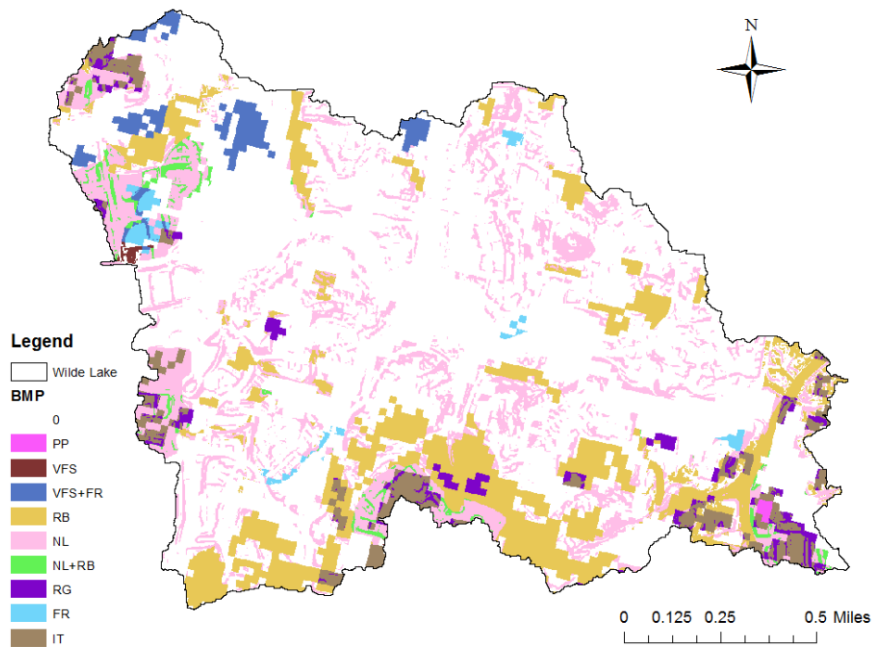
Figure 4-55 Spatially Assigned BMPs in the Wilde Lake Watershed
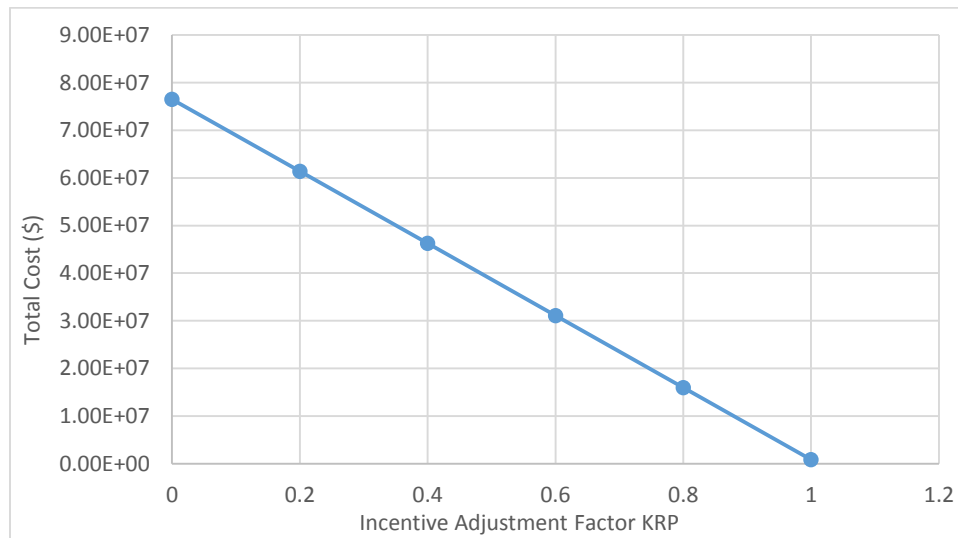
Figure 4-56 Estimated Total Cost of Applying the BMPs as a Function of Residents' Preferences (WL)

The new model which carried out simulation after the BMPs modeled in SWAT was

named WL_SWAT_Post (also WL_SWAT_D). Similar to those carried out in WB, two

sets of comparisons were carried out between the pre and the post model. The first analysis

compared the annual NPS pollutant yields both in terms of per-area yield and total amount

at the HRU level. The second analysis focused on the effected of BMP implementation on

in-stream variables.

In the WL_SWAT_Pre model, the highest annual per-area yield of surface runoff was

700mm, the lowest being zero. On average, the HRUs generate about 275mm of runoff

each year with a standard deviation of 108mm (Table 4-25). Annual sediment yield ranges

from zero to 176 tons/ha, with an average yield of 5.5 tons/ha and a standard deviation of

15 tons/ha. Total nitrogen yield ranges from 0 Kg/ha to 88 kg/ha, with an average yield of

11 kg/ha and a standard deviation of 19 kg/ha. An annual average of 4 Kg/ha of phosphorus,

ranging from 0 to 52 kg/ha, was simulated in the WL_Pre model with a standard deviation

of 5 kg/ha. The statistics also show highly skewed distributions for sediment, total N, and

total P.

Table 4-25 Per-area Yield Statistics in the pre_BMP scenario in the Wilde Lake Watershed

WL_SWAT_Pre	Q (mm)	Sed (Tons/ha)	N (Kg/ha)	P (Kg/ha)
MAX	701.53	176.15	87.87	52.51
MIN	0.00	0.00	0.00	0.00
AVE	274.59	5.55	11.75	3.87
SD	107.93	15.38	19.32	5.11

When the BMPs were modeled in the WL_SWAT_Post model, the average annual

per-area yield of runoff at HRU level was reduced by 10%, sediment yield by 45%, total

N by 39%, and total P by 45%. The maximum per-are yield for sediment and P were

reduced to 30% of the original values. The maximum runoff yield were reduce by 26%.

The maximum nitrogen yield was reduce by 8%.

Table 4-26 Per-area Yield Statistics in the post_BMP scenario in the Wilde Lake Watershed
BMP Assigned by DDSS

WL_SWAT_Post	Q (mm)	Sed (Tons/ha)	N (Kg/ha)	P (Kg/ha)
MAX	515.94	51.10	80.47	12.39
MIN	0.00	0.00	0.00	0.00
AVE	248.45	3.04	7.12	2.12
SD	75.79	6.21	10.95	2.19

The total annual simulated surface runoff (watershed-wide) was reduced by 9%, sediment by 22%, total Nitrogen by 37%, and total phosphorus by 36%, after the BMPs were included (Table 4-27). Compared to the total weight reduction in Watts Branch, the assigned BMPs in Wilde Lake were less effective in reducing surface runoff and sediment yields but more effective in controlling the total Nitrogen.

Table 4-27 Reduction of Runoff Volume and NPS Amount in the Wilde Lake Watershed
BMP Assigned by DDSS

	WL_Pre	WL_Post	Change Ratio
SurfQ (m3)	145145.79	132309.64	-9%
Sed (Tons)	1049.22	813.78	-22%
N (Kg)	6831.52	4274.56	-37%
P (Kg)	1817.76	1165.02	-36%

Besides the on-land variables, in stream variables such as stream discharge, suspended solid, in-stream N and P were also affected by BMP modeling. In the WL_SWAT_Pre model, the statistics of four in-stream variables were analyzed. The mean daily values for sediment and total N were reduced by 25%, total P by 42%. Again, the main daily stream discharge did not change at all, because stream discharge is a combined contribution from runoff, lateral flow, and groundwater flow. The maximum daily stream discharge in both the pre and the post model were the result of a storm event on Sept, 30, 2010. A reduction in stream discharge on that particular day indicated that the BMPs were

effective in reducing the surface runoff in storm events, thus reducing the risk of flood. The total on-land sediment generation was reduced by 22% (Table 4-26) but the sediment reduction rate in stream were 27%. The discrepancy lies in erosion in streams. Surface runoff in the watershed has been reduced by to the installation of BMPs. Less stream discharge generally mean less tractive force which is the driving force for channel erosion. Less surface runoff in storm events reduce channel erosion thus reducing even more suspended solid produced in stream. In summary, the spatially distributed BMPs in Wilde Lake Watershed were effective in reducing surface runoff, sediments, and nutrients on land.

Table 4-28 Comparison of In-stream Variables at the Outlet of the Wilde Lake Watershed BMP Assigned by DDSS

Statistics	Discharge Q (cms)		Suspended Solid (Tons)		N (Kg)		P (Kg)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Mean	0.0087	0.0083	0.28	0.20	2.29	1.70	0.48	0.28
Max	0.46	0.42	36.41	29.97	63.78	53.93	72.73	45.02
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std	0.0194	0.0170	1.39	1.07	2.90	2.23	2.56	1.55

4.3.2.6   Randomly assigning BMPs for Wilde Lake Watershed

In order to test the effective of the DDSS, another post BMP scenario WL_SWAT_R was carried out. In the WL_SWAT_R model, the BMPs were randomly assigned to the HRUs with the highest per-area yield of runoff, sediment, total N, and total P. In the WL_SWAT_D model, about 480 HRUs were assigned a specific type of BMP. Therefore, in this random assignment scenario, each of the eight candidate BMPs (Section 4.2) was randomly assigned to 60 HRUs. The WL_SWAT_R was run again to simulate the hydrological processes in the watershed and the results were compared to those generated by the WL_SWAT_Pre and the DDSS assigned WL_SWAT_D model.

When the BMPs were modeled in the WL_SWAT_R model, the average annual per-area yields of runoff at HRU level was reduced by 40%, sediment by 66%, total N by 0%, and total P by 72% (Table 4-29). Compared to the BMPs assigned by the DDSS, the randomly assigned BMPs resulted in a better reduction rate in surface runoff, slightly worse reduction rate in sediment and P yield, and show no reduction in N at all. The standard deviation of runoff and sediment in the R scenario are similar to the respective statistics shown in the D scenario. However, the standard deviation of N and P are greater than those calculated in the D scenario.

Table 4-29 Per-area Yield Statistics in the post_BMP scenario in the Wilde Lake Watershed
BMP Assigned randomly

WL_SWAT_R	Q (mm)	Sed (Tons/ha)	N (Kg/ha)	P (Kg/ha)
MAX	408.86	66.08	88.51	14.75
MIN	0.00	0.00	0.00	0.00
AVE	247.99	2.68	9.89	2.47
SD	73.11	5.75	17.16	2.73

In terms of total reduction amount (Table 4-30), the total simulated annual surface runoff was reduced by 9%, sediment by 30%, total nitrogen by 11%, and total phosphorus by 23%, after the BMPs were randomly assigned and modeled. The reduction rates for nutrients were smaller than those observed in the DDSS assigned BMPs. Reduction in sediment however, showed a better rate than that in the DDSS scenario.

Table 4-30 Reduction of Runoff Volume and NPS Amount in the Wilde Lake Watershed
BMP Assigned randomly

	WL_Pre	WL_R	Change Ratio
SurfQ (m3)	145145.79	132158.70	-9%
Sed (Tons)	1049.22	732.82	-30%
N (Kg)	6831.52	6073.51	-11%
P (Kg)	1817.76	1400.75	-23%

Similar to the analysis done in section 4.3.2.3, the four in-stream variables simulated in the WL_SWAT_R model were compared to the WL_SWAT_Pre statistics. The average daily stream discharge was reduced by 2%. The mean daily values for sediment and total P were reduced by 25%. Total N were reduced by 9%.

Table 4-31 Comparison of In-stream Variables at the outlet of the Wilde Lake Watershed BMP Assigned randomly

Statistics	Discharge Q (cms)		Suspended Solid (Tons)		N (Kg)		P (Kg)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Mean	0.0087	0.0085	0.28	0.20	2.29	2.09	0.48	0.36
Max	0.46	0.43	36.41	35.36	63.78	67.47	72.73	65.33
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
STD	0.0194	0.0172	1.39	1.22	2.90	2.69	2.56	2.18

Statistics of the on-land variables and the in-stream variables generally indicated that the BMPs assigned by DDSS performed better than the randomly-assigned BMPs in terms of per-area rate and in total rate. The 480 HRU that were given randomly assigned BMPs account for 34% of the total watershed area, compared to 37% in the DDSS assigned scenario. The cost of total BMP cost in the DDSS scenario was also less than that in the Random scenario (Fig. 4-57). In summary, the DDSS performed well in assigning proper BMPs. It not only assigned BMPs that are feasible for specific geological features, but also provided better NPS pollutant reduction rate and lower BMP costs.

One thing needs to be noted: even the BMPs were randomly assigned to the watersheds (both WB and WL) in this experiment, the selection was not entirely random. The BMPs were still applied to the HRUs that have the highest per-area yield of at least one variable of interest. Therefore, if the BMPs were truly randomly assigned, the

performance of the spatially distributed BMPs would be definitely worse than the WL_SWAT_R and the WB_SWAT_R models. The results indicated that the hotspot identification is of importance in prioritizing the most problematic areas. And the DDSS is also important in properly assigning the BMPs in order to maximize the effectiveness of all BMPs at their best effort.
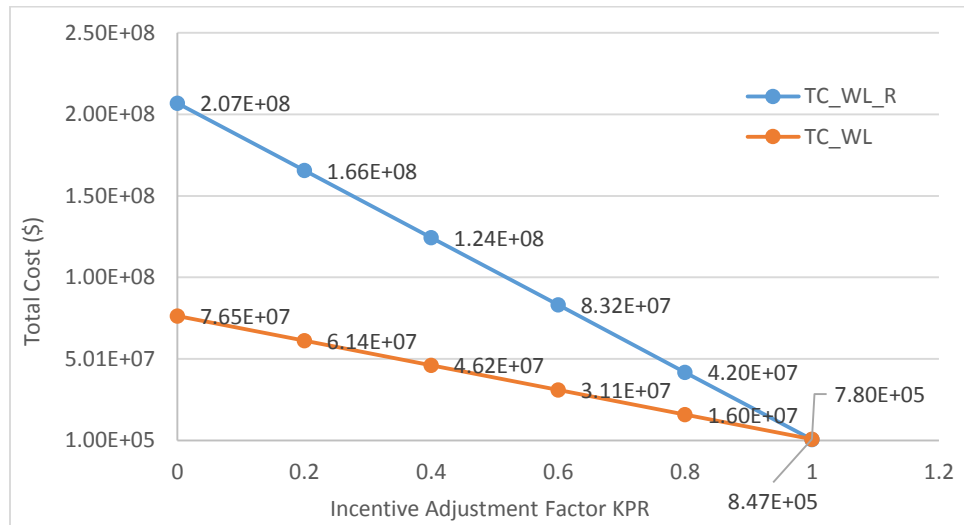
Figure 4-57 Comparison of total cost in the Wilde Lake watershed

DDSS assigned BMPs (WL_SWAT_D) and randomly assigned BMPs (WL_SWAT_R)

4.4   Effects of Climate Change

This section details the effects of future climate conditions on 1) hotspots identified in terms of coverage area and location; 2) BMP recommended in terms of BMP types, numbers, and total cost; and 3) existing BMP plan in terms of NPS reduction rates. Before that, a comparison between the hotspots identified using observed weather data and those identified using simulated weather data for current climate was carried out to ensure fair comparisons in the latter part.

4.4.1 Hotspot Identification Based on Historical Weather Statistics

In this section, the effects of Climate Change (CC) on the allocation of hotspots were analyzed. The analysis focused on hotspot identification, in which on-land variables: surface runoff, sediment, total N, and total P yields were of interest. The variables were compared according to the annual average per-area yield at HRU level and total yield amount at watershed level, which is similar to the analysis explained in Section 4.3.1 and Section 4.3.2.2.

Hotspots in Section 4.3.1 were identified through SWAT simulations with observed precipitation and temperature input data. In the baseline scenario for CC analysis, the hotspots were identified based on SWAT simulation with historical weather statistics (Section 3.4.2). In the baseline scenario (WB_NC_hs), the statistics of the per-area yield of the four variables at HRU level were recorded in Table 4-32. Compared to the statistics in the WB_SWAT_Pre simulation (Table 4-16), the average annual surface runoff (mm) showed a -16% difference, sediment yield a -13% difference, total N a -18% difference, and total P a -10% difference. As for the total amount of annual generation in the whole watershed, underestimation was observed for all variables at a rate of 16%, 13%, 18%, and 8%, respectively (Table 4-33).

Table 4-32 Statistics of Per-Area Yield at HRU level Under Current Climate Condition

NC_hs	Q(mm)	Sed (Tons/ha)	N (Kg/ha)	P (Kg/ha)
MAX	706.39	51.36	68.07	27.54
MIN	0.00	0.00	0.22	0.00
AVE	257.60	3.95	6.69	2.77
SD	152.66	6.78	6.70	3.64

Table 4-33 Comparison of Per-Area Yield Simulated by Observed and Simulated Weather Data

	WB_Pre	NC_hs	Change Ratio
SurfQ (m3)	351641.8	293783.5	-16%
Sed (Tons)	1681.36	1457.4	-13%
N (Kg)	8350.0	6807.4	-18%
P (Kg)	2363.4	2164.7	-8%

The reason for these overall negative differences in the WB_NC_hs simulation is that the WB_SWAT_Pre model was modeled using observed weather data from 2000 to 2013, but the weather used in the no-change baseline scenario was simulated with the historical statistics calculated from data in the past 38 years. First of all, the statistics in the most recent 12-yr period may have been different from those calculated in the last 38-yr period, due to possibly accelerated climate change. Higher temperatures and more severe storms and snow storms have been observed in the last decade. Secondly, a more controlling reason for the discrepancy lies between statistic-based simulation and observations. Weather statistics are calculated from actual weather observations in order to quantify the most common characteristics of the weather population. However accurate the statistics are, simulated weather can never be the true weather. For example, statistically, a 100-yr storm event means a 1/100 chance of occurring. Computer may simulate 3-4 100-yr storm events in one year but in reality, 10 such storm may take place in that particular year. The differences between simulation and reality in the weather input data would significantly affect the simulation of hydrology and water quality.

