Costs of Meeting Water Quality Goals under Climate Change in Urbanizing Watersheds: The Case of Difficult Run, Virginia

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ABSTRACT

Urban environments have been identified as a non-point source contributor of nutrient loadings into watersheds. Interannual surges of nutrient loadings into local water systems are more damaging than mean interannual nutrient loadings. Virginia has outlined the need to reduce urban nutrient loadings. Mean interannual nutrient loadings and interannual nutrient loadings variability are expected to increase under climate change (CC). However, there are few studies that provide a predictive framework for abating nutrient loadings under CC. Thus, there is a lack of information regarding how effective water quality policy will be in the future. Using the Difficult Run watershed in Fairfax County, VA, as a site of study, we used mathematical programming to compare how the costs of abating nutrient loads differed under differing climates in the Mid-Atlantic. We first compared the costs of abating mean interannual nutrient loadings in the watershed based on historical climate conditions to those predicted for CC. We then evaluated how changes in the interannual variability of nutrient loadings for CC affect the costs of meeting watershed goals. We found that abating mean interannual nutrient loadings was substantially costlier for CC relative to meeting the same goals under historical climate conditions. Further, we found that the costs of abating interannual nutrient loadings variability increased under CC relative to meeting the same goals under historical climate. One implication of this study suggests that policy makers seeking to meet water quality goals over time must front-load supplemental BMPs today in order to offset the changes predicted for CC.

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Through it all, my family has stood by me to which I am forever thankful. They may tell me time and time again how proud they are, yet, truly, I am the one who is proud; proud to call my family a family and my home a home.

My thesis is dedicated to all those who believe you're not quite good enough. Regardless of who you are and where you came from and how much you believe in yourself, take comfort in the fact that, "you can". Keep on keepin' on.

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CHAPTER 1: INTRODUCTION

1.1 Background

The Chesapeake Bay is home to one of the world's most unique estuaries. Out of the 850 estuaries in the U.S., the Chesapeake Bay is not only one of the most revered, but also the largest. Spreading over 64,000 square miles across New York, Pennsylvania, Maryland, West Virginia, Delaware, Virginia, and the District of Colombia, the watershed is home to over 100,000 streams, creeks, and rivers, and boasts the world's highest land-to-water ratio at 14:1 (Layzer, 2012). At the height of the Bay's known ecosystem health, over 600,000 acres of underwater grasses flourished providing extensive spawning grounds for myriad fish and blue crab populations. It was estimated that the Bay hosted an oyster population large enough "to filter a volume of water equal to the entire Bay in a matter of days" (Layzer, 2012, p. 450).

The Bay provides many socio-economic benefits to its respective users, both consumptive and non-consumptive. As a source of economic output, fisherman directly benefit from the commercial harvest of fish, oysters, and crabs. The large estuary supports many coastal Atlantic species of fish as an ideal nursery and important seasonal feeding ground (Wood et al., 2002). Though the current literature disagrees on the non-use value of the Bay, there is a consensus that non-consumptive use, recreational fishing for instance, provides direct and indirect positive economic value (Lipton, D., 2008; Bockstael, N.E. et al, 1989; Breece, M. & Poor, P., 2006; Lipton, D., 2004). Additionally, the Chesapeake Bay provides many ecosystem services, such as nutrient recycling and water column filtration (Altieri & Gedan, 2014). Given the Bay's role in providing multiple uses across multiple states, watershed managers and policy makers at the federal, state, and municipal level have been concerned with achieving sustainable management practices for the Bay.

Despite the Bay's unique qualities and revered attributes, the complex ecosystem's health has been on the decline. According to the National Oceanic and Atmospheric Administration (NOAA, 2014), native oysters have dropped to a mere 1% of their historic population. In 2014 the Chesapeake Bay Program reported the Bay grasses reached 75,835 acres, which is roughly 41% of the total 185,000 acre goal

(Chesapeake Bay Program, 2014). Studies have shown that large increases in eutrophication, defined as anthropogenic nutrient and organic enrichment of aquatic ecosystems, began as early as the 1950's (Boesch et al., 2001; Testa et al., 2014; Zhou et al., 2014). In estuarine ecosystems, eutrophication elicits decreases in water clarity via increased phytoplankton biomass, loss of submerged aquatic vegetation, and depletion of dissolved oxygen in bottom waters, defined as hypoxia (Kemp et al., 2005). It is predicted that climate change (CC) will alter coastal estuaries such that they will experience higher temperatures and increased variability in interannual streamflow, which is known to exacerbate eutrophic conditions (Justic et al., 1996).

The Chesapeake Bay has the ability to assimilate nutrients, although its assimilative capacity has since been surpassed. In fact, nutrients such as Nitrogen and Phosphorus are necessary limiting nutrients for all life within waterbodies. Kemp et al. (2005) point out that diverse ecological processes within coastal zones naturally assimilate these nutrients and reduce turbidity via seagrass beds. Various native fish species, bivalves, and crustaceans help mitigate detrimental algal biomass. However, as Zhang et al. (2003) have found, many of the naturally occurring buffering mechanisms can be overloaded with nutrients. Excess nutrient loading[1] render many assimilative processes ineffective. Furthermore, once the non-linear web of nutrient recycling is broken, it is extraordinarily difficult to reestablish (Zhou et al., 2014).

Amidst the growing concern for the Chesapeake Bay's health, numerous policy initiatives by federal, state, and local governments have been enacted with little success. Beginning in the 1960's, key researchers began to notice the detrimental impact of nutrient pollution (Layzer, 2012). In 1973, the Army Corps of Engineers identified excess nutrient loading, with an emphasis on Total Nitrogen (TN), Total Phosphorus (TP), and Total Suspended Solids (TSS), as the primary culprit behind the degradation of the Bay. Though coalitions, working groups, and policy initiatives were already forming, the Clean Water Act introduced in 1972 strengthened regulatory power for tackling the Bay's deteriorating condition. From 1984-2000, multiple incentive and voluntary based schemes were constructed among states aimed at reducing key limiting nutrient transport into the Bay. As the year 2000 approached, research put forth by the Chesapeake Bay

[1] For the purposes of this study, nutrient loadings and nutrient export refer to TN, TP, and TSS loadings.

Commission indicated that total nutrient export had only lessened by marginal percentages (Layzer, 2012). From 2000-2008, state coalitions and agreements worked to reduce urban and farmland runoff and improve wastewater treatment facilities. Recently, the University of Maryland for Environmental Science boosted the grade of the Chesapeake Bay's total health to a C from a D+ (Chesapeake Bay – Report Card, 2014). Conversely, the Water Quality Standards Achievement released by the Chesapeake Bay Program in 2013 stated that only 29 percent of the Bay met water quality standards for dissolved oxygen, turbidity, underwater bay grasses, and chlorophyll a (Bay Health, 2013).

Beginning in the 1990s, the U.S. Environmental Protection Agency (EPA) began feeling outside pressure to list the Chesapeake Bay as an impaired water system. Section 303(d) of the Clean Water Act requires state and federal waters that are no longer meeting basic water requirements to be subjected to a Total Maximum Daily Load (TMDL) for pollutant export. A TMDL is a calculation of the maximum amount of a pollutant that any given water body can receive while still safely meeting basic water quality standards. After Executive Order 13508 in 2009, multiple Senate and House bills introduced in 2009 and 2010, and enormous public pressure, the EPA issued a mandatory, integrated TMDL for the entire Chesapeake Bay watershed in 2010. The TMDL outlined specific steps to attain newly constructed, ambitious reductions in TN, TP, and TSS loadings for each state. Developing Watershed Implementation Plans (WIPs) as well as setting two-year milestones for nutrient pollution reductions are an integral component of the TMDL. The aggregated TMDL Phase II WIPs dictate that by 2025, TN must be reduced by approximately 25.76%, TP by approximately 24.8%, and TSS by approximately 15.4% (Chesapeake*Stat*, 2016). In order to evade potential negative ramifications imposed by the EPA, the Chesapeake Bay's partner states[2] must continue to put forth innovative policies targeting the reduction of nutrient loads into the Bay.

As outlined by the EPA, the Commonwealth of Virginia was required to establish a WIP as part of the larger accountability framework set by the TMDL. Virginia's Phase I

[2] The Chesapeake Bay partner states are Virginia, New York, Pennsylvania, West Virginia, Delaware, and Maryland.

WIP was modified to Phase II in 2012. Of the many enhancements and increased measures of compliance enacted by Phase II, the WIP clearly communicated the need for cost-effective strategies that "reduce and prevent nutrient and sediment losses to improve the quality of local waters and the Chesapeake Bay." (VA Phase II WIP, p. 2). Reductions may be made within each locality by implementing Best Management Practices (BMPs). For the purpose of this study, BMPs are defined as a type of water pollution control that reduces nutrient export via one or more runoff treatment mechanisms. Examples of BMPs include, but are not limited to, bioretention practices, installing green roofs, cultivating urban forest management, restoring urban streams, and reducing shoreline erosion. BMPs are commonly recommended for restoring natural hydrologic cycling and decreasing nutrient export within a given area. Virginia's Phase II WIP strongly encourages the identification and implementation of urban BMPs seeking to reduce nutrient loading into local waters and ultimately the Chesapeake Bay.

CC poses a problem when attempting to reduce nutrient export potential by means of BMP implementation. CC is expected to increase frequency and intensity of precipitation during the spring and winter months in the Mid-Atlantic region (Najjar et al., 2010; Testa et al., 2014; Scully, M., 2010). The same findings state that nutrient export will rise significantly. Increases in the intensity of precipitation during the spring and winter months may lead to a seaward expansion of hypoxic, and even anoxic, waters (Testa et al., 2014). Enhanced TN export potential is attributed to total increases in precipitation, increases in precipitation variability, and higher mean temperatures – all of which are highly probably for conditions predicted for CC (Najjar et al., 2010). Where hypoxia shows a non-linear increase to enhanced TN export, surges of TN loading into the Bay pose a greater problem than sustained, yet stable TN export (Testa et al., 2014). Thus, CC has a two-fold impact in terms of predicted increases in average annual nutrient export and interannual nutrient export spikes.

For altered climate conditions brought about by CC, the probability of drought - as defined by "a 10%-or-more deficit of monthly soil moisture relative to the climatological mean" - increases substantially during the summer months with respect to the 1961-1990 average (Najjar et al., 2010, p. 5; Hayhoe el al., 2007). As Mulholland et al. (2009) illustrated, prolonged drought during the summer months followed by high intensity storm events result in excessive overland run-off, which greatly increases the potential for algal blooms in the lower Chesapeake Bay. Therefore, policy makers who wish to control for total nutrient export potential for CC conditions must control for average interannual nutrient loading and interannual nutrient loading variability.

1.2 Problem Statement

Managing nutrient loadings from non-point sources has become essential for the restoration of U.S. waterways (EPA, 2014). TN, TP, and TSS are the Bay's primary limiting nutrients, the reduction of which is the top priority under the Bay TMDL. Urban runoff is a large component of the eutrophic conditions plaguing the Bay (Altieri & Gedan, 2014). According to Chesapeake*Stat*, the 2009 urban baseline contributions of TN, TP, and TSS to the Chesapeake Bay were 7.7%, 14.7%, and 15.9%, respectively. Urban runoff is an outlet for nutrient export where nutrient loadings from human activities are known to increase intensity, duration, and the extent of hypoxic conditions (Hagy et al., 2004). One of the methods outlined by the Bay TMDL and the VA WIP was to reduce runoff via the implementation of urban BMPs. BMPs in urban areas are necessary given the low levels of water infiltration, large amounts of impervious surfaces, and excess emissions from vehicles and industrial production. In order to more closely replicate the natural systems of nutrient recycling, strategically placed catchment sites and filtration practices – in this case, the BMPs – throughout urban and suburban areas can significantly reduce nutrient laden runoff into local waterways (Wood et al., 2002).