The reason to use the 38-yr statistics as weather input for the baseline simulation is to: 1) ensure a fair comparison between the base line scenarios and other future climate scenarios; 2) test if historical statistics can be used to identify hotspots for current condition (current landuse, soils, and topography) when no near-future observed weather data is available.

B1 Scenario

Legend

☐ Watts Branch Watershed

SurfQ (mm)

■ 0.00 - 115.45
■ 115.46 - 179.50
■ 179.51 - 270.57
■ 270.58 - 387.47
■ 387.48 - 706.39

0   0.375   0.75   1.5 Miles
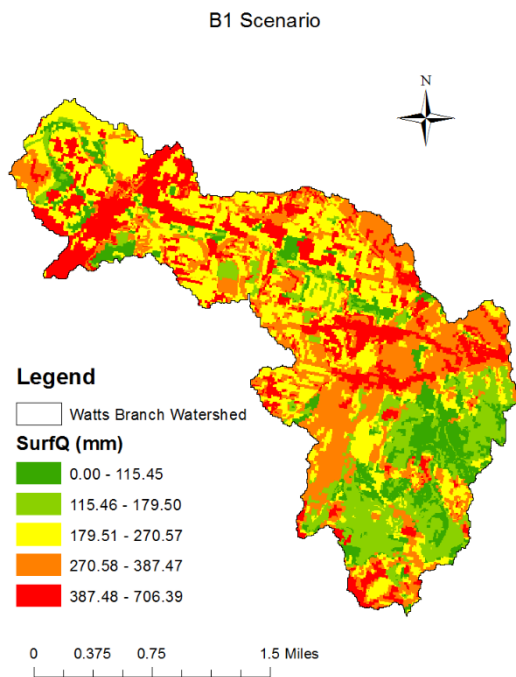
Figure 4-58 Surface Runoff Hotspot in the Watts Branch Watershed (Current Climate Statistics)
HRUs are ranked by runoff depth, and divided into 5 categories by count

Baseline Scenario

Legend

☐ Watts Branch Watershed

Sed (Tons/Ha)

■ 0.00 - 0.05
■ 0.06 - 0.84
■ 0.85 - 2.14
■ 2.15 - 5.78
■ 5.79 - 51.36

0   0.375   0.75   1.5 Miles
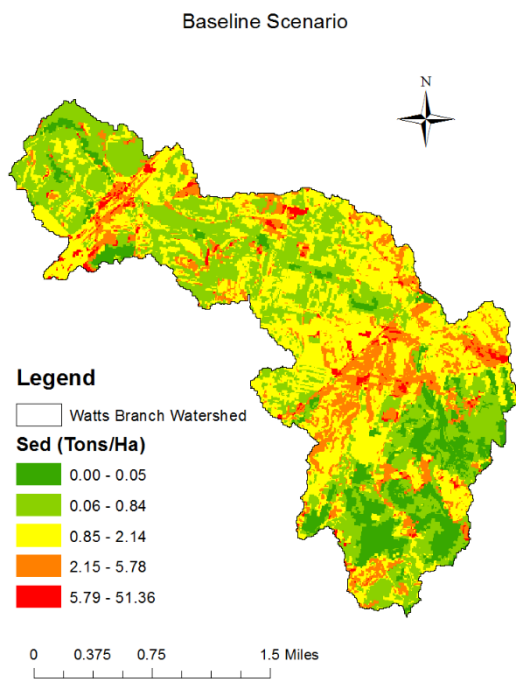
Figure 4-59 Sediment Hotspot in the Watts Branch Watershed (Current Climate Statistics)
HRUs are ranked by sediment yield (tons/ha), and divided into 5 categories by count

210
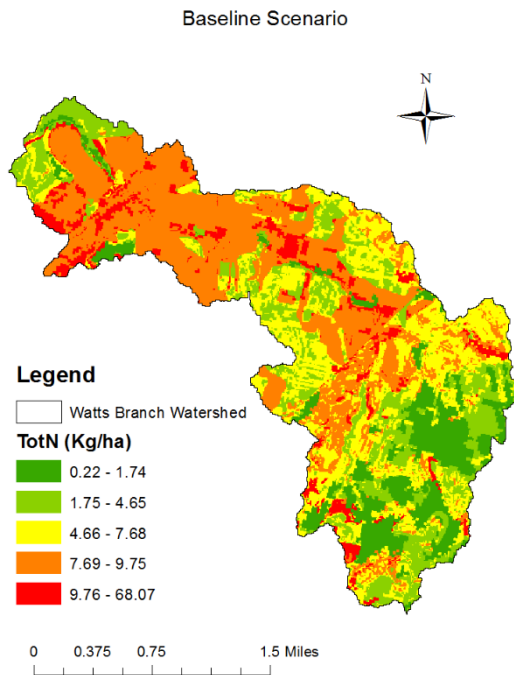
Figure 4-60 Total N Hotspot in the Watts Branch Watershed (Current Climate Statistics)
HRUs are ranked by N yield (kg/ha), and divided into 5 categories by count
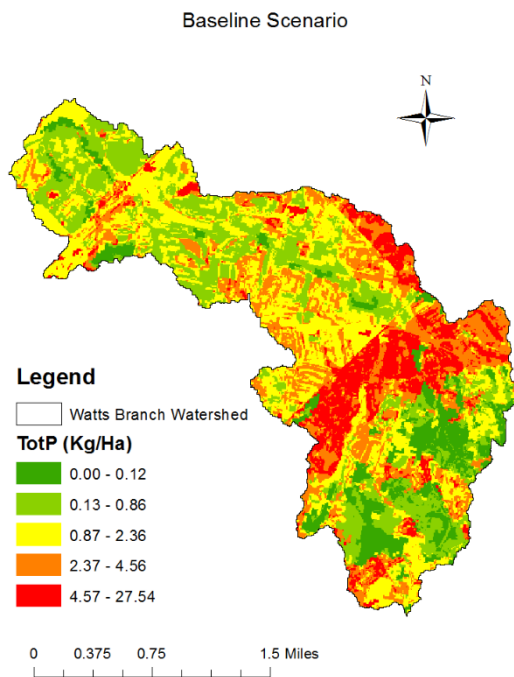
Figure 4-61 Total P Hotspot in the Watts Branch Watershed (Current Climate Statistics)
HRUs are ranked by P yield (kg/ha), and divided into 5 categories by count

Although a general 10-15% difference was observed, the location and distribution of the hotspots were almost identical for sediment (Fig. 4-59) and total P yield (Fig. 4-61). For surface runoff (Fig. 4-58) and total N (4-59), the baseline scenario was able to cover 92% and 78% of the hotspots identified in the WB_SWAT_Pre model (percentage shown in terms of HRU number, Table 4-34). Added hotspot in the table below means HRU that was not identified as hotspots in WB_SWAT_Pre while being identified in the baseline WB_NC_hs model. Missing hotspot means HRU that was identified as hotspots in WB_SWAT_Pre while not being identified in the baseline WB_NC_hs model.

Table 4-34 Comparison of Hotspots Identified Using Observed and Simulated Weather Data In the Watts Branch watershed

	Q			Sed		
	Missing	Added	Match	Missing	Added	Match
HRU No.	27	27	339	0	0	366
Area (Ha)	20.04	17.05	186.6	0	0	24.92
	N			P		
	Missing	Added	Match	Missing	Missing	Added
HRU No.	80	80	286	4	80	80
Area (Ha)	78.29	31.27	49.6	1.48	78.29	31.27

The results indicated that once the model is calibrated, SWAT predictions using simulated weather data would not seriously affect hotspot locations and distribution. This ensured the validity of the following analysis and comparison between the baseline scenario and the other 6 future climate scenarios.

4.4.2 Changing Climate on Hotspot Identification

The per-area yield statistics of each constituent of interest in the six future climate scenarios are listed in the Tables 4-35 to 4-38. According to tables in Section 3.4.1, SA2

scenario has the highest temperature increase, followed by SA1B, SB1, A1B, B1, and A2. The severe scenarios have much higher temperature increases. Precipitation show similar trends to that of temperature. SA2 has the highest percentage change in precipitation, followed by SA1B, SB1, A2, A1B, and B1. As for temperature extremes, the three moderate scenarios were modeled with a 5% increase in standard deviation of temperature, while the severe scenarios with 20% increase. Standard deviation of precipitation were increase by 6.3mm in SA2, 5.8mm in SA1B, 4.0mm in SB1, and 1.5mm in all the moderate scenarios. The degree of change intensifies from B1 to SA2 scenario in general. The tables and figures are organized in a way to present the results from the least changing scenario to the more intense changing scenarios.

The maximum and mean annual surface runoff in HRU level generally followed the trend in rainfall increase. Surface runoff was simulated to be the highest in the severe scenarios, followed by the moderate scenarios, then the baseline simulation. A2 scenarios (A2 and SA2) show the highest surface runoff generation in each set of climate scenarios (moderate and severe). The minimum annual surface runoff at HRU level in Watts Branch watershed was nearly 0mm in the baseline and the moderate scenarios. The minimum values increased to 15 mm in the SA2 scenario. Severe scenarios also show higher standard deviation for surface runoff than those shown in the moderate scenarios. Surface runoff generation is affected by both temperature and precipitation given an unchanged landuse, soil types, and land slope. Therefore, when both precipitation and temperature increased, an expected increase or decrease in standard deviation (SD) is not likely. The results in the three moderate scenarios indicated that the SWAT model was more likely to respond to a change in precipitation increase rather than a temperature increase.

Table 4-35 Annual Per-area Surface Runoff at HRU level in Different Climate Scenarios

Surface Runoff (mm)	NC_hs	B1_hs	A1B_hs	A2_hs	SB1_hs	SA1B_hs	SA2_hs
MAX	706.39	734.77	734.57	736.08	783.35	800.45	799.00
MIN	0.00	0.00	0.00	0.00	0.10	1.92	14.99
AVE	257.60	272.48	273.20	273.64	295.58	319.04	336.50
SD	152.66	158.36	158.01	158.14	162.73	162.83	159.92

As for per-area yield of sediment, the three moderate scenarios showed a small amount of increase as compared to the baseline simulation (Table 4-36). Noticeable increases were observed in the severe scenarios, with the highest increase in the SA2 scenario. The same trend was observed in the max values and the standard deviation. Two reasons are presented here for sediment increases in the severe scenarios. First of all, sediment yield is highly related to the total amount of surface runoff and peak runoff. Increases in sediment yield follows the increasing trend observed in total mean runoff (Table 4-35). Secondly, the precipitation in the severe scenarios was simulated with higher standard deviation, which may lead to higher peak runoff and consequent higher sediment yield consequently. Statistics are calculated by HRU, n = 1832.

Table 4-36 Annual Per-area Sediment Yield at HRU level in Different Climate Scenarios

Sediment (Tons/ha)	NC_hs	B1_hs	A1B_hs	A2_hs	SB1_hs	SA1B_hs	SA2_hs
MAX	51.36	53.41	53.44	53.50	57.93	59.32	59.63
MIN	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AVE	3.95	4.07	4.08	4.08	4.39	5.20	5.76
SD	6.78	7.07	7.07	7.08	7.67	7.95	8.22

As for per-area yield of nutrients, the three moderate scenarios did not show any obvious differences from the baseline scenario. However, the average annual N yield was more than doubled in the SA1B and the SA2 scenarios. One possible reason is that higher air temperatures promote plants growth which requires more fertilizer application. At the same time, higher surface runoff would wash away more fertilizer, resulting in a much

higher nutrient contribution into the receiving water bodies. In the SB1 scenario though, the average annual per-area nitrogen yield was less than the yield in the NC baseline scenario. One possible reason is that the moderate air temperature increase and precipitation change in the SB1 scenario somehow decrease the total amount of fertilizer application, thus reducing the N source in the watershed. One thing needs to be noted that a decrease in the average per-area yield in the HRU level did not necessarily result in a decrease in the total N yield in the watershed level. A1B scenario resulted in less average nutrients yield than the B1 scenario does, which is opposite to the trends observed in runoff and sediment generation. The differences are negligible though. One possible reason is the combined effects of temperature change and precipitation change on vegetation, which in turn affect the N and P yield in the area. The amount of fertilizer being automatically applied to the HRUs was higher in the severe climate conditions than applied in the moderate climate conditions in general.

Table 4-37 Annual Per-area N Yield at HRU level in Different Climate Scenarios

Total N (Kg/ha)	NC_hs	B1_hs	A1B_hs	A2_hs	SB1_hs	SA1B_hs	SA2_hs
MAX	68.07	61.76	59.95	61.17	63.83	140.00	130.02
MIN	0.22	0.58	0.34	0.59	0.72	0.83	0.88
AVE	6.69	6.74	6.69	6.77	5.93	14.96	15.10
SD	6.70	6.32	6.25	6.39	6.40	16.41	15.89

Table 4-38 Annual Per-area P Yield at HRU level in Different Climate Scenarios

Total P (Kg/ha)	NC_hs	B1_hs	A1B_hs	A2_hs	SB1_hs	SA1B_hs	SA2_hs
MAX	27.54	27.15	27.02	27.22	28.00	28.67	28.66
MIN	0.00	0.00	0.00	0.00	0.00	0.00	0.01
AVE	2.77	2.71	2.70	2.71	2.77	4.03	4.41
SD	3.64	3.59	3.59	3.60	3.68	4.29	4.45

4.4.2.1   Spatial distribution of surface runoff hotspots under future climate conditions

The spatial distribution of the surface runoff hotspots did not change much in simulations with different climate scenarios (Table 4-39). Hotspots identified in six future climate scenarios were compared with those identified in the baseline (WB_NC_hs) simulation. The added, missing, and matching hotspots in terms of HRU numbers and coverage area are listed in the Table 4-39. A2 showed the least missing hotspots and added hotspots in terms of both HRU number and area coverage. SB1 showed the highest added hotspots in terms of both HRU numbers and coverage area. But still, at least 86% of matching hotspots were observed in terms of the number of HRUs, and 87% in terms of total hotspots area, in the SB1 scenario.

The results indicated that future climate may not have significant effects on the distribution of surface runoff hotspots. Similar hotspots locations would be identified no matter which climate scenario is used for management plan, whether it is a current one or a moderate one or a severe one. The BMPs installed or planned to be installed in the hotspots area will still be useful for controlling the amount of surface runoff. Number "Missing" always equals "Added" because the number of HRUs is the same in all scenarios, and the top 20% HRUs were selected. Area Lost and Gained are different because HRUs have different area.

Table 4-39 Comparison of SurfQ_hs Location under Future Climate Scenarios

SurfQ Hotspots Compared to Baseline		Missing	Added	Match
B1	HRU No.	29	29	337
	Area (ha)	20.34	18.37	183.31
A1B	HRU No.	24	24	342
	Area (ha)	14.79	18.2	188.86
A2	HRU No.	19	19	347
	Area (ha)	15.47	5.35	188.18
SB1	HRU No.	50	50	316
	Area (ha)	19.27	59.85	184.38
SA1B	HRU No.	49	49	317
	Area (ha)	26.04	42.96	177.61
SA2	HRU No.	33	33	333
	Area (ha)	18.97	18.56	184.68
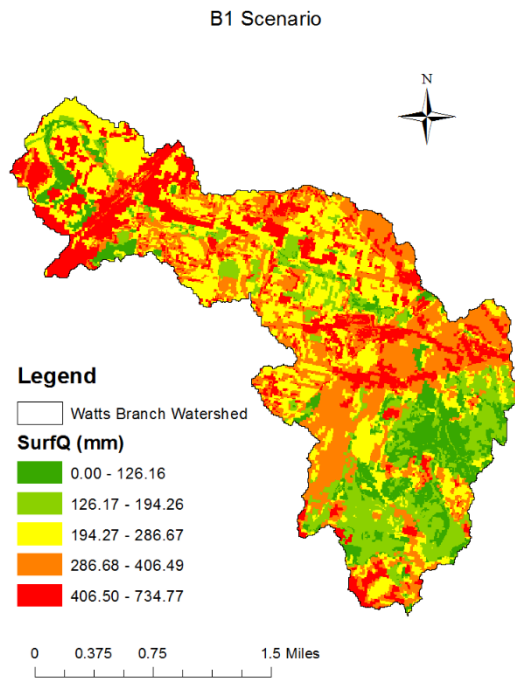
Figure 4-62 Surface Runoff Hotspot in the Watts Branch Watershed (B1 Scenario)
HRUs are ranked by runoff depth, and divided into 5 categories by count
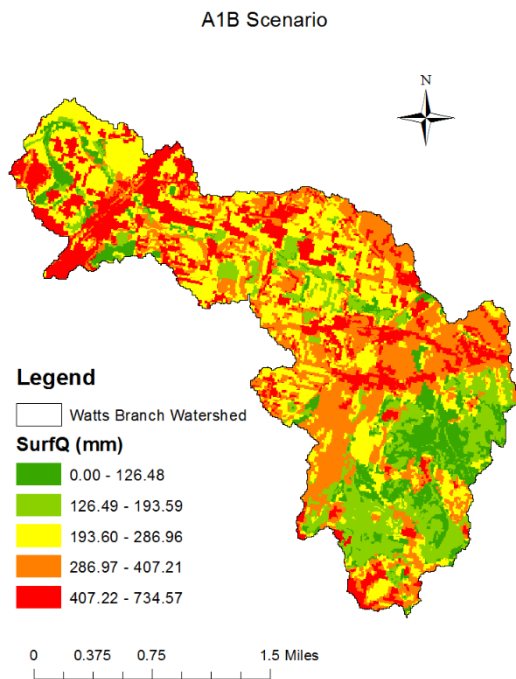
A1B Scenario

Figure 4-63 Surface Runoff Hotspots in the Watts Branch Watershed (A1B Scenario)
HRUs are ranked by runoff depth, and divided into 5 categories by count
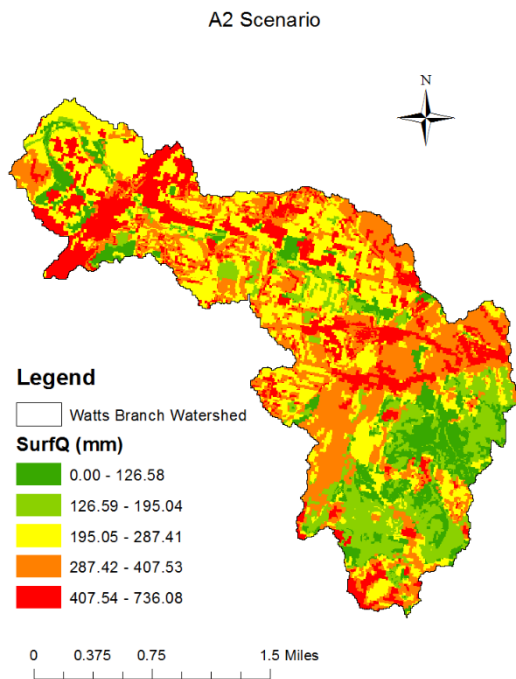
A2 Scenario

Figure 4-64 Surface Runoff Hotspots in the Watts Branch Watershed (A2 Scenario)
HRUs are ranked by runoff depth, and divided into 5 categories by count

Severe B1 Scenario

Legend

Watts Branch Watershed

SurfQ

- 0.10 - 136.66
- 136.67 - 226.53
- 226.54 - 301.15
- 301.16 - 429.41
- 429.42 - 783.35

0   0.375   0.75   1.5 Miles
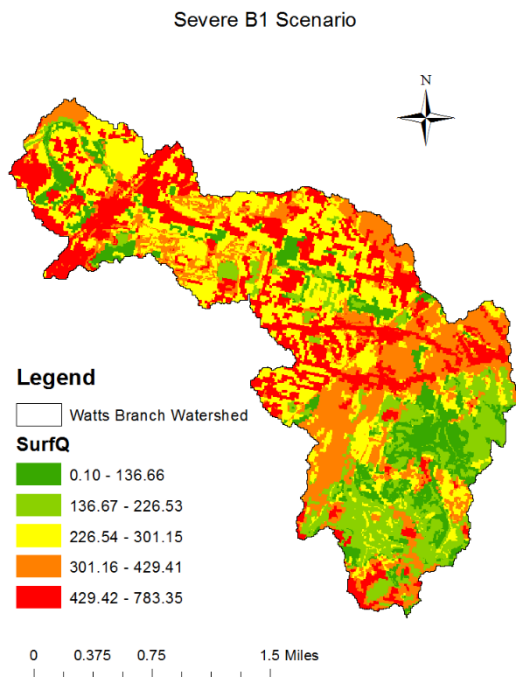
Figure 4-65 Surface Runoff Hotspots in the Watts Branch Watershed (SB1 Scenario)
HRUs are ranked by runoff depth, and divided into 5 categories by count

Severe A1B Scenario

Legend

Watts Branch Watershed

SurfQ (mm)

- 1.92 - 157.81
- 157.82 - 263.85
- 263.86 - 326.12
- 326.13 - 452.24
- 452.25 - 800.45

0   0.375   0.75   1.5 Miles
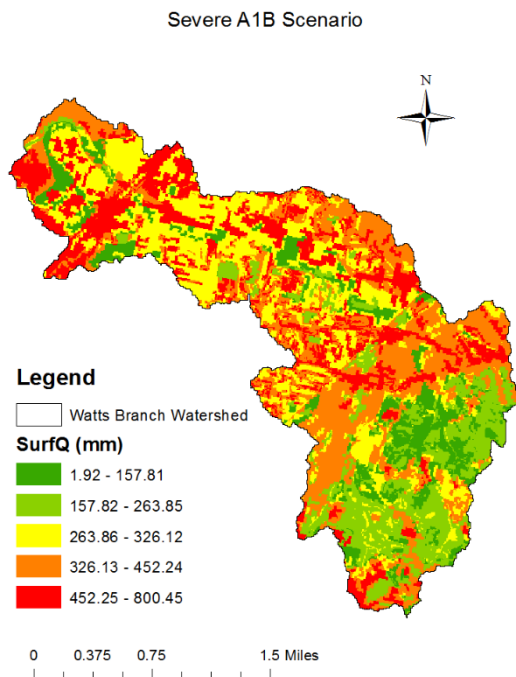
Figure 4-66 Surface Runoff Hotspots in the Watts Branch Watershed (SA1B Scenario)
HRUs are ranked by runoff depth, and divided into 5 categories by count
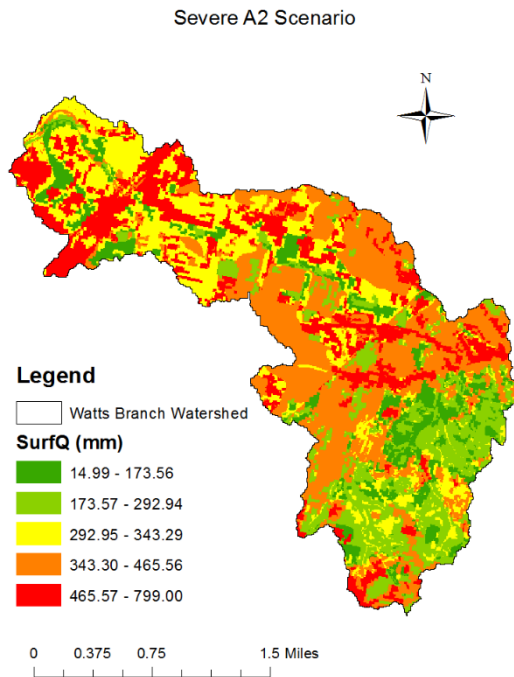
Figure 4-67 Surface Runoff Hotspots in the Watts Branch Watershed (SA2 Scenario)
HRUs are ranked by runoff depth, and divided into 5 categories by count

Besides the distribution of the hotspots, the breakpoint values in each category also deserve attention. The colors on the maps indicate the same percentiles, but the values of the percentiles are different. Fig. 4-68 shows the breakpoint values for surface runoff in each of the categories obtained from simulations under the six future climate scenarios. The divisions of the runoff categories shown in the three moderate climate conditions are essentially the same. As the climate condition gets severer, higher surface runoff generation is observed in general.
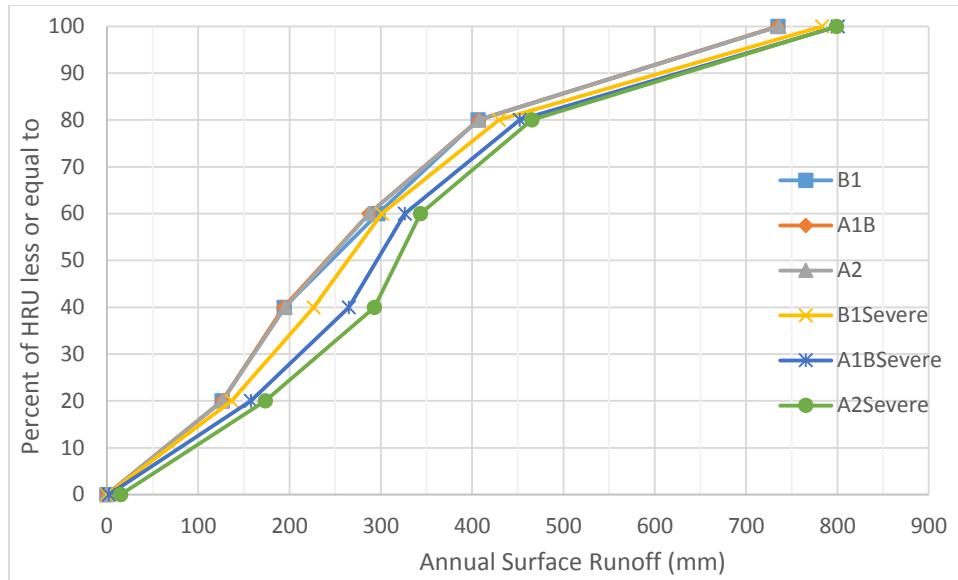
Figure 4-68 Breakpoints of surface runoff categories under different climate conditions

4.4.2.2   Spatial distribution of sediment hotspots under future climate conditions

Unlike the SurfQ_hs, the distribution of sediment yield did change under different climate conditions. In the A2, A1B, B1, and SB1 scenarios, the location of the hotspots were almost identical to the hotspots identified in the baseline NC scenario. Despite the differences in magnitude, the four scenarios show identical distribution of hotspots. The three moderate scenarios even show similar annual sediment yield, thus resulting a similar classification of the legends. As temperature increase and precipitation increase get higher in the more severe climate scenarios, SA2 and SA1B, a significant increase in sediment yield in general was observed. In the SA1B scenario, the matching number of hotspots decreased to nearly 80%. Added hotspots account for 93.03ha, which is about 4 times the area of the hotspots identified in the baseline scenario. A comparison between the SA1B and the A1B scenario showed that a lot of the high yield area in A1B (range and yellow) generated more sediment in the more severe climate condition. The phenomenon is more

significant in the SA2 scenario. The added hotspots accounts for 140 ha, which is nearly 6 time the area of hotpots in the baseline scenario.

Increase in sediment yield is expected under severe climate conditions. Higher precipitation amount and greater precipitation intensity would generate larger volume of stormwater in a shorter time period. Therefore, greater degree of erosion and more sediment yield are expected. One question arises when comparing the sediments hotspots distribution to the surface runoff hotpots distribution in the previous part. That is: why surface runoff hotspots distribution did not change much when climate change get intense but sediment did? Surface runoff is evenly distributed throughout the Watts Branch watershed, a 20% HRU would account for 20% of watershed area and 30% of total runoff volume (Section 4.3.1). However, the sediment hotspots only account for 3% of the watershed area and 20% of total sediment tonnage. In terms of surface runoff, the whole watershed responds to severe climate more evenly, which means a similar amount or a similar percentage of surface runoff increase was simulated over the entire watershed. However in terms of sediments, the watershed's response is non-linear or un-even. The increase in sediment yield is much higher in certain locations. This is due to the process of sediment generation. Sediment yield is related to not only runoff volume and peak runoff, but also related to soil erodibility, soil cover, and slope. The relationship between runoff volume and sediment yields is a non-linear one. Although runoff rate is closely related to sediment yield, an increase in surface runoff does not necessarily mean a significant increase in sediment yield.

Table 4-40 Comparison of Sed_hs Location under Future Climate Scenarios

Sediment Hotspots		Missing	Added	Match
NC + B1	HRU No.	2	2	364
	Area (ha)	0.38	0.23	24.54
NC + A1B	HRU No.	2	2	364
	Area (ha)	0.38	0.23	24.54
NC + A2	HRU No.	2	2	364
	Area (ha)	0.38	0.23	24.54
NC + SB1	HRU No.	2	2	364
	Area (ha)	0.38	0.23	24.54
NC + SA1B	HRU No.	47	47	319
	Area (ha)	6.29	93.03	18.63
NC + SA2	HRU No.	87	87	279
	Area (ha)	10.57	140.1	14.35

Figure 4-69 Sediment Hotspots in the Watts Branch Watershed (B1 Scenario)
HRUs are ranked by sediment yield (tons/ha), and divided into 5 categories by count

223

A1B Scenario

Legend

Watts Branch Watershed

Sed (Tons/Ha)

- 0.00 - 0.05
- 0.06 - 0.84
- 0.85 - 2.18
- 2.19 - 5.95
- 5.96 - 53.44

0   0.375   0.75   1.5 Miles

Figure 4-70 Sediment Hotspots in the Watts Branch Watershed (A1B Scenario)
HRUs are ranked by sediment yield (tons/ha), and divided into 5 categories by count

A2 Scenario

Legend

Watts Branch Watershed

Sed (ton/ha)

- 0.00 - 0.05
- 0.06 - 0.84
- 0.85 - 2.19
- 2.20 - 5.95
- 5.96 - 53.50

0   0.375   0.75   1.5 Miles

Figure 4-71 Sediment Hotspots in the Watts Branch Watershed (A2 Scenario)
HRUs are ranked by sediment yield (tons/ha), and divided into 5 categories by count

224

Severe B1 Scenario

Legend

Watts Branch Watershed

Sed (Tons/Ha)

- 0.00 - 0.07
- 0.08 - 0.87
- 0.88 - 2.38
- 2.39 - 6.43
- 6.44 - 57.93

0   0.375   0.75   1.5 Miles

Figure 4-72 Sediment Hotspots in the Watts Branch Watershed (SB1 Scenario)
HRUs are ranked by sediment yield (tons/ha), and divided into 5 categories by count

Severe A1B Scenario

Legend

Watts Branch Watershed

Sed (Ton/Ha)

- 0.00 - 0.10
- 0.11 - 1.50
- 1.51 - 3.58
- 3.59 - 8.26
- 8.27 - 59.32

0   0.375   0.75   1.5 Miles

Figure 4-73 Sediment Hotspots in the Watts Branch Watershed (SA1B Scenario)
HRUs are ranked by sediment yield (tons/ha), and divided into 5 categories by count

225

Severe A2 Scenario

Legend

Watts Branch Watershed

Sed (Tong/ha)

0.00 - 0.11
0.12 - 1.79
1.80 - 4.30
4.31 - 9.50
9.51 - 59.63

Figure 4-74 Sediment Hotspots in the Watts Branch Watershed (SA2 Scenario)
HRUs are ranked by sediment yield (tons/ha), and divided into 5 categories by count

Fig. 4-75 shows the breakpoint values for sediment yield in each of the categories obtained from simulations under the six future climate scenarios. The divisions of the sediment categories shown in the three moderate climate conditions are essentially the same. As the climate condition gets severer, higher sediment yield is observed in general.

Figure 4-75 Breakpoints of sediment categories under different climate conditions

4.4.2.3   Spatial distribution of N hotspots under future climate conditions

Similar to Sed_hs, the distribution of Nitrogen yield changed over different climate scenarios. In the A2, A1B, B1, and SB1 scenarios, the matching hotspots are relatively high in number and in coverage area. However, in the SA2 and SA1B scenarios, the coverage area dropped to 1/3 of the total hotspots area identified in the baseline scenario. A dislocation of the hotspots does not mean a decrease in nitrogen yield in the missing hotspots area. A detailed comparison of the hotspot maps in A2 and SA2 scenarios reveals that the total N yield increased throughout the watershed. Majority of the orange area in A2 have a total N yield of 8.08 – 9.51 Kg/ha. In the SA2 map, the same area is mostly covered by yellow and light green, which has a range of 2.73-8.57 Kg/ha, and 8.58 – 12.88 Kg/ha. The lowest yield in the hotspot in SA2 was 22.45 Kg/ha, which is way higher than the one in the A2 scenario. This explains why a large number of missing hotspots are observed. The adding hotspots may result from an "upgrade" from category Orange into Red.

The reasons for significant increase in total N yield include higher surface runoff, greater precipitation volume, and plant growth. Under higher temperature and more precipitation, vegetation tend to grow faster, which requires more fertilizer application. At the same time, more grass means higher amount of organic N. Therefore, higher N yield in the watershed as a whole was observed.