There is a vast literature outlining strategic steps for BMP selection and placement (Chickakly et al., 2013; Ji et al., 2014; Braden et al., 1989; Schwabe, 2001). Urban hydrologists have sought to minimize total nutrient loading by running hydrological simulations implementing individual or sets of BMPs within watersheds to pinpoint nutrient export hotspots (Semadeni-Davies et al., 2006). Although these studies provide spatial accuracy, they often failed to consider the full economic costs of BMP implementation.

Many economic studies have sought to minimize the total cost of BMP placement for a desired level of nutrient export reduced (Kramer et al., 2006). Recently the economic literature has begun to incorporate greater levels of variability of nutrient loads and site-specific constraints into optimization models integrating local watershed hydrology simulation with cost minimization (Bishop et al., 2005; Renschler & Lee, 2005). Advances in computing technology, Geographic Information Systems (GIS), and hydrological simulation models have led to multi-objective optimization models with objectives that include minimizing nutrient export (Chickakly et al., 2013). These models are becoming increasingly sensitive to spatial considerations for BMP placement. However, comparatively fewer studies have yet to holistically consider site-specific BMP location and nutrient loading variability for altered climate conditions brought about by CC.

CC's effect on water quality control costs is not well-understood and presents problems with the selection of BMPs regarding future water quality control (Pyke et al., 2011). Researchers are unsure, for example, of the direct effects of warmer temperatures on the N cycle, which creates uncertainty pertaining to TN export. There is also little research on the effects of increased interannual nutrient export variability induced by CC on water quality control costs (Woznicki et al., 2010). As Zhou et al. (2014) point out, high levels of nutrient export variability are expected to further exacerbate deteriorating conditions in the Bay by means of increased seaward hypoxia. Thus, examining management strategies which couple the uncertainty generated by CC with the spatial considerations of BMPs will advance urban land management and generate valuable insight for watershed managers and policy makers. This study seeks to develop a predictive framework comparing the costs of controlling for average interannual nutrient export and interannual nutrient export variability observed for historical climate conditions to those predicted for CC conditions holding all else equal.

1.3 Research Objectives

The global research objective of this study is twofold. First, this study seeks to better understand the costs of reducing mean interannual nutrient export in built environments for current and altered climate conditions. Second, this study seeks to better understand the costs of reducing the interannual nutrient export variability in built environments for current and altered climate conditions. The specific research objectives are:

1. Compare the cost of achieving mean interannual nutrient export reductions for historical climate to the cost of achieving mean interannual nutrient export reductions predicted for CC;
2. Compare the cost of reducing interannual nutrient export variability for historical climate to the cost of reducing interannual nutrient export variability predicted for CC;
3. Compare the cost of achieving mean interannual nutrient export reductions to the cost of reducing interannual nutrient export variability for historical climate and for CC.

By completing these objectives, cost-effective strategies for reducing nutrient loading in built environments may be readily identified. This study compares the cost of controlling for nutrient export today to the cost of controlling for nutrient export for CC conditions, *ceteris paribus*[3]. Incorporating simulated hydrological loadings for altered climate conditions in the analysis provides information regarding future water quality control costs for reducing nutrient export. Developing cost-effective solutions for controlling nutrient loading variability may permit watershed managers to better control for interannual nutrient export spikes. The completion of this project's objectives will provide useful information regarding TMDL allocations in built environments and future stormwater control.

1.4 Study Area Overview

The Difficult Run watershed was chosen as the study area due to the many qualities that it shares with other urban watersheds throughout the Chesapeake Bay watershed. The watershed is located in the north-central portion of Fairfax County, Virginia. It is the largest watershed within the county draining 58.3 square miles, or some 37,924 acres, into the Potomac River. Fairfax County has seen extensive development and population growth over the last century transforming it into an active, suburban community. Difficult Run's primary land use is residential, although there are fragmented patches of industrial, highly urbanized, and urbanized land use. Chesapeake Bay

[3] More specifically, land use changes and other factors that are predicted to change in the future time period of study are held constant such that we may analyze the how CC alone affects these water quality policies.

preservation areas and other resource protection areas bordering the watershed's major streams form the majority of the open space.

1.5 Data Overview

A robust database for the Difficult Run watershed has been made available for this study. These data come from multiple sources in multiple formats matching the needs of this study. Simulated hydrological data are calibrated and validated using historical nutrient loading data collected by three stream gages maintained by the USGS. The stream gage database contains information concerning storm flows and pollutant loads in order to aid Fairfax County in evaluating its stormwater management plans. In 2007 the county developed an in-depth watershed management plan outlining detailed information regarding topography, hydrographic properties, current BMP facilities, water quality, flooding, and aquatic habitat (Fairfax County DPWES, 2007). BMP cost parameters were taken from King & Hagan (2011). These costs are comprehensive in that they include pre-construction, construction, land, opportunity, and post-construction costs. Lastly, Fairfax County has an open geodatabase from which geospatial information was compiled, analyzed, and extracted using GIS (ArcMap 10.3.1; ESRI; Redlands, California).

1.6 Hypotheses

As an applied, interdisciplinary decision project determining cost-effective solutions for TN, TP and TSS reductions in built environments, it is important to note one of the larger maintained hypotheses. We assume that the stakeholders of said research are cost minimizers. That is, people designing water quality management plans favor the least-cost method of achieving water quality goals. The three hypotheses for this study are:

1. **Controlling for nutrient loading and nutrient loading variability will create a convex cost frontier:** Urban BMPs will be selected such that the most cost-effective are selected first. Each additional unit of desired nutrient loading reductions will increase in cost on a per-unit basis.
2. **Controlling for mean interannual nutrient loadings for altered climate conditions will be costlier than controlling for the historical interannual average of nutrient loadings:** CC is expected to increase total nutrient export in

the Mid-Atlantic. With increased TN, TP, and TSS export, the total cost of urban BMP implementation to meet the same water quality standards for altered climate conditions is predicted to increase.

3. **Controlling for interannual nutrient loading variability for altered climate conditions will be costlier than controlling for interannual nutrient loading variability for historical climate:** Watershed managers may wish to control for nutrient loading surges expressed as extreme positive deviations from mean levels of nutrient export. Interannual variability in nutrient loading induced by CC is predicted to increase. Thus, we predict the cost of controlling for interannual nutrient loading variability for altered climate conditions will rise.

CHAPTER 2: CONCEPTUAL FRAMEWORK

2.1 Introduction

Mathematical optimization has many uses. Where real-world applications abound within industrial systems engineering, logistics and supply chain management, and farm planning, mathematical optimization models offer a flexible framework applicable to many problems across many disciplines. Optimization models are, in a broad sense, defined as "quantitative models that seek to maximize or minimize some objective function while satisfying a set of constraints," (Collier & Evans, 2014, p. C3). Constructing an optimization model begins with generating an objective function. The objective function is comprised of decision-making variables (DMVs) and their respective coefficients. DMVs are the quantity of the variable that the decision maker controls. For example, the number of technicians to employ during the evening shift in a manufacturing plant may be a DMV in an optimization model for labor scheduling, be it minimizing the total cost of labor or maximizing the total value of production. Unconstrained optimization – synonymous with unbounded optimization – does not face a finite stock of available resources. The optimal feasible solution is only limited by the functional form of the objective function. Constrained optimization, however, limits the range of DMVs available by imposing resource constraints on the model. Algorithms then proceed to iteratively cycle through sets of DMVs bounded by the feasible region until an optimal feasible solution set is found.

Numerous economic applications of mathematical programming maximize a given objective function subject to a finite resource stock in order to maximize economic returns. Conversely, many other studies set target revenues for which the objective function is constructed to find the minimum amount of inputs needed to satisfy the target (Martinez-Costa et al., 2014). Studies using mathematical programming range from generating least-cost combinations of fertilizer applications for meeting a multi-objective farm plan to maximizing expected economic returns subject to a limited number of stock portfolios (Aldeseit, 2014; Markowitz, 1991).

Linear Programming (LP) is a specific form of mathematical optimization widely used amongst economists and operations research analysts. LP requires a continuous objective function and linearly constructed constraints. LP's most common application involves allocating resources to activities (Hillier & Lieberman, 2015). As there are many different kinds of resources used in LP, m denotes the number of different resources available to allocate to the activities, n. Where resources are limited, LP selects the levels of activities that generate the optimal value of the performance measure, be it cost, revenue, or profit. Let Z be the total value of the performance measure; x_j be the DMVs and level of activity j where j =1, 2,…, n; α_j be the change in Z resulting from a change in the level of activity j; θ_k be the amount of resource k available for allocation to activities j where k = 1, 2,… m and; β_{kj} be the amount of resource k required by activity j. Knowing that x_j represents the DMVs and that α_j, θ_k, and β_{kj} are parameters within the model, an example LP maximization model is illustrated below:

$$(1a)\ \ Max\ Z = \sum_{j=1}^{n} \alpha_j x_j$$

$subject\ to$:

$$(1b) \sum_{j=1}^{n} \beta_{kj} x_j \leq \ \theta_k \qquad\qquad k = 1, 2, \ldots, m$$

$$(1c)\ \ x_j \geq 0 \ \forall \ x_j$$

where equation (1a) represents the objective function, equation (1b) represents the resource, or functional, constraints imposed on the model, and equation (1c) represents a series of nonnegativity constraints.

LP is commonly used for many applications. LP problems maximizing an objective function generate the largest possible value whereas problems minimizing an objective function generate the smallest possible value. It is important to note, however, that in many real-world applications there are multiple optimal solutions. Operations researchers often find this outcome favorable in that it provides flexibility on behalf of the use of the resource stock. In order for a mathematical programming model to be suitable for LP formulation, certain assumptions must be met.

- Proportionality – Each activity's contribution to the objective function value Z must be directly proportional to its corresponding level of activity, x_j
- Additivity – For all functions in the LP model, the function in question is the sum of the individual contributions respective of their activities
- Divisibility - All DMVs are continuous and may hold any value in order to satisfy the resource and nonnegativity constraints
- Certainty – The values assigned to all parameters within the models are assumed to be known with certainty

By satisfying the above assumptions, operations researchers may conclude that the feasible solution is globally optimal. Following the Weierstrass Approximation Theorem where the function $f(x)$ is continuous and the opportunity set is compact, the above assumptions guarantee a global optimal solution either in the interior or on the boundary of the model's feasible region (Jeffreys & Jeffreys, 1988).

In reality, rarely are all four of these assumptions met. Relationships amongst variables may be nonlinear violating the proportionality and/or additivity assumption. Knowing the values of the assigned parameters with certainty is especially difficult where values regarding prices, yields, or construction costs, for example, are all volatile. In order to combat the uncertainty posed by stochastic parameters, researchers conduct sensitivity analyses. To conduct sensitivity analysis, the researcher or research team adjusts the "sensitive" parameters within the model in order to assess how the solution changes. The importance of the results produced by the sensitivity analysis varies, although in situations where specific constraints must be met at all costs – the parts per million of Benzene emitted from steel production, for example – the results of the post-optimality analysis are paramount.

2.2 Optimization Applications in Water Quality

Optimization and simulation models are frequently used to carry out analysis regarding water quality improvement (Bosch et al., 2006). Regional, state, and local governments with impaired water bodies may be subject to a TMDL. A TMDL is a calculation of the maximum amount of a pollutant that a waterway can receive while maintaining basic water quality standards (EPA, 2015). Water systems must meet certain environmental criteria, high abundance and richness of benthic organisms for example, less they be deemed impaired (Chesapeake Bay Program, 2015). Sources of pollutants contributing to a water system's impairment, be it a limiting nutrient or an EPA labeled toxin, come from both anthropogenic and natural sources. TMDLs may differentiate the specific maximum allowable pollutant load emitted from point sources and non-point sources. Where emitters are not given the right to pollute, they must abate their respective residuals deemed harmful to the environment. Thus, many economic analyses regarding TMDLs have dealt with the assessment and implementation of different pollution abatement options (Bosch et al., 2006).