Table 4-41 Comparison of N_hs Location under Future Climate Scenarios

Total N Hotspots		Missing	Added	Match
NC + B1	HRU No.	69	69	297
	Area (ha)	26.30	20.34	54.57
NC + A1B	HRU No.	65	65	301
	Area (ha)	18.19	18.14	62.68
NC + A2	HRU No.	73	73	293
	Area (ha)	20.84	21.17	60.03
NC + SB1	HRU No.	104	104	262
	Area (ha)	8.21	57.59	72.66
NC + SA1B	HRU No.	245	245	121
	Area (ha)	54.40	74.79	28.47
NC + SA2	HRU No.	246	246	120
	Area (ha)	52.96	73.06	29.91
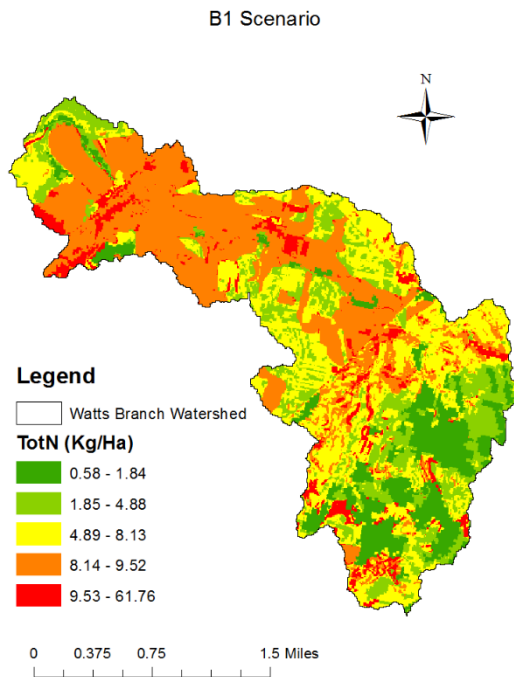
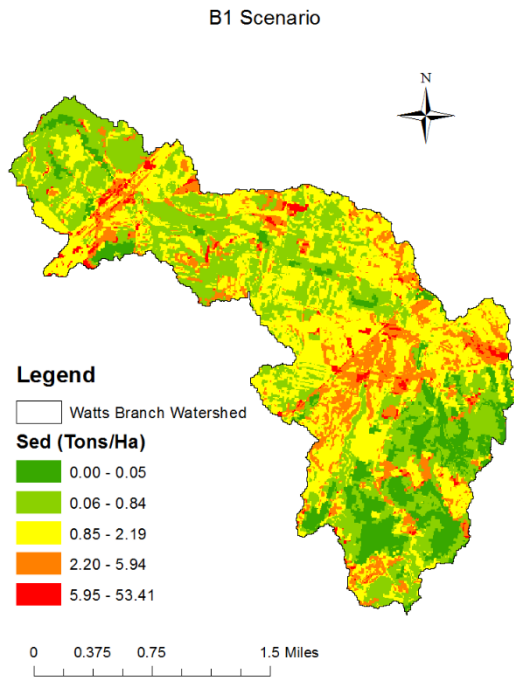

Figure 4-76 Total N Hotspots in the Watts Branch Watershed (B1 Scenario)
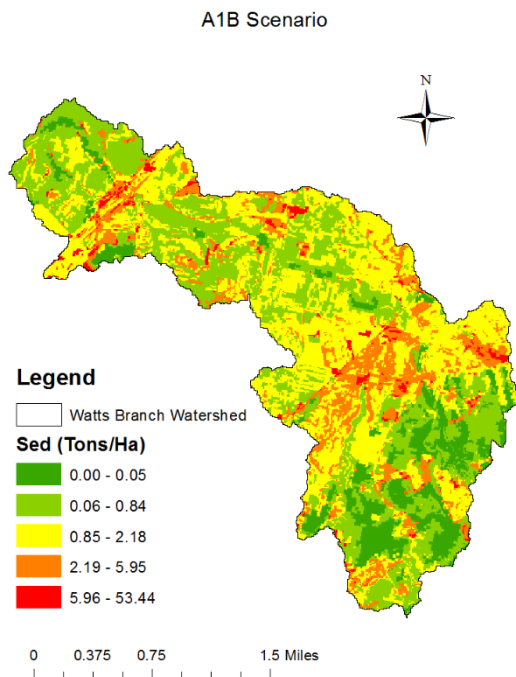HRUs are ranked by N yield (kg/ha), and divided into 5 categories by count

Figure 4-77 Total N Hotspots in the Watts Branch Watershed (A1B Scenario)
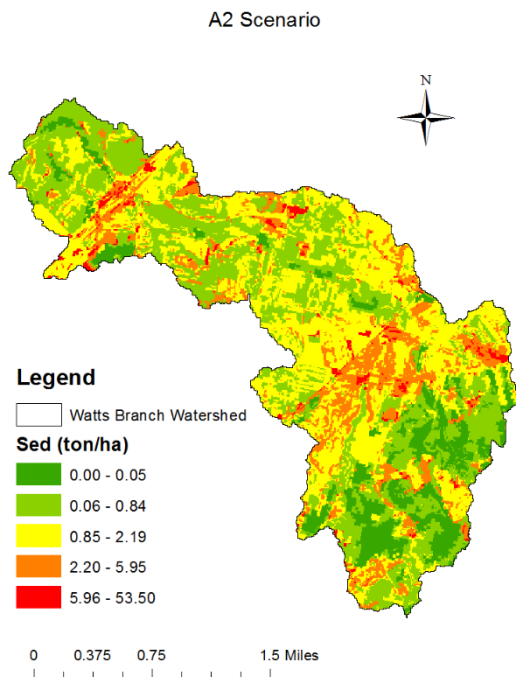HRUs are ranked by N yield (kg/ha), and divided into 5 categories by count

Figure 4-78 Total N Hotspots in the Watts Branch Watershed (A2 Scenario)
HRUs are ranked by N yield (kg/ha), and divided into 5 categories by count

229

Severe B1 Scenario
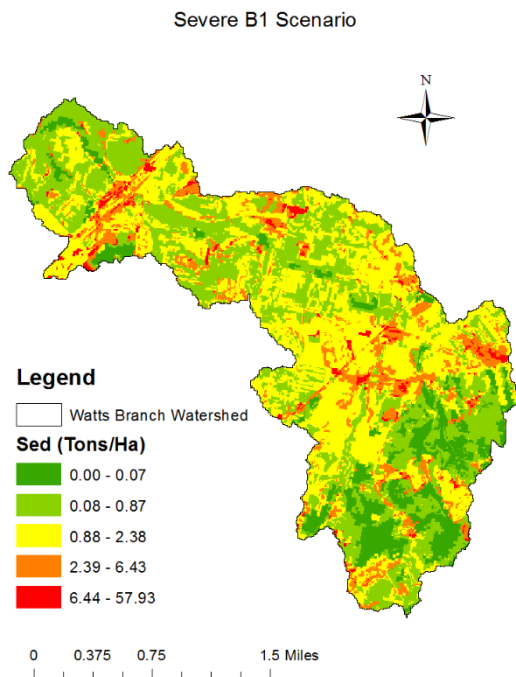
Legend

Watts Branch Watershed

TotN (Kg/Ha)
- 0.72 - 1.71
- 1.72 - 4.44
- 4.45 - 6.32
- 6.33 - 7.85
- 7.86 - 63.83

0   0.375   0.75   1.5 Miles

Figure 4-79 Total N Hotspots in the Watts Branch Watershed (SB1 Scenario)
HRUs are ranked by N yield (kg/ha), and divided into 5 categories by count

Severe A1B Scenario
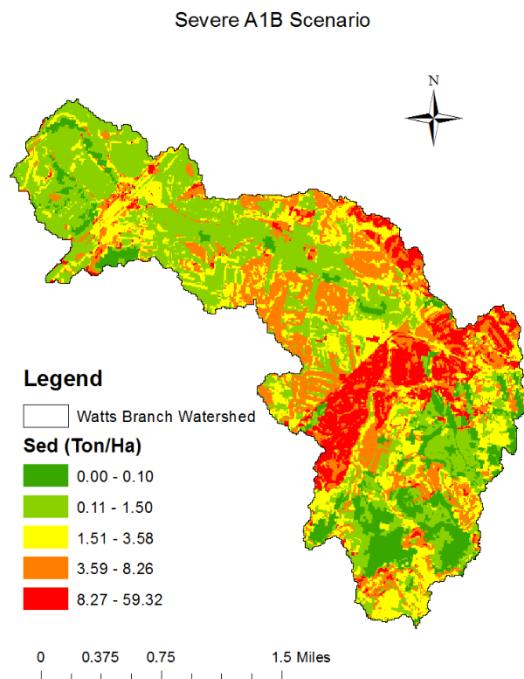
Legend

Watts Branch Watershed

TotN (Kg/Ha)
- 0.83 - 2.28
- 2.29 - 8.08
- 8.09 - 12.75
- 12.76 - 22.39
- 22.40 - 140.00

0   0.375   0.75   1.5 Miles

Figure 4-80 Total N Hotspots in the Watts Branch Watershed (SA1B Scenario)
HRUs are ranked by N yield (kg/ha), and divided into 5 categories by count

Figure 4-81 Total N Hotspots in the Watts Branch Watershed (SA2 Scenario)
HRUs are ranked by N yield (kg/ha), and divided into 5 categories by count

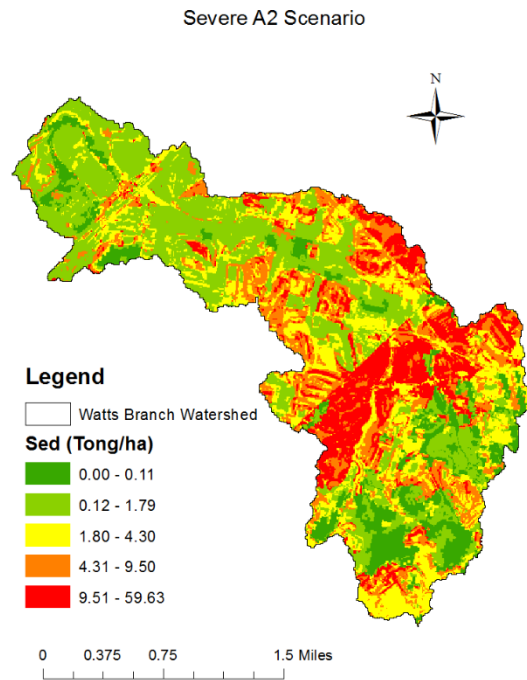Fig. 4-82 shows the breakpoint values in each of the categories obtained from simulations under the six future climate scenarios. The divisions of the N yield categories shown in the three moderate climate conditions are essentially the same. As the climate condition goes severer, higher N yield is observed in general.
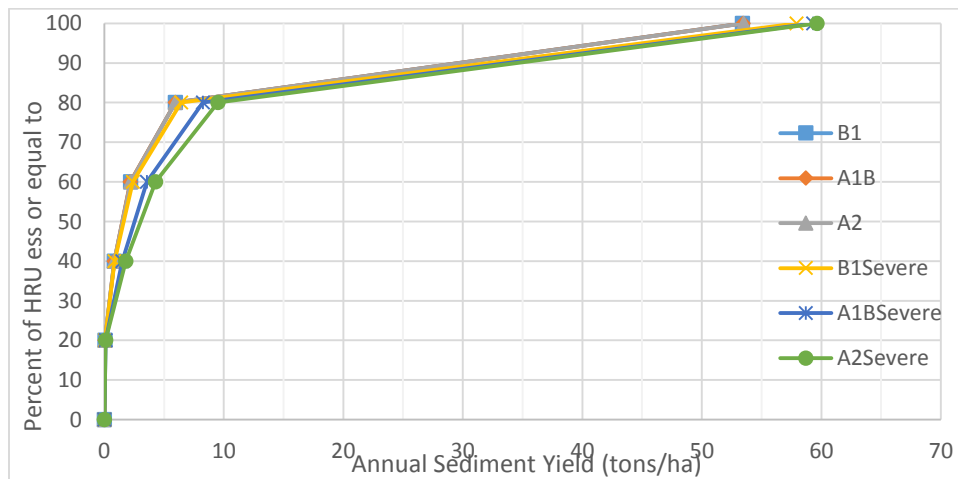

Figure 4-82 Breakpoints of N yield categories under different climate conditions

4.4.2.4   Spatial distribution of P hotspots under future climate conditions

The differences observed for P hotspots distribution in various scenarios are similar to those observed in sediment hotspots. In the A2, A1B, B1, and SB1 scenarios, the location of the hotspots was almost identical to the hotspots identified in the baseline scenario. Despite the differences in magnitude, the four scenarios show identical distribution of hotspots. The three moderate scenarios simulated similar annual P yield, thus resulting a similar classification of the legends. As temperature increase and precipitation increase get higher in the more severe climate scenarios, SA2 and SA1B, a noticeable change in hotspots distribution was observed. Take A2 and SA2 as an example again. The maximum P yield in an HRU did not increase much (Figs. 4-82 and 4-85), which may be limited by the total amount of P applied to and originally exited in the HRU. However, the overall P yield increased significantly. The P yield in the hotspots in A2 ranges from 4.46 – 27.22 Kg/ha. The hotpots in SA2 have a P yield ranging from 8.53 – 28.66 Kg/ha. 20% of HRU had P yield greater than 4.46 in A2, and over 40% of HRUs in SA2. The main reasons for P yield increase are increased fertilizer application and higher sediment yield. Because of the low mobility, P is generally not added to the watershed through atmospheric deposition. Moreover in SWAT, P is modeled as 1/6 of N amount. These are the reasons why a higher P increase was observed in the severe climate scenarios.

Table 4-42 Comparison of P_hs Location under Future Climate Scenarios

| Total P Hotspots		Missing	Added	Match
NC + A2	HRU No.	10	10	356
	Area (ha)	25.11	1.53	105.55
NC + A1B	HRU No.	10	10	356
	Area (ha)	25.11	1.53	105.55
NC + B1	HRU No.	9	9	357
	Area (ha)	24.28	1.52	106.38
NC + SA2	HRU No.	109	109	257
	Area (ha)	13.44	157.97	117.22
NC + SA1B	HRU No.	42	42	244
	Area (ha)	19.81	53.83	110.85
NC + SB1	HRU No.	19	19	347
	Area (ha)	33.35	2.46	97.31
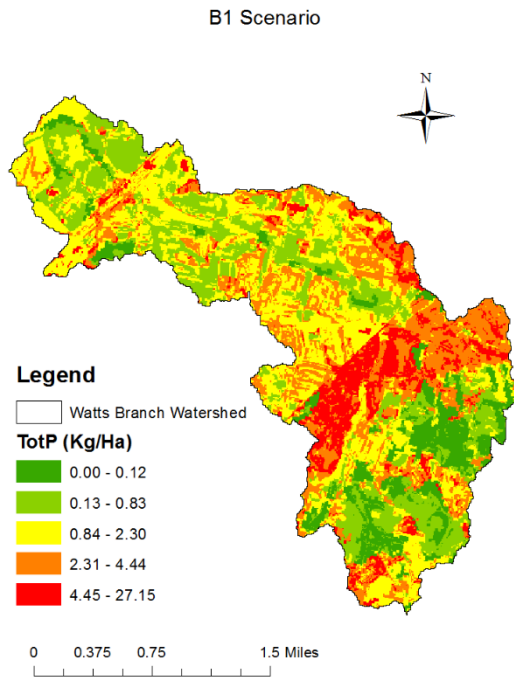
Figure 4-83 Total P Hotspots in the Watts Branch Watershed (B1 Scenario)
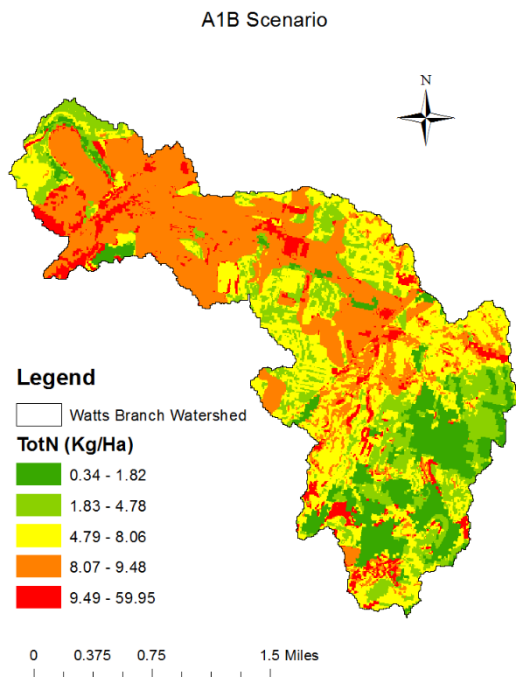HRUs are ranked by P yield (kg/ha), and divided into 5 categories by count
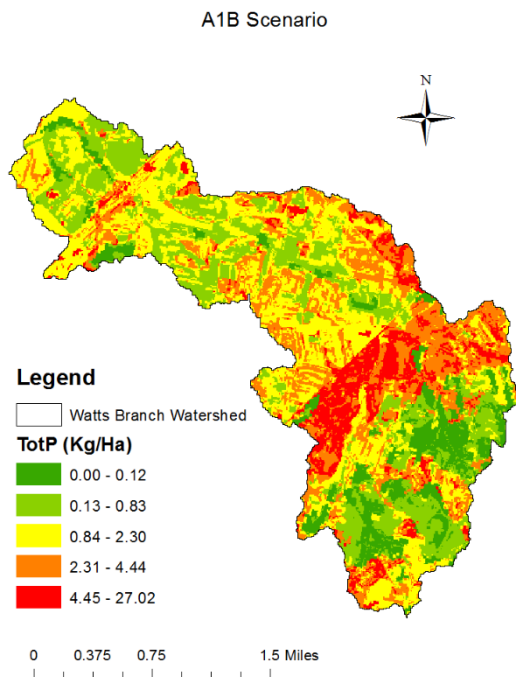
Figure 4-84 Total P Hotspots in the Watts Branch Watershed (A1B Scenario)
HRUs are ranked by P yield (kg/ha), and divided into 5 categories by count
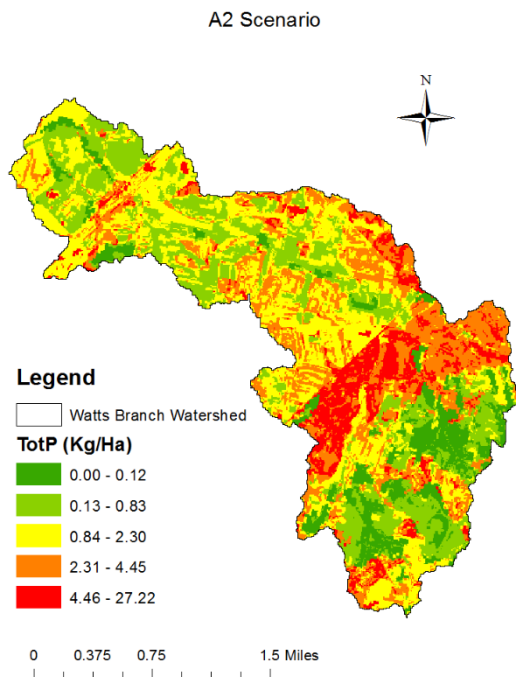
Figure 4-85 Total P Hotspots in the Watts Branch Watershed (A2 Scenario)
HRUs are ranked by P yield (kg/ha), and divided into 5 categories by count

Severe B1 Scenario

Legend

Watts Branch Watershed

TotP (Kg/Ha)