Point source pollution abatement optimization models provide useful insight regarding optimal paths to meeting a TMDL. For instance, a company may own multiple pollution emitting sources and face increasing per-unit costs, or marginal costs, of abatement. Thus, the company may turn to mathematical programming to minimize the total cost of abatement subject to a specific income goal. In this scenario, the findings may point out that some plants' marginal cost of abatement is significantly higher than others. Thus, cost savings in abatement may be attained by allowing non-uniform abatement procedures across plants. More specifically, the cost of reducing each additional unit of pollution may be set equal, which, assuming no transactions costs, meets the pollution goal at the least cost (Van Houtven et al., 2012). In other scenarios, the firm may seek to maximize revenue subject to a maximum allowable amount of pollution emitted. Though the objective function is constructed differently, the optimization should yield a similar solution set containing the most cost-effective means of meeting a specific pollution cap.

In order to understand how researchers began applying optimization models to the management of non-point source (NPS) pollution, it is important to know what constitutes NPS pollution and how it is generated. NPS pollution comes from many different diffuse sources. It is generally deposited across varying surfaces where precipitation travels across the surface picking up NPS pollutants as it moves downslope. The runoff then transports the natural and human-made NPS pollutants to local lakes, rivers, wetlands, coastal waters, and ground water networks. Depending on the type of pollutant, the ramifications can be quite severe, hypoxia in the Chesapeake Bay being an example.

NPS pollution is generally more difficult to manage than point source pollution due to a host of issues such as political opposition, high transactions and enforcement costs, and uncertainty regarding pollutant loads (Kirshen et al., 2013; Stephenson et al., 2010; Bosch et al., 2006; Abrahams & Shortle, 2004). Where TN, TP, and TSS are labeled pollutants largely stemming from non-point sources (EPA, 2015; Chesapeake Bay Program, 2015), many studies utilizing optimization have analyzed watershed management practices for agricultural and urban watersheds. Indeed, it is recognized that agricultural NPS pollution is the leading cause of many impaired water systems across the U.S. (EPA, 2015). Thus, previous studies have utilized multi-objective optimization models to generate farm plans to maximize profit, minimize risk, lower nutrient loading, minimize the cost of nutrient management, incorporate site-specific management, and so forth (Ji et al., 2014; Wei, 2001; Qiu et al., 2001). Densely populated urban watersheds with minimal pervious surface produce runoff laden with nutrients (EPA, 2015). Researchers often use cost minimization models to minimize the cost of nutrient removal within urban landscapes subject to an allowable amount of nutrient export (Behera & Teegavarapu, 2015). Although many researchers have put forth optimization frameworks capable of evaluating NPS pollution management practices, there remains many unexplored concepts and applications regarding this complex issue.

2.3 Cost Minimization

Where resources are scarce and need be allocated efficiently, cost minimization studies provide useful information for decision makers. Cost minimization analyses develop the least-cost set of decision making variables subject to technical constraints and some user-specified objective or objectives. Applications of minimization models are extensive within the management of pollution and natural resources (Bosch et al., 2006). Cost minimization techniques are commonly used to solve for the least costly path to satisfy a pollution cap. As pollution caps can be set to ameliorate a plethora of environmental factors, knowing how to achieve these environmental standards at the least-cost is valuable information. Freeman et al. (1973) suggested minimizing the total abatement cost of pollution while simultaneously minimizing the cost of environmental damage caused by pollution. Using this method forces the model to choose between pollution abatement and pollution producing practices where the total cost of environmental management is minimized. Indeed, TMDLs are often met using cost minimization techniques (Bosch et al., 2006). As models become larger, additional assumptions are often made, which may reduce the accuracy of the cost estimates. Conducting smaller analyses where the researcher is minimizing the cost of meeting runoff standards over smaller spaces such as fields, sub-watersheds, or watersheds provides more accurate estimates and is more common (Chichakly et al., 2013).

Minimizing the cost of BMPs across a defined urban watershed subject to a pollution reduction goal is well researched and effective (Perez-Pedini et al., 2005; Rabotyagov et al., 2010). As Chichakly et al. (2013) discussed, urban resource managers and developers face challenges when deciding which types, sizes, and location of BMPs will most effectively reduce runoff. Thus, decision makers may utilize multi-objective constrained cost minimization models to determine the optimal type, placement, and size of BMPs to be constructed throughout the watershed to satisfy pollution abatement requirements.

Prior to introducing environmental stochasticity into the analysis, it is important to understand the standard cost minimization framework. Allowing this analysis to be applied to the pollution abatement goals for an area with finite resources, let: k be the number of resources to allocate to activities n; BMP_j be the level of activity j where j =1, 2,…, n; $\propto_j$ be the rise in Z resulting from a marginal increase in the level of activity j; Z be the total annual for a chosen percent reduction in some pollutant Ω; θ_k be the amount of resource k available for allocation to activities j where k = 1, 2,… m; β_{kj} be the marginal amount of resource k taken by activity j; ρ_j be the average Ω reduction made by BMP_j in the watershed; and μ be the total simulated annual average of Ω for the watershed. Knowing that BMP_j represents the DMVs and that $\propto_j$, β_{kj}, and ρ_j, are parameters within the model, the LP cost minimization model is mathematically expressed below:

$$(2a) \quad min\ Z = \sum_{j=1}^{n} \propto_j\ BMP_j$$

$subject\ to$:

$$(2b)\ \sum_{j=1}^{n} \beta_{kj} BMP_j \leq \theta_k \qquad\qquad k\ =\ 1,2,\ldots,m$$

$$(2c)\ \sum_{j=1}^{n} \rho_j BMP_j \geq (\mu * target\ \%\ \Omega\, reduction)$$

$$(2d)\ BMP_j \geq 0$$

where equation (2a) represents the objective function, equation (2b) represents the resource, or functional, constraints imposed on the model, such as land constraints and municipal requirements, equation (2c) represents the pollution goal that must be realized, and equation (2d) is a non-negativity constraint.

2.4 Linear Programming under Uncertainty

LP models that contain environmental variables may subsequently contain parameters not known with certainty. Violating the fourth assumption of mathematical optimization leads to less accurate or biased results. The stochasticity that environmental variables introduce into the model brings added complexity and variability that traditional minimization or maximization models cannot handle. Uncertainty in water quality management stems from naturally occurring processes governing water resources, conflicting policy objectives and constraints, flawed water quality simulation data, and inherent changes of NPS pollution over time and space (Ji et al., 2014; Wu et al., 1997; Beck, 1987). The literature often states that strict and certain compliance with environmental standards is nearly impossible to attain due to the diffuse nature and stochasticity associated with water quality management (Qiu et al., 2001). Indeed, when the Chesapeake Bay TMDL was set a margin of safety for nutrient export was incorporated to account for the highly variable nature of environmental factors (EPA, 2015). For many applications, altering the sensitive parameters and studying how the optimal solution set changes is sufficient for determining the best course of action regarding decision making. However, that has not stopped researchers from continuing to create new methods for mitigating uncertainty. Though there are many models borne from the need to account for uncertainty (Ji et al., 2014), we limit the discussion to the following models as they are most relevant to this study.

2.4.1 Robust Optimization with Independent Parameters

Conducting sensitivity analysis for LP models with uncertainty regarding the true values for given parameters is an important way of learning additional information about the solution set (Hillier & Lieberman, 2015). Sensitivity analysis largely concerns itself with identifying the parameters that cannot be altered without altering the optimal solution. If these parameters are estimated incorrectly, the researcher runs the possibility of generating an erroneous feasible solution (Hillier & Lieberman, 2015). In the case of simulated environmental control measures, the true values of the control parameters may not be known with certainty until the control measure is implemented and data values are then recorded. For example, say a team of civil engineers develop a new urban BMP that has a simulated TSS loading reduction coefficient of 80%. However, when put into practice the researchers find that the loading reduction coefficient is closer to 60%. In the case of meeting a watershed TSS pollution cap, this BMP would severely distort the solution set's effectiveness bringing the possibility of fiscal penalties for violating the cap. Thus, even after a parameter value has been carefully estimated, there is a chance of violating constraints after the control measure is installed. By evaluating the potential ramifications of a varying parameter, researchers may determine whether a functional constraint is a hard constraint or soft constraint – the former being a constraint that must be met while the latter being a constraint that need not always be met.

Robust optimization is a form of LP especially designed for dealing with problems containing hard constraints. A hard constraint is a functional or technical constraint that must be satisfied. The Bay TMDL is an example of a hard constraint. The TMDL mandates that all Chesapeake Bay partner states and the District of Colombia must conform to an aggregate cap on nutrient export by 2025. Each entity further states within their respective WIP how much abatement they will achieve by 2025. Violation of the outlined WIP nutrient export cap may result in exorbitant penalties. Thus, Virginia and its partner states face a hard constraint on their respective nutrient loading into the Bay.

The goal of robust optimization is to find a solution set for the model that is virtually guaranteed to remain feasible and remain close to optimal for all potential combinations of the true parameter values (Hillier & Lieberman, 2015). Assuming that the model's parameters are independent, four assumptions are generally made regarding robust optimization. We assume that there is a range of uncertainty surrounding a given parameter; the parameter can take any value in this range of uncertainty; the parameter value is independent of other parameter values; and all functional constraints are constructed with inequalities. With the above assumptions met, the researcher need only assign the most conservative parameter estimate values to ensure a near optimal feasible solution. In the case of Virginia meeting its TMDL obligations, the commonwealth may select a statewide plan that overshoots the pollution target such that it is guaranteed to meet its pollution reduction goals.

Robust optimization, though effective, may not always be the best option for controlling uncertainty (Hillier & Lieberman, 2015). Policymakers may face limited resources and political opposition, thus requiring first, second, and even third best-case scenarios. As an example, VA may develop a first best-case scenario using robust programing where the target nutrient export loading reduction is always met regardless of ambient conditions. The second and third best-case scenarios, however, may allow for the possibility of not consistently meeting the pollution reduction goal accompanied by a reduced pollution reduction expenditure. To generate information regarding the second and third best-case scenarios, other programming methods may be used. Chance Constraint Programming (Charnes & Cooper, 1963) and Target Minimization of Total Absolute Deviation, or MOTAD (Tauer, 1983), optimize a given objective function while generating information regarding the risk thereof. Mean-Variance Optimization (Markowitz, 1952) is a quadratic programming model that performs a similar analysis where the "riskiness" of a given solution set is generated. Decision makers may benefit greatly from the additional information surrounding risk provided by these techniques.

2.4.2 Chance Constraint Programming

LP parameters might remain uncertain until the feasible solution set is implemented. If it is the case where the upper and lower bounds of a given parameter are unknown, robust programming is no longer feasible. Assuming that the distribution of parameter values is normal, the LP modeler may turn to Chance Constraint Programming (CCP).

CCP is a versatile programming method used in many applications of safety-first environmental analysis (Guo & Huang 2009; Liu et al., 2003). There is a rich literature outlining various applications of CCP in water quality management (Ji et al., 2014). Specifically, substantial progress has been made controlling for the uncertainty in NPS water quality management (Guo & Huang, 2009; Bosch et al., 2006; Wu et al., 1997). Where chance constraints serve as a safety-first style constraint, environmental concerns of decision makers may easily be addressed (Qiu et al., 2001).