- 0.00 - 0.15
- 0.16 - 0.85
- 0.86 - 2.33
- 2.34 - 4.57
- 4.58 - 28.00

0   0.375   0.75   1.5 Miles
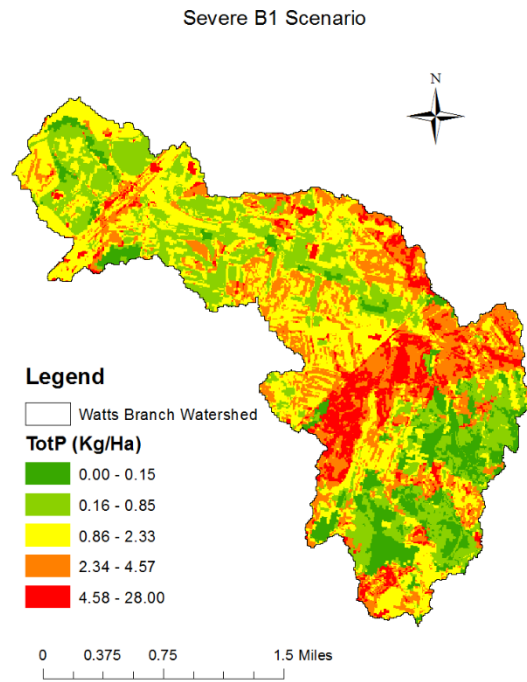
Figure 4-86 Total P Hotspots in the Watts Branch Watershed (SB1 Scenario)
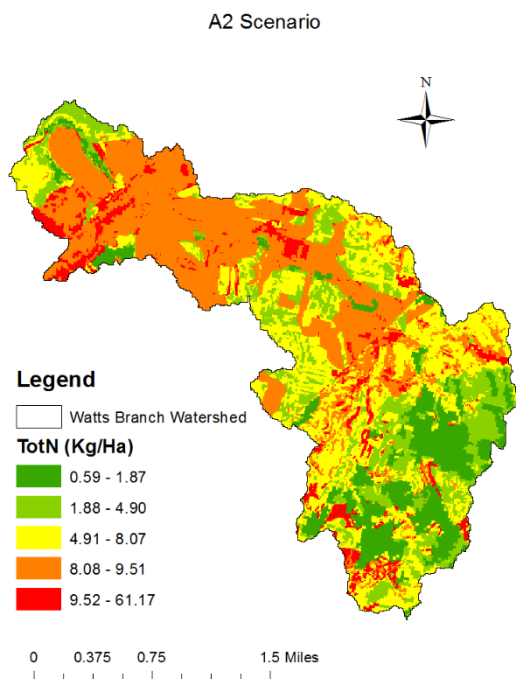HRUs are ranked by P yield (kg/ha), and divided into 5 categories by count

Severe A1B Scenario

Legend

Watts Branch Watershed

TotP (Kg/Ha)

- 0.00 - 0.19
- 0.20 - 1.57
- 1.58 - 3.93
- 3.94 - 7.55
- 7.56 - 28.67

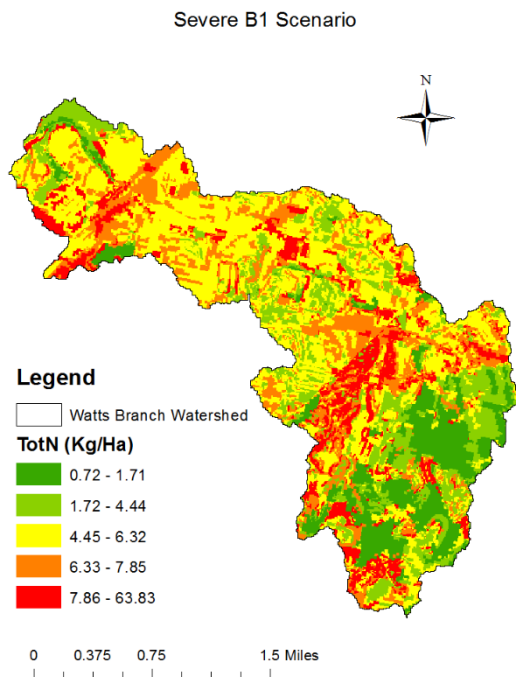0   0.375   0.75   1.5 Miles
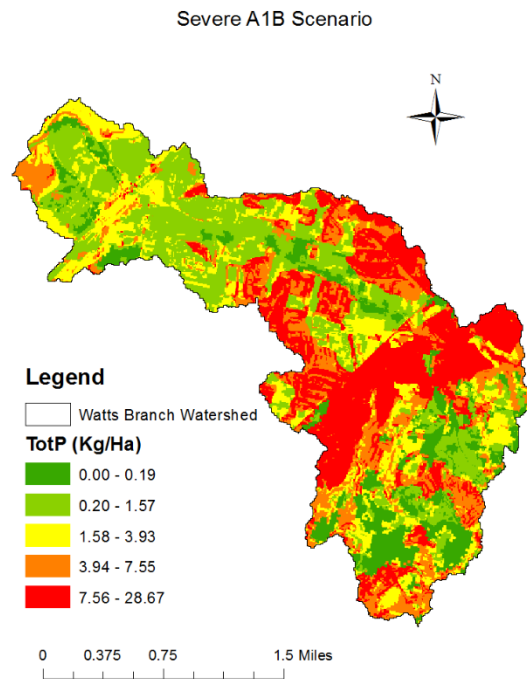
Figure 4-87 Total P Hotspots in the Watts Branch Watershed (SA1B Scenario)
HRUs are ranked by P yield (kg/ha), and divided into 5 categories by count

235

Severe A2 Scenario

Legend

☐ Watts Branch Watershed

TotP (Kg/Ha)
- 0.01 - 0.22
- 0.23 - 1.86
- 1.87 - 4.67
- 4.68 - 8.52
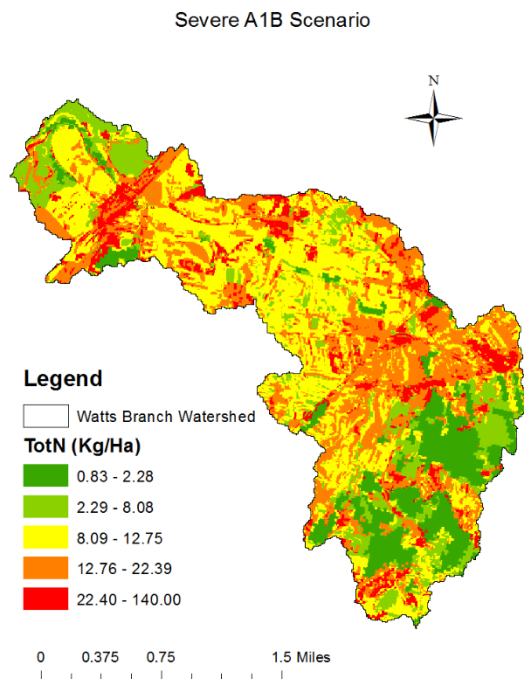- 8.53 - 28.66
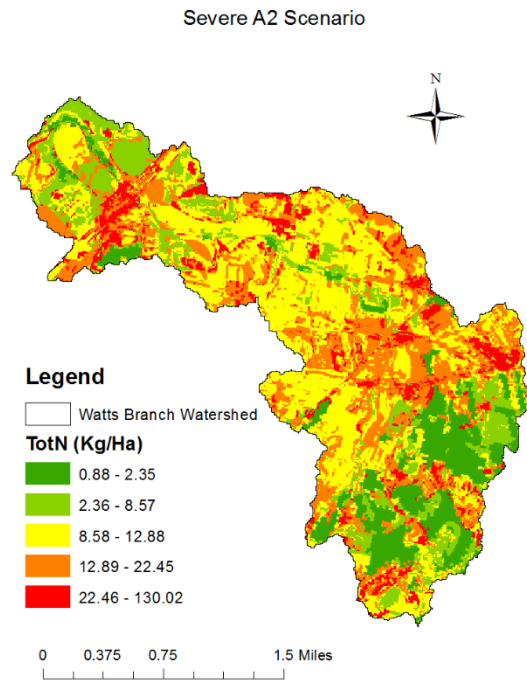
0   0.375   0.75   1.5 Miles
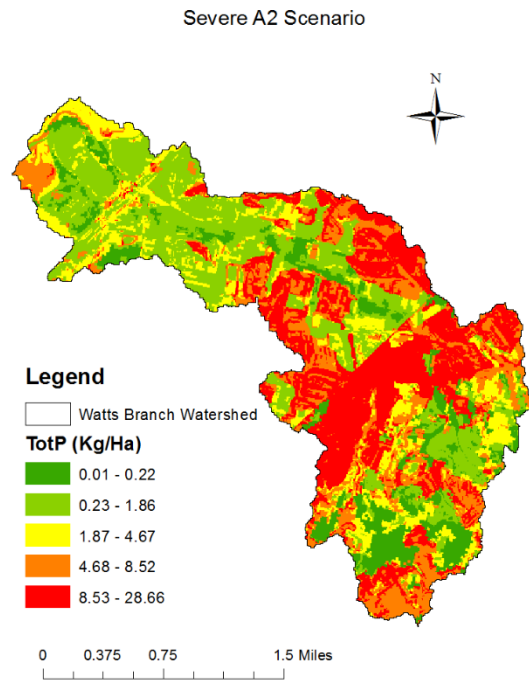
Figure 4-88 Total P Hotspots in the Watts Branch Watershed (SA2 Scenario)
HRUs are ranked by P yield (kg/ha), and divided into 5 categories by count

Fig. 4-89 shows the breakpoint values in each of the categories obtained from simulations under the six future climate scenarios. The divisions of the P yield categories shown in the three moderate climate conditions and the severe B1 scenario are essentially the same. As the climate condition goes severer, higher P yield is observed in general.

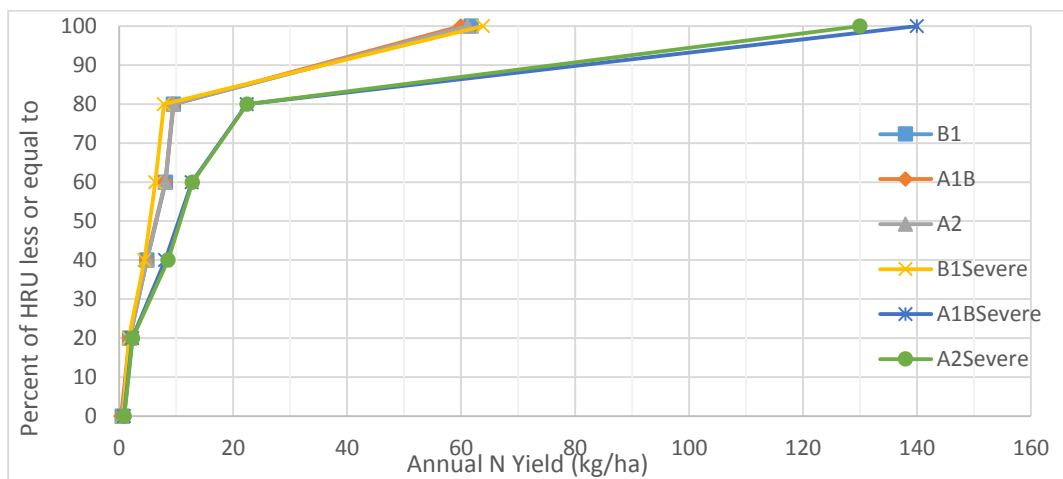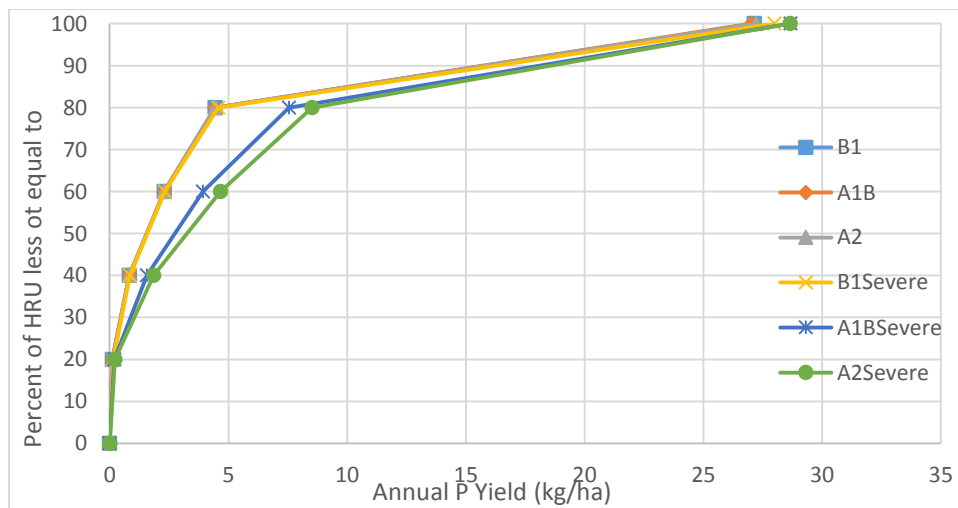Figure 4-89 Breakpoints of P yield categories under different climate conditions

4.4.2.5   Comparison of total annual yield in the future climate scenarios

The total amount of annual runoff volume, sediment tonnage, and nutrients weights in the six future climate scenarios along with the baseline scenario are listed in Table 4-43. Percentage changes as compared to the baseline simulation are also listed for all four variables in the six climate conditions. Surface runoff volume increases as the precipitation increases, as expected. Sediments and nutrients did not show a noticeable change in the three moderate scenarios. When climate change get severe, sediment and nutrients yield increased by as much as 200%. Slight reductions in P yields in the three moderate scenarios were observed.

Table 4-43 Comparison of Total NPS Amount under Future Climate Scenarios in WB_hs

Scenario	SurfQ		Sediment		Total N		Total P	
	$*10^3 m^3$	Change	$*10^3$ Ton	Change	$*10^3$ Kg	Change	$*10^3$ Kg	Change
NC	293.8	---	1.457	---	6.807	---	2.165	---
A2_hs	311.4	6.0%	1.433	-1.7%	6.897	1.3%	2.040	-5.8%
A1B_hs	311.0	5.9%	1.431	-1.8%	6.847	0.6%	2.025	-6.5%
B1_hs	310.4	5.7%	1.435	-1.6%	6.902	1.4%	2.043	-5.6%
SA2_hs	376.4	28.1%	4.466	206.5%	13.38	96.5%	4.814	122.4%
SA1B_hs	357.7	21.7%	3.385	132.2%	13.20	93.9%	4.369	101.8%
SB1_hs	332.6	13.2%	1.485	1.9%	5.692	-16.4%	2.047	-5.4%

4.4.3   Changing Climate on BMP Assignment an Cost Issue

When making stormwater management plans in a watershed scale, different climate scenario will result in different BMP assignment, thus resulting in different total costs. Analysis was carried out to identify any differences in BMP assignment in terms of BMP types and total cost under different climate scenarios. The BMPs prescribed by the DDSS under the three moderate climate scenarios are similar to those assigned in the baseline scenario. Slight differences were observed in the assignment of rain gardens, which were assigned to 260 HRUs (or hotspots) and covered an area around 45 ha. Fewer hotspots in

the moderate climate scenarios were assigned native landscaping, which was designed for controlling sediments and nutrients. Since the total amount of P and sediments were less in the moderate climate scenarios compared to those simulated in the baseline scenario, less recommended native landscaping was expected. Slightly fewer infiltration trenches and more rain gardens were recommended watershed wide. This is because the average annual per-area sediment yields were higher in the moderate climate change conditions. Infiltration trench was avoided in high sediment yield area, and rain gardens were designed to be the replacement of infiltration trenches.

Table 4-44 BMP Assignment under Different Climate Scenarios in WB

	BMP	Pervious pavement	Vegetated filter strip	Rain barrel	Native landscaping	Rain garden	Infiltration trench	RB + NL
NC	No.	46	8	11	273	258	109	13
	Area (ha)	22.96	0.21	1.17	121.75	42.24	137.07	0.38
B1	No.	46	8	15	211	275	89	12
	Area (ha)	22.96	0.21	10.68	81.31	51.51	121.91	0.31
A1B	No.	46	8	18	213	264	101	12
	Area (ha)	22.96	0.21	10.8	86.07	43.73	134.7	0.31
A2	No.	46	8	11	205	270	99	12
	Area (ha)	22.96	0.21	1.17	86.61	48.16	127.15	0.31
SB1	No.	46	8	39	224	252	122	12
	Area (ha)	22.96	0.21	13.21	104.37	36.27	178.77	0.31
SA1B	No.	46	9	33	258	262	143	41
	Area (ha)	22.96	0.18	12.96	175.01	44.86	161.26	45.78
SA2	No.	46	4	30	247	246	148	66
	Area (ha)	22.96	0.06	13.05	161.78	40.21	149.24	74.45

In the much more severe SA2 and SA1B scenarios, noticeable changes included increasing number of rain barrels, more infiltration trench, more rain barrel + native landscaping, and increasing area of native landscaping. Changes in coverage area generally indicated a change in distribution and location of hotspots. Increases in BMP numbers generally means more hotspots and more problems observed in the watershed. The BMP recommendations in SB1 scenario were more similar to those assigned in the moderate

future climate scenarios. This is because the model simulation under SB1 is quite similar to those under the moderate future climate conditions.

In the planning phase, the total coverage area, total constituents being targeted, and the total budget are the three most important factors that affect decision making. The three factors were calculated in each of the future climate scenarios and were compared to those calculated in the NC scenario. In the baseline scenarios, the total spatially assigned BMPs covered 30% of total watershed area and targeted 43% of total annual runoff volume, 50% annual sediment yield, 44% of total annual N yield, and 54% total P yield. The BMPs assigned in the three moderate scenarios covered slightly less watershed area and targeted less runoff and NPS pollutants. SB1 showed slightly higher area coverage and targeted pollutant amount. As for SA2 and SA1B, a much higher area coverage were recommended. The constituents being treated were also significantly increased. But consequently the total cost for installing BMPs were much higher (20%) than the expected cost calculated in the baseline scenario.

Table 4-45 BMP Coverage Area, Treating Amount, and Costs in Different Climate Scenarios

		NC	B1	A1B	A2	SB1	SA1B	SA2
Watershed Area		31.3%	27.8%	28.7%	27.6%	34.2%	44.5%	44.4%
Treating Amount	SurfQ	42.6%	39.4%	40.3%	38.6%	45.6%	57.8%	56.2%
	Sed	59.3%	56.1%	56.6%	56.2%	60.5%	80.2%	81.0%
	N	43.8%	38.9%	40.3%	39.3%	48.2%	63.9%	63.5%
	P	53.5%	49.7%	50.1%	49.3%	56.1%	73.5%	69.9%
Fixed Cost ($ x10^6)		1.47	1.30	1.34	1.29	1.60	2.08	2.08
BMP Cost ($ x10^6)		548.86	539.74	547.38	542.23	577.21	626.85	643.15

In summary, in NPS pollutant control planning, decisions made on BMP assignments using the current climate condition for hotspots identification would be quite similar to the

decisions made using the moderate scenarios even the SB1 scenarios. If the most severe future climate condition SA2 was used for planning, a much higher cost would be expected.

4.4.4   Climate Effects on Existing BMP

Another interesting question is that when the BMP assignment planning has already been made based on the current climate condition (no change, baseline scenario), how future climate conditions would affect the effectiveness of the existing BMPs plans. To answer this question, another set of analysis was carried out. In this set of simulations, a baseline simulation (NC_bmp) was carried out using the WB_SWAT_Post model with BMPs simulated under no-change climate condition. The difference between the NC_hs and the NC_bmp simulations was that no BMP was modeled in the NC_hs model. In the NC_bmp model, spatially distributed BMPs were modeled in HRUs which were identified as hotspots in the WB_SWAT_Pre model. The analysis examined the expected reduction rates for the four on-land constituents. Another six simulations were done using the same WB_SWAT_Post model but using weather inputs generated from the different future climate conditions. These six simulations were carried out to examine the effectiveness of existing BMPs which were modeled in the WB_SWAT_Post.

The second to fourth rows of Table 4-46 list the annual yield of runoff volume, sediment tonnage, and nutrients weights in the baseline scenario and the six future climate scenarios. The fifth to the eighth rows show the percentage difference between results from each climate scenario and those from the baseline BMP scenario (NC_bmp). When the BMPs were already simulated in the model, the three moderate future climate scenarios

did not result in significant change in the total amount of each constituent. Moreover, the three scenarios generated approximately the same amount of each pollutant of concern, with 5.7% increase in surface runoff, 2.5% in sediment yield, 4% in nitrogen yield, and 1% decrease in phosphorus yield. Comparing the percentage change between the moderate A2_bmp scenario (SWAT simulation with BMPs modeled under A2 climate scenario) and those in the A2_hs scenario (SWAT simulation without BMPs modeled under A2 climate scenario) (Table 4-43), the surface runoff change rates were the same. The sediment yield showed a reduction in the A2_hs while resulting an increase in the A2_bmp simulation. This indicated that the existing BMPs does not exhibit an expected reduction rate under changing climate. The same conclusion can be made based on the higher increase rate of N and lower decrease rate of P. In the severe climate scenarios, surface runoff generation increase by 13% to 30%, which shows similar results in the _hs analysis. Sediment yield in SA2 scenario is 340% higher than that simulated in the baseline bmp scenario. Total N is 100% higher, and total P is 185% higher than those simulated in the NC_bmp scenario.

Table 4-46 Comparison of Total NPS Amount under Future Climate Scenarios in WB_bmp

Scenario	SurfQ		Sediment		Total N		Total P	
	$*10^3 m^3$	Change	$*10^3$ Ton	Change	$*10^3$ Kg	Change	$*10^3$ Kg	Change
NC	256.1	---	0.856	---	5.359	---	1.291	---
A2_bmp	270.4	5.6%	0.878	2.5%	5.586	4.2%	1.275	-1.3%
A1B_ bmp	270.6	5.7%	0.881	2.9%	5.574	4.0%	1.28	-0.8%
B1_ bmp	271.4	6.0%	0.878	2.5%	5.569	3.9%	1.274	-1.4%
SA2_ bmp	289.2	12.9%	1.151	34.4%	4.932	-8.0%	1.444	11.8%
SA1B_ bmp	310.0	21.1%	2.772	223.6%	10.227	90.9%	3.21	148.6%
SB1_ bmp	326.7	27.6%	3.761	339.2%	10.867	102.8%	3.685	185.4%

The results show a lot of similarity with Table 4-43 in terms of percentage change when comparing the six future climate scenarios with the NC scenario. Whether or not the BMPs are modeled in SWAT, future climate change would affect the model simulation in

similar degree. The moderate climate scenarios generally do not affect model simulation much, though slight increase and decrease (less than 10%) were observed in the total amount of NPS pollutants. Severe climate scenarios SA2 and SA1B significantly affected SWAT simulation in terms of sediments and nutrients. All the constituents are more than doubled in these two scenarios. The SB1 scenario showed much lower percentage differences as compared to the other two severe scenarios. The possible reason is that SB1 is a milder future climate condition as compared to the SA2 and SA1B. The results indicate that the more dramatically climate changes, the more change is expected in the watershed response. And if climate change is under control, following scenario B1 would be most advantageous to keep BMP implementation costs down.

Assuming that the hotspots were identified based on the baseline scenario (NC_hs) and the BMPs were assigned to these hotspots (NC_bmp). An expected reduction rate of the four constituents can be calculated by comparing the NC_hs and NC_bmp simulation results (Table 4-47). The expected reduction rates are 13% for surface runoff, 41% for sediment, 21% for N, and 40% for P. In the baseline scenario without climate change, a 13% of reduction rate was expected for surface runoff, 41% for sediment yield, 21% for total Nitrogen, and 40% for total phosphorus. The comparison between the _bmp simulations with the _hs simulation revealed the true reduction amount and rate under a specific climate change condition. The reduction rate for surface runoff was almost identical in all climate scenarios. The result again illustrated that surface runoff was evenly distributed throughout the urban watershed and that the watershed respond to climate change in a linear way in terms of surface runoff. Reduction rate in total Nitrogen was also relatively steady at the rate of 20%. This is partially because of the correlation between

surface runoff and nitrogen yield as is observed in Sections 4.3.1 and 4.4.3.2. The expected 40% of reduction rate for sediments and phosphorus was not achieved. Under moderate climate condition, the reduction rates for the two were slightly less than 40%. As the climate condition grows more severe (SB1 to SA1B to SA2), the reduction rates decreased to 16% for sediments and 23% for phosphorus. Although the reduction rate decreased, the actual reduction amount increased. One reason for a lower reduction rate is because of the huge increase in the pre-BMP simulations under different climate conditions. Another reason may be related to the limitation of the BMPs themselves.

Table 4-47 Reduction Rate of Constituents due to Prescribed BMPs under Different Climate Conditions

		NC_bmp	B1_ bmp	A1B_ bmp	A2_ bmp	SB1_ bmp	SA1B_ bmp	SA2_ bmp
Reduction Rate (%)	Q	-12.83	-12.85	-12.98	-12.90	-13.07	-13.33	-13.18
	Sed	-41.24	-38.75	-38.46	-38.82	-22.49	-18.12	-15.78
	N	-21.28	-19.25	-18.6	-19.07	-13.36	-22.51	-18.78
	P	-40.35	-37.55	-36.76	-37.59	-29.47	-26.52	-23.45
Reduction Amount ($*10^2$)	Q (m3)	-377.0	-400.2	-403.7	-400.5	-434.6	-476.7	-496.2
	Sed (Ts)	-6.010	-5.553	-5.504	-5.569	-3.340	-6.132	-7.048
	N (Kg)	-14.49	-13.28	-12.74	-13.16	-7.604	-29.72	-25.12
	P (Kg)	-8.734	-7.661	-7.444	-7.680	-6.034	-11.59	-11.29

Chapter 5.   Conclusion and Discussion

In this research, virtual computer watershed models were developed for the Watts Branch Watershed, an urban watershed, and the Wilde Lake Watershed, a suburban one, using the distributed hydrologic model SWAT. Both models were calibrated over daily/event-based stream discharge and a limited number of water quality sample data. The models were validated and found to produce accurate simulations of hydrology and water quality in the two study watersheds.

Simulations from the calibrated SWAT_Pre (both for WB and WL) models were used to identify four sets of hotspots related to surface runoff, sediment yield, total nitrogen, and total phosphorus, respectively. As part of the Diagnostic Decision Support System, the hotspot identification process successfully located the most problematic areas in terms of per-area yield of each of the four variables within each study areas. The identified surface runoff hotspots were generally related to large impervious area. Nutrients hotspots were usually observed in mid/low density residential areas. Sediment hotspots were located in small areas which account for less than 10% of total watershed area. The Diagnostics Expert System (DES) identifies the possible physical reasons why those hotspots generated excessive amount of runoff and NPS pollution compared to the rest of the watershed. The DES gathered information such as soil property, land slope, landuse, and urban characteristics by searching for SWAT parameters which represent the geographical features of the hotspots. High curve numbers and large fractions of impervious surface were identified as the major reasons for high surface runoff. Sediments were caused by large runoff volume, erodible soils, high slopes, and lack of soil cover. Nutrients hotspots were generally related to surface runoff, sediment yield, or high fertilizer application in

residential areas. The Prescriptive Expert System (PES) provided the proper remedy to the symptoms diagnosed by the DES. Appropriate LID BMPs were assigned to different HRUs which were identified as one or more types of hotspots. Native landscaping and infiltration trench were recommended the most in the WB watershed in terms of coverage area. Native landscaping and rain barrels were recommended the most in the WL watershed in terms of coverage area. In the two study watersheds, one urban and one suburban, the distribution of hotspots and of prescribed BMPs were different. However, except for surface runoff hotspots, the hotspots for the other three NPS were all localized in small areas with high concentration in both watersheds.

A systematic approach was developed to model urban LID BMPs in the SWAT model. The method provides an easy but reliable way to simultaneously quantify the effectiveness of various types of BMPs in large spatial scale. The BMPs were expressed in the SWAT model through adjusting one or several parameters which represent the hydrological processes involved in the BMPs' mechanism. The parameters included curve number (CN2), fraction of impervious area (FIMP), soil erodibility (USLE_K), maximum canopy storage (CANMX), and others. The long term, combined effectiveness of recommended BMPs were quantified though modeling. Together with BMP coverage area and expected reduction rate, total installation cost of all BMPs assigned in the study areas was calculated to support decision making. The total cost (TC) consists of a fixed fee which is related to the total BMP coverage area, and a BMP cost which is calculated as a function of residents' preferences (or BMP adoption rate) and the sum of basic building cost for each BMP. The calculation of total costs can be useful in developing proper incentive programs which are designed for promoting BMP adoption rates.

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To test the effectiveness of the DDSS, SWAT simulations with randomly assigned BMPs (SWAT_R) were also carried out. Although the total cost of BMPs in the WB_SWAT_R simulations was less than that calculated in the WB_SWAT_D model, a noticeable higher reduction rate of NPS was observed in the WB_SWAT_D model. Moreover, the WB_SWAT_D model provided more physically suitable BMPs to the hotspots. By avoiding changing the geographical environment to accommodate a specific BMP, assigning BMPs according to the physical condition of the hotspots lowers the required budget even more.

Two sets of future climate scenarios (moderate and severe) for a total of 6 climate scenarios (B1, A1B, A2, SB1, SA1B, and SA2), were simulated in the Watts Branch watershed. Two sets of analysis were carried out to test the effects of future climate conditions; in the WB_hs simulations, the DDSS was applied to optimally assign BMPs under the assumed changed climate, then assess their performance. In the WB_bmp simulations, the watershed with BMPs assigned under current climate was subjected to the changed climate. Results indicated that the moderate climate scenarios and the SB1 scenarios would not significantly affect the spatial distribution of hotspots. Stormwater management plans developed based on un-changing climate would not be significantly different from those developed based on the moderately changed climate in terms of BMP coverage area, NPS reduction rate, the numbers and types of BMPs prescribed, and the total cost of BMP implementation. Simulations under SA1B and SA2 climate scenarios not only increased the overall runoff and NPS yield watershed-wide, but also altered the location of the NPS hotspots. Under these two climate conditions, more BMP coverage area and higher total BMP cost were simulated.

If a stormwater management plan has already been established based on the current climate condition, the future climate projected by IPCC for year 2020 (the moderate scenario) would not seriously affect the effectiveness of the prescribed BMPs. If the IPCC predicted climate condition in year 2100 (the severe scenario) occurred within the BMPs' life time, many of the non-hotspots HRUs would become hotspots and start to generate high amount of NPS without proper BMP controls. The prescribed BMPs would still be effective in helping to control the overall water quality in the study area. However, the reduction rates would drop. It is safer to make sustainable management plans under the severe future climate condition in order to achieve desired reduction rate in the long-term, but the consequence would be a large increment to the BMP implementation budget. The conflicting goal of higher reduction rate and lower cost form a dilemma in decision making. That is expected to intensify with climate change. One advantage of the DDSS developed in this study is that it can make a new plan based on a new condition in a timely fashion. Since the climate is not expected to change substantially in the next 10 years, a compromise was developing a new plan using the DDSS 4-6 years after the current plan started, with necessary amendments to the plan accordingly.

5.1   SWAT Model Calibration

As discussed by Shirmohammadi et al. (2010), modelers need to keep in mind the uncertainties in the model simulations and apply the calibration results with caution. Hydrologic models are capable of mimicking natural processes and assisting in people's understanding of the hydrological world. However, actual watershed processes are more complex and variable than what can be represented in most sophisticated models (Haan et

al., 1995). There is a degree of uncertainty associated with almost all predictive models and measured data (Shirmohammadi et al., 2006). Uncertainties are involved in input variables such as climate data and soil data, individual models in terms of model structure and algorithm, calibration and validation of models, and temporal and spatial scales (Sohrabi et al. 2003; Shirmohammadi et al., 2006; Shirmohammadi et al., 2010; Sexton et al., 2011a; Sexton et al., 2011b). Although not quantified, uncertainties involved in SWAT modeling in this research can trace back to model inputs: weather data and terrestrial data, the SWAT model itself, the discharge and water quality data, and the model calibration processes. The calibrated models developed in this study were used to help us better understand the NPS generation amount and location within urban and suburban watersheds rather than providing exact NPS yield estimation.

One interesting finding in the research regarding the SWAT model is that the un-calibrated SWAT models performed reasonably well in simulating daily stream discharge in the Watts Branch watershed. Compared to the statistics obtained from the calibrated WB_SWAT_Pre model in the calibration period (Table 5-1), the uncalibrated model gave a relatively good estimation in terms of goodness-of-fit statistics, with an NSE of 0.60, a correlation coefficient r of 0.83, and a 15% negative bias. This relatively good model simulation can be explained by several reasons. First, the Watts Branch watershed is relatively small (10.4 km^2 or 4 mi^2) compared to the study areas in majority of the SWAT related research. Second, the weather station (DCA) from where the weather inputs were retrieved is less than 5 miles from the WB watershed. Moreover, the weather station is located in the airport, from where complete and reliable weather data is expected. Therefore, instead of having multiple faraway weather stations and the need to assign weather stations

using a Thiessen Polygon or other interpolation methods, the whole watershed can use data

from a single weather station and get quite accurate and complete precipitation and air

temperature throughout the study period. Thirdly, as a highly urbanized watershed, the

Watts Branch watershed has a large amount of impervious area. The impervious surface

responds to precipitation events in a relatively simple manner as compared to pervious soil

surfaces. Precise weather input and relatively simple watershed response are the main

reasons why the un-calibrated models performed well in this study area. These results

indicate that SWAT is a useful tool for simulating stream discharge in small ungauged

urban/suburban watersheds. In cases when no stream discharge observation is available, or

the calibration of the model is un-achievable, the uncalibrated SWAT model is able to give

reasonable stream discharge simulation.

Table 5-1 A Comparison between the Calibrated and the Un-calibrated WB_SWAT models

Model	Discharge (cms)				Sediment (Tons/day)	Total N (Kg/day)	Total P (Kg/day)
	r	NSE	Rel. Bias	Ave.	Ave.	Ave.	Ave.
Uncalibrated WB_SWAT	0.83	0.60	-15%	0.1250	109.58	12.76	12.1
Calibrated WB_SWAT_Pre	0.85	0.67	-19%	0.1158	3.63	16.89	5.37

Underestimation of discharge was observed in both the calibrated and the un-

calibrated models (Table 5-1). In the literature, a bias higher than 10% is typical for daily

SWAT simulation. Generally, high evapotranspiration is the main reason for under-

estimating stream discharge. In this study, CANMX (the maximum amount of canopy

storage) was already small (less than 1 mm), so a 0.8-0.9 ESCO (higher ESCO means

higher soil water availability for re-evaporation) may have resulted in more soil water

evaporation than what the watershed usually has. In urban areas, human related activities

are another reason. Generally, tap water is the main water source for daily uses, and the main sources of the water are large reservoirs or streams outside the study area. Water sources from outside of the watershed may render the water balance invalid within the watershed. Irrigation of lawns and gardens, and car washing may increase the total amount of water discharged into the streams. In this study, automatic irrigation was activated for lawns and only occurred when the simulated vegetation (Bermuda grass) growth was hindered. However, in reality, residents may irrigate lawns on a regular basis or whenever their schedule allows. To maintain the lawn, people generally do not wait until the grass is wilting to irrigate. Therefore, more water coming from irrigation may enter the WB watershed than simulated by SWAT, increasing the physical stream discharge and accounting for the underestimated discharge in the simulation. Another possible reason is the uncertainty involved in the precipitation data. Gauge measurements tend to underestimate the true precipitation, largely because of wind-induced turbulence at the gauge orifice and wetting losses on the internal walls of the gauge (Groisman & Legates, 1994). Monthly estimates of precipitation bias vary from 5% to 40% (Groisman & Legates, 1994). Bias in the precipitation originates from various sources: errors in measurement due to wind, wetting, drifting, evaporation, instrument and/or human error; errors due to the difference in measurement and model grid scale; and errors due to the interpolation technique selected (Salamon & Feyen, 2009). Biases are larger in winter than in summer and increase to the north in the United States due largely to the deleterious effect of the wind on snowfall (Biemans et.al. 2009; Wolff et al., 2013). Both external water contributions and measurement errors in precipitation are believed to have caused the underestimation of stream discharge simulations.