The formulation of chance constraints is straightforward. We illustrate the case where the only uncertain parameters are those on the right-hand side of the inequality. Drawing from the previously developed cost minimization example, the uncertain parameter is an example pollutant, mean interannual TSS loading for a watershed denoted by μ_{TSS}. The standard deviation of μ_{TSS} is denoted by σ_{TSS}. It is assumed that the TSS loading have a normal distribution and are independent of other parameters. Where the original loading reduction constraint is

$$(2c)\quad \sum_{j=1}^{n} \rho_j BMP_j \geq (\mu_{TSS} * target\ \%\ TSS\ loading\ reduction)$$

the transformed chance constraint will require that the loading constraint be met with a certain user-specified probability. Allowing γ to be the minimum acceptable probability that equation (2c) will hold, the chance constraint is formulated below:

$$(3)\quad P\left\{\sum_{j=1}^{n} \rho_j BMP_j \ \geq (\mu_{TSS} * target\ \%\ TSS\ loading\ reduction)\right\} \geq \gamma$$

Equation (3) states that the probability of satisfying a given TSS loading reduction goal must be greater than or equal to γ. However, as this equation is no longer linear, a global optimal solution is no longer ensured. To avoid this problem, we use the commonly transformed deterministic equivalent of the chance constraint. The deterministic equivalent is only valid for data with a normal probability distribution. The equation is mathematically expressed below:

$$(4c)\ \sum_{j=1}^{n} \rho_j BMP_j \geq (\mu_{TSS} + K_\gamma \sigma_{TSS}) * \ target\ \%\ TSS\ loading\ reduction$$

where K_γ is the constant that can be retrieved in a table for a normal distribution for probability γ. That μ_{TSS} is the annual mean TSS loading for the watershed, the right-hand side of equation (2c) has been transformed into a safety-first style constraint where $K_\gamma \sigma_{TSS}$ builds a margin of safety for meeting the loading constraint. Unlike robust programming, this value is calculated using the data surrounding the mean parameter value itself. With the chance constraint developed, the modified cost minimization model with chance constraints is illustrated below:

$$(4a)\quad min\ Z = \sum_{j=1}^{n} \propto_j\ BMP_j$$

$subject\ to$:

$$(4b)\ \sum_{j=1}^{n} \beta_{kj} BMP_j \leq \theta_k \qquad k\ =\ 1,2,\dots,m$$

$$(4c)\ \sum_{j=1}^{n} \rho_j BMP_j \geq (\mu_{TSS} + K_\gamma \sigma_{TSS}) * \ target\ \%\ TSS\ loading\ reduction$$

$$(4d)\ BMP_i \geq 0$$

CCP is not without its limitations. Previous studies show that misspecification of the distribution of the environmental variables significantly affects environmental and economic trade-offs (Qiu et al., 2001). CCP construction usually only handles right-hand side randomness in the constraints. In many cases the right-hand side randomness of a given parameter may not be independent of other parameters. For example, where nutrient loading is expected to increase in the Mid-Atlantic region with CC (Najjar et al., 2010), BMPs effectiveness values are expected to decrease (Hathaway el al., 2014; Woznicki et al., 2010). In this case, the randomness of one parameter is a covariate of another parameter, which violates the second assumption of LP modeling and a critical assumption of traditional CCP models. One way to account for this problem is to incorporate randomness in the left-hand side of the constraint as well as the right. As these two environmental variables are covariate of one another, however, we violate the Law of Additivity bringing about the possibility of non-optimal solutions. Further, attempting to incorporate chance constraints in the left-hand side of a set of constraints can create nonlinear constraints negating the guarantee of a global optimal solution. Many researchers have successfully derived linear approximations of these models in the form of inexact left-hand side CCP (Ji et al., 2015; Ji et al., 2014; Xie et al., 2011). Though effective, these models go beyond the scope of this study.

2.4.3 Target MOTAD

Target Minimization of Total Absolute Deviation (Target MOTAD) developed by Tauer (1983) is a mathematical programming model designed to maximize expected returns while simultaneously ensuring that returns in any given state of nature never fall below a specified critical level. Target MOTAD was originally designed to calculate the optimal bundle of activities for a given target level of income while simultaneously calculating expected risk of an expected return. The model is also able to evaluate economic and environmental effects while accounting for the highly variable nature of environmental factors. Target MOTAD, like CCP, assumes that parameter values are not correlated. Unlike CCP, however, the formulation allows researchers to proceed without having to assume that the environmental variables are normally distributed (Qiu et al., 2001). Rather, Target MOTAD treats the constrained variables "as an empirical distribution and optimizes over the column space of the sample." (Qiu et al., 2001, p. 402). The results of the analysis are valid as long as the true underlying distribution is accurately represented by the empirical distribution.

Target MOTAD is a two attribute risk and return model. The objective function maximizes total expected returns, which are calculated by activity x_j multiplied by its respective expected return $\propto_j$ for $j = 1, 2, \ldots, n$. Where the model developer specifies a target level of desired income, risk is then measured by summing the total expected value of the negative deviations below the target, also referred to as a Lower Partial Moment (LPM). Target MOTAD allows for E-V analysis where a risk-return frontier is traced out by varying the risk aversion parameter λ. The expected returns are plotted along the Y-axis and the variance in the expected returns is plotted along the X-axis. The frontier is a visual representation of tradeoffs occurring between risk and net return (Tilley et al., 2007). The model may be stated mathematically as

$$(5a)\ \ Max\ E(Z) = \sum_{j=1}^{n} \propto_j x_j$$

subject to:

$$(5b)\ \ \sum_{j=1}^{n} \beta_{kj} x_j \le \theta_k \qquad k = 1, 2, \dots, m$$

$$(5c)\ \ T - \sum_{j=1}^{n} \alpha_{rj} x_j - y_r \le 0 \qquad r = 1, 2, \dots, s$$

$$(5d)\ \ \sum_{r=1}^{s} p_r y_r = \lambda \qquad \lambda = M \to 0$$

$$(5e)\ \ x_j \ge 0\ \forall\ x_j$$

$$(5f)\ \ y_r \ge 0\ \forall\ y_r$$

where E(Z) is the expected return of the objective function; x_j is the level of activity j; $\propto_j$ is the expected return of activity j; β_{kj} is the functional requirement of activity j for resource k; θ_k is the level of the available resource k; T is the specified target level of return or income; α_{rj} is the expected return for activity j in the year r; p_r is the probability that the year or state of nature r will occur; y_r is the return deviation below T for year or state of nature r; λ is the expected sum of deviations below T varied from M to 0; m corresponds to the number of functional constraints or resource constraints; s denotes the year or state of nature*;* and M is an arbitrarily large number representative of the riskiness of a given return (Tauer, 1983; Teague et al., 1995).