The un-calibrated model performed better in terms of bias. One possible reason for slightly poorer bias in the calibrated SWAT_Pre model is that PEST was trying to improve the simulated sediment yield. Table 5-1 and Fig. 4-5 (Section 4.1.2.2) both indicated that the average sediment yield was successfully brought down to a reasonable magnitude. Without calibration, SWAT simulated 110 tons/day of sediments on average. The number was 3.63 tons/day in the calibrated model. The WB_SWAT model was calibrated over a limited number of water quality samples collected in about 10 storm events (Section 3.1.2.2). The calibration results of sediment yield illustrate that the model calibration does still benefit substantially from limited event-based data.

When calibrating a model, most researchers would calibrate over hydrologic components first and ensure accurate simulation in stream discharge before calibrating any water quality related constituents. In this research, stream discharge, sediments, and nutrients were calibrated at the same time. After calibration, only channel roughness parameters and channel cover parameters were adjusted to bring down the simulated sediment yield, but the effects were limited. A more effective way of keeping sediment yield in a reasonable magnitude is to reduce simulated surface runoff and stream discharge. Therefore, if hydrology was calibrated before calibrating the sediments and nutrients, the simulated sediment may be much higher than the current estimation.

Calibration over limited water quality observations does not guarantee accurate daily in-stream NPS simulations, which may be observed even in SWAT calibrations with adequate daily water quality data (Bracmort, et al. 2006; Gitau et al. 2008; Panagopoulos et al. 2011; Liu et al. 2013). However, the magnitude of total annual sediment yield can be brought down to a much more reasonable level with even a limited amount of data as shown

here. Inadequate amount of observations for calibration is a common problem modelers face, especially in study areas where observations are hard to obtain or do not exist. If this happens, every possible sources for water quality data should be investigated to obtain at least some reference points. In this research, event-based nutrients data were used for calibrating the WB watershed; event-based flow and nutrients data were used for calibrating the WL watershed. Dredging data was obtained in the Wilde Lake to estimate the annual sediment yield in the area; this information was used for model calibration. The results indicated that event-based, daily, monthly, and annual observations were all useful. Government project reports and cost estimation can also be good sources for water quality data.

The annual N yield in the calibrated model was higher than the N yield in the uncalibrated model. The reason for that is the modeling of automatic fertilization. In the default SWAT input files, scheduled management operations such as irrigation and fertilization are only modeled in the first year of the study period. In the WB_SWAT_Pre model, auto-irrigation and auto-fertilization was modeled every year to simulate lawn maintenance. The increase in fertilizer application is the reason for higher N yield. Total phosphorus in the calibrated model was much lower than that was simulated in the un-calibrated model. The main reason is the reduction in sediment yield resulting from calibration with observed data. As is well known, phosphorus attached to sediments is the main source of P yield because of its low mobility and solubility. Reduction in average sediment yield in the calibrated model resulted in a reduction in the amount of phosphorus being transported into the stream by sediments.

In summary, an uncalibrated SWAT model is still useful in simulating stream discharge in un-gauged small urban/suburban watershed as long as the weather input is complete and accurate. If no ground measurements are available, precipitation data obtained from NEXRAD may work well, if not better. An uncalibrated model, however, is not recommended for in-stream sediment and nutrients simulation. The default sediment yield is large. The nutrients show relatively good simulation without calibration. The scheduled management operations in the .mgt files are recommended to be adjusted for better nutrients simulations in an un-calibrated SWAT model. Since SWAT model would still benefit from calibrating over limited number of water quality data, any type of observation data is expected to be helpful for obtaining a better performing SWAT model.

5.2   Hotspot Identification

When the concept of Critical Source Area (CSA, also hotspots) was first developed, computer modeling was a relatively new tool and spatial distributed hydrologic models were relatively rare. The simpler P index method was an appealing tool to identify the critical areas. But this risk-based approach is more proper to be used at field scale, rather than at watershed scale (Lemunyon & Gilbert, 1993; White et al., 2009; Shen et al., 2011). Moreover, not actually quantifying the amount of P loss has been another concern for researchers (White et al., 2009). With the fast development of computer hardware and software, process-based hydrologic models linked to GIS have been more extensively used in all water quantity and water quality related research, including identification of the CSAs (White et al., 2009; Singh et al., 2011; Niraula et al., 2012; Panagopoulos et al., 2013; Giri et al. 2014; Chen et al., 2014).

Although the research on sediment and nutrient CSA (hotspots) is popular, hotspots related to surface runoff have received little attention. Agricultural watersheds are the primary contributor of NPS in the US, so the majority of the research has been limited to: 1) agricultural areas; and 2) sediments and nutrients only. Surface runoff quality has rarely been a serious concern in an agricultural watershed. This is partially because excessive surface runoff has naturally been related to large area of impervious surface. Therefore, surface runoff has less been studied in agricultural watersheds. The correlation between surface runoff and impervious surface in turn limited the research in urban watersheds to water quantity issue: stormwater and flood control. However, large scaled BMPs such as detention basin and bio-retention basin seems more capable of controlling stormwater volume in a spatially distributed way (Chichakly et al., 2013; Loperfido et al., 2014). More research has been carried out on Low Impact Development (LID) in terms of its effectiveness in reducing the runoff volume (Shuster & Rhea, 2013; Hamel et al., 2013; Loperfido et al., 2014). But the water quality aspect of the urban LID has been somehow neglected, especially in the field of hotspots identification. Of course, the current types of research in urban watershed is largely modulated by the unique characteristics of urban area: more population, less available public spaces. However, the TMDL goals cannot be successfully achieved without involvement of public support and involvement, especially in urban areas (Jacobs & Buijs, 2011; Barbosa et al., 2012; Piemonti et al., 2013; Chanse et al., 2014, Leisnham et al., 2013). Therefore, more research should be carried out in urban watersheds in terms of NPS CSA and surface runoff CSA.

The threshold for selecting hotspots is relatively subjective. One can define the threshold as a fixed value or a percentage of HRUs. For example, hotspots can be defined

as the HRU which generate more than 500 mm of surface runoff annually, or the top 20% of HRUs (in number) which generate the highest surface runoff. Whether to use a fixed value or a percentage of HRUs, and which value or percentage to use is determined by individual researchers and specific research objectives. When using the DDSS, if nutrients hotspots were of concern, the threshold values for the other three variables can be set to a large value, making sure that no hotspots would be identified for constituents not of concern. The threshold values for total nitrogen yield, on the other hand, can be adjusted accordingly. Treating only one type of NPS hotspots may save the overall budget. Eventually, the thresholds can be determined based on actual effects to stream biological integrity (eg. Oysters in the bay).

The term "per-area yield at HRU level" has been mentioned throughout this research as the indicator for hotspot identification. Explanations for why this is a better indicator than the total amount yield at HRU level has been provided in Section 4.3.1 with examples. The reason can also be explained in another way. Taking sediment yield as an example, the average risk of sediment yield at the watershed level can be represented as the total amount of sediment generated in the watershed divided by the total watershed area. This value can also be referred to as the expected per-area yield at watershed level. The HRUs which have a per-area yield higher than this average risk level can be considered high risk; and the HRUs which have a per-area yield lower than the average can be considered as low risk. A greater difference between the high-risk yield and the average-risk yield indicates a higher risk level. The HRUs that have the highest risk of generating sediments would be identified as hotspots.

Another interesting finding related to CSA identification is that hotspots identified by SWAT model using observed weather data were quite similar to those identified using simulated weather data. Although overall underestimation of all on-land variables was observed in the latter, the spatial distribution of runoff and NPS hotspots was not significantly altered. This, on the one hand, verified the effectiveness of the SWAT weather generator. The Weather Generator is capable of simulating proper precipitation and temperature for SWAT modeling. On the other hand, this gives researchers confidence in SWAT prediction using weather statistics. Although using the simulated weather input delivered good SWAT simulation results, it does not imply that the simulated weather input can be used for model calibration because simulated weather is not likely to be properly synchronized with observed flow and constituents concentrations.

Niraula et al. (2012) concluded in their research that lumped calibration of the SWAT model using data at the watershed outlet has little effect on the locations of CSAs. They suggested that SWAT can be used without calibration for identification of CSAs in watersheds that lack sufficient data for model calibration, but not for all other modeling purposes. However, a preliminary analysis carried out in this research suggested a different conclusion (Table 5-2). Both the calibrated and the un-calibrated models were used to simulate the hotspot in the Watts Branch watershed. Note that the calibrated models here are different from the WB_SWAT_Pre model. The calibrated model here do not implement SWAT's management operation, which was necessary to ensure a fair comparison between the calibrated and the un-calibrated default SWAT model. The main disagreement lies in the sediment hotspots. In the calibrated model, the hotspots identified only account for 2.35% watershed area but they cover 40% of the area in the uncalibrated model. And the hotspots

were almost totally dislocated because the missing hotpots accounted for 2.22% of watershed area. Therefore, the conclusion drawn here is that uncalibrated models were useful in identifying the runoff and nitrogen hotspots, but are not recommended for identifying sediment and P hotspots. For more information, please refer to Wang et al. (submitted in 2014).

Table 5-2 Hotspots Differences between Calibrated and Uncalibrated Models

Top 20% HRU be Hotspots		Surface Runoff		Sediment Yield		Total N		Total P	
		Calib.	Un.	Calib.	Un.	Calib.	Un.	Calib.	Un.
Hotspot Identified	Coverage Area (%)	19.51	24.27	2.35	39.65	15.85	16.42	4.22	14.46
	Treated Weight (%)	30.8	36.19	21.24	31.68	31.53	31.66	21.83	28.06
Missing Hotspots	Coverage Area (%)	---	5.29	---	2.22	---	0.49	---	2.1
	Treated Weight (%)	---	7.62	---	18.71	---	0.76	---	9.35
Added Hotspots	Coverage Area (%)	---	10.05	---	39.53	---	1.06	---	12.34
	Treated Weight (%)	---	13.01	---	29.16	---	0.9	---	15.58

Several possible reasons for the different conclusions drawn in the two studies were identified. The watershed being studied in Niraula et al. (2012), Saugahatchee Creek watershed (SC), was a 180 km^2 forest dominated watershed, while the one used in study, WB, was a 10.4 km^2 highly urbanized watershed. Only 256 HRUs were defined in SC but 1832 in WB. The WB model was much more finely resolved than the SC. Moreover, Niraula et al. (2012) used lumped calibration, which did not include spatial variation of SWAT parameters. This model calibration method may lead to a good match between simulated and observed stream discharge and in-stream variables (discharge, sediments, and nutrients). However, without spatial variation in calibration, the results were not convincing because the hotspots were identified based on the on-land generation of surface runoff, sediments, and nutrients. Possibly a more important reason is that Niraula used a 5% HRU thresholds in landuse, soil types, and slope classes in defining the HRUs. A

threshold of 5% landuse means if the area of certain landuse in the subbasin is less than 5% of the total area of this particular subbasin, any unique combination associated with this landuse is not defined as an HRU. The main problem with thresholding is the elimination of areas where extreme watershed responses occurs, many of which are likely to be CSAs (Wang et al., submitted in 2014).

5.3   Urban BMP Modeling

Research on BMP modeling is closely related to the major concerns in different types of watersheds. Nutrients and sediments are the main concern in agricultural watersheds. Therefore, BMPs being considered in agricultural watersheds are conservation practices such as contour farming and no tillage, which are modeled through adjusting parameters related to soil characteristics. In contrast, stormwater volume is often the main concern in urban watersheds. Urban BMPs are commonly modeled as a Continuous Stirred Reactor (CSTR) with a desired volume (SUSTAIN, Lai, et al. 2007). The CSTR modeling method is useful in two circumstances. Firstly, it is a good way to quantify the effectiveness of an existing BMP or to examine whether the designed BMP is able to reduce expected stormwater volume. Specific volume and dimensions of the existing BMPs are required to achieve this. Secondly, the CSTR BMP modeling method is an excellent method for specific BMP designs. Given a storm event, hydrologic models can simulate the watershed response and calculate the peak runoff and total runoff volume, the main design criteria for urban BMPs. And the CSTR method can be used to determine the dimension of the proposed BMP to achieve a desired reduction goal.

However, CSTR BMP modeling method has limitations. The first one is the requirement of BMP dimensions. Modeling a BMP with specific dimension can generate accurate modeling results. However, when making stormwater management plans, the dimensions of the BMPs are not available. It is hard to determine the effectiveness of the BMPs without knowing the dimensions when using the CSTR BMP modeling method. In this study, a series of spatially distributed BMPs were assigned to the whole watershed. Eight types of BMPs were applied to over 800 HRUs. It is unrealistic to specify the dimensions to all these BMPs to estimate an expected reduction rate for planning purposes. Second, existing urban BMP/LID modeling software such as SWMM and SUSTAIN, requires sub-daily precipitation input. The simulation of BMP effectiveness is based on one design storm, which means no long-term effectiveness of the BMPs is determined. If an assessment of long-term effectiveness is desired, a substantial amount of hourly precipitation data is required to achieve the goal. Moreover, daily precipitation data is not available everywhere, let alone the more intensive hourly data. Third, no vegetation growth modeling is available in either SWMM or SUSTAIN. Plants are an important part of urban LID BMPs. Rain gardens, green roof, native landscaping are all related to plant growth. Plants perform differently in summers and in winters. In summer, more canopy storage is expected because of fully developed leaf area. At the same time, more evapotranspiration is expected; more fertilizer is needed for growth; and more nutrients are absorbed by plants. In winter, when the leaves fall out, bare tree branches do not store as much rainwater and transpire little soil water. Therefore, for those BMPs whose effectiveness is closely related to plant growth, the long-term effectiveness cannot simply be determined in one or two storm events.

Because of these limitations and the specific need of this research, SWAT was selected as the modeling platform for both hydrologic modeling and urban BMP modeling. SWAT can be used to simulate daily discharge in small urban watersheds even without calibration (Section 5.1). SWAT requires daily precipitation and temperature data, which are generally easier to obtain. Additionally, its weather generator gives satisfactory simulated weather data (Section 5.2), which can be quite useful for simulating watersheds where a weather station is unavailable or was discontinued due to budget cutbacks. SWAT is a distributed model, which allows for hotspot identification with high resolution on a large watershed scale and for different BMP to be assigned to different locations (HRUs). SWAT is also a process-based model, in which simulations are based mostly on hydrologic processes rather than empirical equations. Process based models use parameters with physical meanings to simulate the hydrological processes within each calculation unit (HRU in this research). This enables the possibility of modeling a BMP using different physically-based parameters and modeling a BMP in one HRU without affecting hydrological and chemical processes in other HRUs. Another advantage of using SWAT is that it simulates vegetation growth. Vegetation growth is simulated according to plant type, daily precipitation, daily temperature, management practices, and nutrients availability. Once the plant type is determined and management practices provided, SWAT can simulate the seasonal differences and life cycle of plants according to weather input. And the seasonal differences of BMP effectiveness are quantified accordingly.

In contrast to the CSTR BMP modeling method, which focuses on runoff volume, the parameter-adjusting method developed in this research focused on targeting impervious surface and managing vegetation, the two factors identified as the most effective way in

urban stormwater control (Loperfido et al. 2014). Instead of modeling the BMPs as a separate part of the natural hydrologic system, the LID BMPs are incorporated into the model in a more natural way, that matches how GI is defined by USEPA (2014b): GI elements are used to restore the urban land into a pre-developed (natural) condition. The effectiveness of the BMPs are determined in part by the percentage of impervious area that is being treated and converted (Section 4.3.2.1). The amount of water retention is modeled as soil water storage and sub-surface flows. Rainwater harvesting is modeled as natural vegetation canopy. Native landscaping is modeled by replacing Bermuda grass with plants that are native to the study area and require little or no fertilizer. All the BMPs are modeled as part of the watershed in a less artificial way. The urban LID BMP modeling method developed in this research provides other advantages. The most important one is that no dimension is needed to model individual BMPs. The combined effectiveness of all BMPs assigned in the watershed can be determined in a time-efficient manner. Long-term effectiveness of the spatially assigned BMPs can be examined. Since any future change related to the watershed, whether a change in landuse, or a change in climate condition, can be easily modeled in SWAT, the effectiveness of the BMPs under changing conditions can easily be determined as well.

Although the modeled BMP effectiveness in this study was generally less than the observed reduction rates quoted in Table 3-16 (Section 3.2.3), the modeled BMP effectiveness is still reasonable. The main reason is that the BMP does not occupy the whole HRU. For example, when testing the observed effectiveness of green roof, effluent from the roof area before and after the implementation of the BMP were compared. However, green roof cannot treat and control rainwater that does not fall on the roof area,

which is only one part of the land surface (HRU area). Therefore, the observed reduction, which is a reduction in the roof area, is expected to be higher than the modeled reduction, which is a reduction in the whole HRU. Again, the DDSS developed in this research is more of a planning tool, rather than a designing tool. The actual BMP reduction rates vary depending on specific designs. An infiltration trench with a depth of 1 ft. would, for example, result in less reduction than the one with a depth of 1.5 ft. (given the same surface area).

In summary, the parameter-adjusting BMP modeling method developed in this research is an effective urban BMP modeling tool. It incorporates the function of BMPs into the actual hydrological processes and quantifies a reasonable reduction rate of surface runoff and NPS without specifying the dimension of individual BMPs. It can provide a combined effectiveness of all BMPs prescribed in a watershed, and a way to quantify the BMPs' long-term effectiveness under changing landuse/climate conditions.

It is important to note that these LID BMPs are recommended in urban watersheds. The BMP representation developed in this research should only be applied to urban HRUs. It makes no sense to set up a rain barrel in forest landuses, or to replace the cropland with native plants to reduce nutrients loading (this is why fertilizer reduction was introduced as one of the BMPs in this research). There is no impervious area in a wetland to build pervious pavement. Therefore, the BMP modeling method used in this study can only be used in HRUs that are labeled as URBAN in SWAT.

5.4   Application of the DDSS

The Diagnostic Decision Support System is designed for LID BMP selection. Although the topic of selecting BMP/Conservation Practices has been extensively studied recently, the selection criteria are limited to BMP reduction rate and total BMP costs. Some features have been observed in the selection processes presented in previous research.

First, the candidate BMP options were generally limited to 2-4. The effectiveness of each BMP option was quantified by applying the BMP to the entire watershed. The one that showed the highest NPS reduction rates or a best balance between reduction rate and cost would be the optimal BMP (Zhang & Zhang, 2011; Panagopoulos et al., 2011& 2013; Ahmadi et al., 2013; Chichakly et al., 2013; Park et al., 2014; Liu et al., 2014; Giri et al., 2014). Therefore, no spatial variation nor variation in BMP types was taken into consideration in terms of BMP implementation. Both Lam (2011) and Chiang (2012) have concluded that only when different types of BMPs were combined can the overall water quality be improved. Therefore, selecting one type of BMP is not likely to provide the best results.

Second, some researchers have noticed that different BMPs should be applied in the study area. However, the various BMP types were applied solely based on landuse: contour farming for all agricultural landuse and rain garden for all urban landuse (Panagopoulos et al., 2012; Jayakody et al., 2014). Or several BMPs were developed as a BMP bundle, which was then applied throughout the watershed (Panagopoulos et al., 2012; Jayakody et al.; 2014). A better BMP selection method was developed by Artita et al. (2013). The method

was able to spatially assign 5 types of BMPs throughout the watershed. But the BMPs were all large-scale BMPs, and were assigned to subbasin level.

Besides, previous research generally focused on non-urban watersheds and non-LID BMPs. The selection process was based on optimization of reduction rate (or/and cost), which do not take feasibility into account. Research using feasibility as the selection criterion has been conducted to spatially assign BMPs in agricultural watersheds (Montas et al., 1992 & 1999; Djodjic et al., 2002; Sadegh-Zadeh et al., 2007). The method developed in this research adopted the concept of Expert Systems from this group of research and extended the concept into urban BMP recommendation.

In this research, BMPs were first assigned to different types of hotspots, and then re-selected if more than one BMPs were assigned to a single HRU. Therefore, five sets of BMP series were actually recommended according to different NPS of concern. In practice, user can decide which set to be used according to the research interest and primary concern. If surface runoff is the only variable of interest, the recommended BMPs based on the SurfQ_hs can be used. If sediments and nutrients are of concern, simply reset all BMPs recommended for SurfQ to zero and run the DDSS again. A series of BMPs will be recommended for sediment and nutrients control. With user defined hotspots thresholds and BMP recommendation series, the DDSS can be tailored into a user-defined and site-specific tool.

Philadelphia has been trying to build a greener city with cleaner water. The Philadelphia Water Department (PWD) tried to control the stormwater at its source and increase GI elements city-wide in order to decrease the amount of stormwater drained into

the sewer system. However, PWD was facing problems placing the BMPs. Their approach was to randomly walk around the city and try to find any space available for a rain garden or other kind of LID BMPs (PWD, 2014). The sentiment behind this Green City idea is admirable. However, the effectiveness of how the goal is to be achieved is doubtful. Random targeting may not be a good way to control areas with the highest risk of stormwater and NPS yield. Building a rain garden in the low risk area cannot significantly improve the overall water quality in the watershed, and would lead to unnecessary expense. With the help of this DDSS, one can at least go directly to the hotspot area and keep in mind what NPS problem is involved and what type of BMP is recommended.

The PWD have figured out a better way to deal with the previous problem: creating incentive programs to promote BMP adoption and BMP building rate in Philadelphia (PWD, 2014). Besides BMP assignment, the DDSS can also be used by communities to help determine a proper incentive program. Developing a proper incentive program is not simple. A lot of factors need to be taken into account. Whether the program should use a fixed deduction amount or other forms of compensation such as stormwater retention credit, should the program target residential areas or non-residential area, are all factors that shape the development of the incentive program. The District Department of Environment (DDOE) and PWD have been pioneers in developing incentive programs. DDOE uses a stormwater retention credit to encourage building of BMPs in residential areas. PWD launched the Green Acre Retrofit Program to encourage adoption of BMPs in non-residential areas. The DDSS may not be used alone to determine a complex incentive program like what DDOE and PWD have achieved. However, it would support the decision

making through quantitative analysis of BMP costs. Take a fix deduction amount as an example.

$$K_{PR} = f(RP) = g(DA) \qquad\qquad Eq. 5.1$$

$$TC = f_a \cdot A + BC \cdot K_{RP} + F(DA)$$

$$= f_a \cdot A + BC \cdot g(DA) + F(DA) \qquad\qquad Eq. 5.2$$

where DA is the Deduction Amount. $F(DA)$ is the total amount of deduction paid to BMP adopters which is a function of DA. Residents' Preference RP is a function of DA. Therefore, the incentive adjustment factor K_{PR} is also a function of DA. Higher DA would generally result in a higher residents' preference, thus resulting in a lower $g(DA)$ but a higher $F(DA)$. Therefore, TC becomes a function of deduction amount. Since $F(DA)$ is positively related to DA, but $g(DA)$ is negatively related to DA, it is possible that a specific DA would provide the minimum total cost. Then a decision can be made based on the minimum cost.

In summary, the DDSS developed in this study is useful and unique in terms of its feasibility concern, spatial variation in BMP types at HRU level, ability to quantify effectiveness of different BMPs in one SWAT run, and focusing on urban LID BMPs. It is a useful tool for researchers and policy makers dedicated to reducing stormwater volume and improving overall water quality in urban/suburban area.

5.5   Effect of Climate Change on DDSS

Climate change are becoming more and more obvious. Besides the general warming in surface temperature, more extreme and unusual climate has been observed recently: increasing snow storms in the East Coast region, more hurricane in the summer months, more urban flood in DC area, historical low winter temperature, and frequent snow storms in mid/late spring. These changing climate conditions have caused series of problems for daily life. Future climate should be taken into consideration when making long-term management plans.

According to IPCC 2007 AR4, the climate will not change much in the next 10 years. Assuming the prediction is correct, SWAT simulations and the DDSS results indicated that moderate climate conditions (10-yr prediction) would not significantly affect the spatial distribution of NPS pollution, which agreed with Bosch et al. (2014). Any stormwater management plans made based on the moderate future climate scenarios would be similar to any plan based on the current climate condition in terms of coverage area, treated amount, and expected total costs. The analysis based on the 100-yr climate projections (the severe scenarios) clearly showed that the whole watershed would respond differently under large degree of increase in temperature and rainfall depth.

One may argue that no BMP is designed with a 100-yr life-time. But the analysis is worthwhile for several reasons. First of all, the analysis provided quantitative results on how severe weather condition would affect the watershed in general. It provided numerical evidence that changed climate would affect the overall water quality and water quantity at the watershed scale, especially when the change is dramatic. Second, the 100-yr climate

condition is not guaranteed to occur after 100 years, uncertainty should also be taken into account. Although the IPCC projections were based on reliable global climate models, uncertainty still exists numerically, spatially, and temporally. The numerical uncertainty is present in how the IPCC projections are obtained. The IPCC projections are actually the sample mean of 20-30 climate models (figures in Section 3.4). Therefore, the uncertainty involved in the ensemble is also the uncertainty involved in the IPCC projection. Greater temperature increase may be simulated by certain climate model even in the 10-yr projections. Numerical uncertainties can also trace back to each climate model. The results generated by each climate model are also sample means with uncertainty, let alone the uncertainty involved in model input and the climate models themselves.

Spatial uncertainty lies in the spatial discretization of global climate change projections. The IPCC projection used in this research was the global average change. Different regions have their own climate projections: some areas may face greater increases in temperature and precipitation; some other areas may encounter smaller changes; and decrease in temperature can also be observed in certain areas. Even if the North American Regional Projections were used, spatial differences still exist due to factors such as latitude, coastal/inland location, effect of mountains and valleys, etc. Therefore, small watershed such as Watts Branch may or may not show similar climate change pattern as the Regional Projections.

Temporal uncertainty exist in the fact that the IPCC climate projections are evolving. IPCC AR4 published in 2007 was used in this study. A newer version of IPCC AR5 is already available in 2014. Different emission scenarios were defined in the new AR5 reports. Different climate projections were provided in the AR5. Computer models are still

just tools that assist people's understanding of the world. However accurate they are, the models can never become truth. Systems as complex as population and the earth are beyond our ability to predict. The predicted climate conditions may also change with time. Therefore, no one is 100% sure that the predicted global climate condition in year 2100 will not occur in the next 10 years in the study area. An analysis based on the 100-yr future climate scenarios may be valid in the next 10-20 years. It is never wrong to be prepared for the worst.

Researchers are increasingly worried about how climate change would affect the BMPs' effectiveness. However, the majority of the sensitivity analysis of BMPs under climate change in prior research were carried out in a one-BMP-at-a-time way and each type of BMPs was applied to the entire study area in watershed scale studies (Chiang et al., 2012; & Nejadhashemi, 2014). In this research, different future climate scenarios were examined on their effects on a LID/BMP plan rather than on a single type of BMP. The effects of climate change on a BMP plan are not limited to the BMP reduction rates, but also the location of the BMPs, types of recommended BMPs, and the total costs.

As a conclusion, the analysis regarding climate change and the DDSS is of great importance in a way that it quantifies the effects of climate change on watershed responses and NPS control plans. Both the moderate and the severe climate conditions used in this research provided us with general idea of what watershed condition should be expected and how to prepare plans to deal with the changes. The flexibility of the SWAT model, easy application of the DDSS, and the efficient urban LID BMP modeling method developed in this research would be able to facilitate any changes related to landuse, climate, prioritized hotspots (number and location), and management plans. When budget

is not of concern--which is rare--stormwater management plans are recommended to be developed for the most severe future climate scenario (SA2). However, a plan developed on current or near future (10-yr) climate conditions would be more cost-effective. As suggested by Woodbury and Shoemaker (2012), "unless effective management practices are put in place, NPS loading is projected to increase regardless of climate". Therefore, a less preferred plan will always be better than no plan at all.

5.6   Future Work

In this research, the DDSS and the urban LID modeling method provided a framework of using SWAT and Expert System to assist stormwater management planning. Although useful and effective, improvement can be made to the DDSS with more research and study. The interesting results and findings in the study also provided several future research opportunities.

5.6.1   The Usage of Un-calibrated SWAT model

Different conclusions were drawn from Niraula et al. (2012) and in this study regarding how well un-calibrated models perform in terms of hotspot identification (Section 5.2). The differences were caused by factors such as the dominant landuse type, the size of the study area, and the HRU definition thresholds. Therefore, in order to draw a more comprehensive and convincing conclusion, more research need to be carried out.

At least nine different watersheds are needed in the proposed future research, if available. Three forest dominated watersheds should be studied, with a size of small, medium, and large. Three agricultural watersheds and three urban watersheds with sizes that match the forest ones should also be evaluated. SWAT can be used to model the nine watersheds, with zero thresholding in HRU definition. The magnitude of both in-stream variables (watershed level) and on-land variables (HRU level) should be compared between the calibrated and the un-calibrated SWAT models in each watershed. The spatial distribution of the on-land variables, or the hotspot locations should be compared as well. Different hotspots identification thresholds, 10%, 20%, or 30% HRU, can also be investigated to determine how accurately un-calibrated models can locate hotspots at different thresholds.

This proposed research is not hard theoretically, but it does present some challenges. The selection of the nine watersheds can be one challenge. In terms of watershed sizes, researchers need to determine how large is large enough, and how similar is similar enough. In terms of dominant landuses, one should determine whether a 60% or an 80% landuse type can be considered dominant. Model calibration is another challenge. Obtaining weather data and observation data for 9 watersheds is not easy, let alone proper model calibration for nine watersheds.

5.6.2   Hotspot Identification with Distance Index

While identifying hotspots at HRU level, the smallest calculation unit in SWAT, provides high resolution hotspot location, the method has limitations. As defined in SWAT,

pollutant and water routing is not simulated for each HRU within individual sub-basins because loads generated at any point within the sub-basin are directly discharged into the streams regardless of position (Gassman et al., 2007; White et al., 2009). Not including overland routing may raise concerns about sediments and phosphorus transport (Chen et al.; 2014). One solution adopted by many researchers was to identify hotspots at subbasin level (Giri et al., 2012 & 2014; Sommerlot et al., 2013; Artita et al., 2013). A large number of subbasins were delineated in the study area, and water quantity and quality related variables generated in the subbasin level were employed as the hotspot identification criteria. Although the researcher feel more confident in overland routing of sediments and P, they were concerned about the low resolution and wanted to have hotspots at a finer scale.

Therefore, the hotspots identification process and criteria can be further improved by taking into account the distance between each HRU and the stream. Sediment generated in an edge-of-stream HRU is more likely to reach the stream than sediment generated in a far-away upland HRU which may be trapped or settle on land. The edge-of-field NPS yield at the HRU level and the distance between the HRU and the stream may be coupled for prioritizing the hotspots. A simple way is to include a risk index related to distance. A better solution is to modify the SWAT model to simulate overland routing for both surface runoff and NPS.

Including the distance is a better solution for more accurate hotspot identification. However, even without including the distance and overland routing, the hotspot identification used in this study is still valid and useful. When targeting the HRUs with high NPS yields, NPS at the source will be reduced, the overall amount contributing to the

stream would also be reduced, regardless of any transit loss. Moreover, when sediments settle on land, they can be washed closer to the stream in the next storm events. Therefore, the total annual sediment generation in the HRU may eventually reach the streams. The total amount of annual contribution from an HRU to the stream would still remain the same.

5.6.3   Refinement of BMP Adoption Model

In this research, a simplified conceptual approach to resident preference (RP) was developed and utilized in BMP cost estimation. The long-term research plan intends to incorporate a BMP adoption model developed and proposed by collaborators in the Department of Landscape Architecture and the Department of Environmental Science and Technology (Leisnham et al., 2013). To this effect, surveys have been conducted in the two study watersheds, targeting different socio-economic groups. The future challenge is to incorporate the uncertainty involved in social factors, observed in survey results, into the BMP adoption model and BMP cost estimation module.

Once developed, this enhanced BMP adoption model is expected to be expressed as a function of demographic information such as population, education background, household income, and others. Researchers and planners will then be able to estimate the BMP adoption rate for a given study area based on the demographic data without actually conducting on-the-ground surveys. Consequently, policy makers will be able to determine the estimated total BMP cost and propose appropriate, socially acceptable, stormwater management plans.

5.6.4 Taking Seasonality into Consideration

In this study, the effectiveness of BMPs was quantified on an annual basis, as were the effects of future changed climate. However, seasonal sensitivity and monthly variation of watershed response to different climate conditions have been observed (Ahmadi et al., 2014; Woznicki & Nejadhashemi, 2012). Therefore, analysis related to seasonal urban BMP reduction rates should be carried out for a better understanding of their operations, especially for those related to vegetation growth.

Seasonality analysis can also be carried out by including monthly variation in future climate conditions. The annual temperature increase does not mean the temperature in each month is increased as well. A more realistic changing pattern may include extended summers with higher temperature and colder winters. When the monthly variations of climate change are incorporated into the weather generator, a more accurate and realistic evaluation of the effects of climate change on urban BMPs can be performed. To do this, the mean and the standard deviation of the weather should be varied on a monthly basis. A better approach may also consider applying weather data generated from a climate model such as the Community Earth System Model (CESM) (NCAR, 2015), Coupled Physical Model, CM3 (GFDL, 2015), and Hadley Centre Climate Model version 3 (HadCM3) (CALCC, 2015).

5.6.5 A Polyvalent DDSS for Agricultural BMPs and Urban BMPs

Djodjic et al. (2002) and Sadegh-Zadeh et al. (2007) have developed a decision support system for agricultural BMP selection for total N and total P control, respectively.

An urban DDSS has been developed in this research to control surface runoff, sediment, and nutrients. Since the concept behind these studies are Expert System and BMP feasibility, the three systems can actually be integrated into one comprehensive DDSS which can be applied in all types of watersheds that involve human-related activities (urban, suburban, and agricultural watersheds).

The polyvalent DDSS could use the hotspot identification method described in this research, or include a HRU distance index (Section 5.6.2). The DES which diagnoses the possible causes and the PES which prescribe the BMPs could branch into two directions: an agricultural DDSS and an urban DDSS. A segment component for sediment hotspot identification in agricultural watershed can be added into the first branch to make the agricultural DDSS more comprehensive. The proposed polyvalent DDSS will be useful for assessment and management plan developed in watersheds with mixed landuses.

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