Many applications of Target MOTAD are seen in farm management. It is assumed that the farmers are risk averse, therefore they desire additional information about the possibility of not reaching their target level of income (Hazell & Norton, 1986).

Teague et al. (1995) extend the use of Target MOTAD to conduct farm-level economic analysis while incorporating varying levels of environmental uncertainty. The model chooses the optimal set of activities, x_j, maximizing expected net revenues, E(Z), while achieving a threshold value or target, T, with some user-specified environmental risk level, λ. Their identified target is an environmental index for pesticide and nitrogen applications. Total deviations in the nitrogen or pesticide index value above the target indicate the potential for adverse environmental effects. They find that as the environmental risk measure is increased, the farm's expected net revenue rises. In other words, as farmers attempt to mitigate the risk of violating their level of environmental compliance, be it suggested or mandated, they face higher control costs due to the environmental variability in the empirical distribution of nitrogen loading or pesticide applications.

Qiu et al. (2001) modify Target MOTAD to evaluate environmental risks using safety-first constraints. Safety-first models, as outlined by Roy (1952), assume there is some minimal target to be achieved. Thus, the safety-first model seeks to minimize the probability of the target not being achieved. For Qiu et al. (2001), the target is the maximum allowable amount of nutrient export across a small watershed and the revenue generating activities are crop rotations. The researchers maximize expected net revenue subject to a target level of nutrient export reduction. This safety-first approach concerns itself with current pollution levels and the probability of pollution levels above some target or specified threshold value. Directly critiquing Teague et al. (1995), Qiu et al. (2001) argued that the traditional Target MOTAD model's environmental risk measure neither has a scientific basis nor stays consistent with conventional risk-utility models. Thus, they transform equation (5d) such that the model endogenously chooses the level of environmental risk. Where a decision maker wishes to enact a safety-first constraint for environmental quality, the preliminary equation may be written as follows

$$(6) \quad \sum_{r=1}^{s} Pr\left(\sum_{j=1}^{n} v_{rj}x_j > G_e\right) \leq 1/L$$

where G_e is the environmental goal and L is the "inverse of the acceptable probability of environmental pollution greater than the environmental goal G_e." (Qui et al., 2001, p.

405). The authors employ a stochastic Upper Partial Movement (UPM) approach for the construction of the safety-first constraint, which measures the economic or environmental risk as the weighted sum of above-target deviations opposed to below-target deviations (LPM). In other words, the interest falls on the probability of *exceeding* a pollution cap rather than falling below. The economic model employing safety-first environmental constraints using UPM is stated as:

$$(7a)\ \ Max\ E(Z) = \sum_{j=1}^{n} \propto_j x_j$$

$subject\ to$:

$$(7b)\ \ \sum_{j=1}^{n} \beta_{kj} x_j \leq b_k \qquad k = 1, 2, \ldots, m$$

$$(7c)\ \ t - \sum_{j}^{n} \propto_{rj} x_j - y_r \leq 0 \qquad r = 1, 2, \ldots, s$$

$$(7d)\ \ \sum_{r=1}^{s} p_r y_r - \theta(t) = 0$$

$$(7e)\ \ t + L^{*}\theta(t) \leq G_e$$

$$(7f)\ \ x_j \geq 0\ \forall\ x_j$$

$$(7e)\ \ y_r \geq 0\ \forall\ y_r$$

where t is an endogenously determined target for the environmental goal G_e under user specification L^*; b_k is the level of the available resource k; y_r is zero or the deviation above t for state or year r, and; $\theta(t) = \theta(1, t) = \rho(1, t)$ is the expected deviation above level t. All other variables are as previously defined in equation set (5). This model requires the specification of L^* rather than the selection of an arbitrarily chosen risk value λ used in Target MOTAD. More specifically, this model requires that a decision maker specify an environmental goal and the allowable probabilities of violating that goal, and then the model will endogenously choose the associated environmental risk levels. The results of this particular study show that increasing the environmental compliance probabilities substantially decreases the total expected income across the watershed.

Albeit the previously discussed models lend themselves to extensive analysis surrounding environmental uncertainty, NPS pollution, and farm management, they both fall short when considering the objectives of this study. Traditional Target MOTAD applications maximize expected returns subject to a set of constraints. Thus far, the majority of the advancements in Target MOTAD and safety-first modeling fall on the risk specification equations. There are comparatively fewer applications of these models that minimize some objective function rather than maximizing it (Tilley et al., 2007). Our study requires the objective function to minimize the total cost of BMPs across the Difficult Run watershed while simultaneously assessing risk for the optimal solution sets.

2.5 Model Selection

Three different mathematical optimization models were selected to accommodate the needs and data limitations of this study. First, we developed a cost model and minimized the cost of BMPs throughout the Difficult Run watershed subject to target nutrient loading reductions and geospatial considerations. By using mean values under both climate scenarios, this model served as a baseline of comparison to the following risk models. Second, we tested the annual watershed nutrient loading distributions for normality. If the nutrient loadings are normally distributed, the CCP model will be constructed in the same format as the cost minimization model with the exception of the watershed loading constraint, which is modified to act as a safety-first constraint. This constraint allows for the option to parametrically vary the probability of failing to meet the nutrient loading reduction goal and assess how each BMP portfolio changes. If the nutrient loadings are not normally distributed, we will use a modified Safety First programming model for producing a least cost portfolio of BMPs while analyzing environmental risk for a user-defined water quality goal. This model, however, allows for environmental risk assessment by varying the probability of success for meeting an environmental goal rather than the probability of failure. Additionally, the modified Safety First programming model differs from CCP in that the Safety First programming model endogenously chooses the Target level of allowable pollution within the watershed, which need be set in order to satisfy a user-defined environmental goal under its accompanying desired probability of success.

CHAPTER 3: DATA AND METHODS

3.1 Statement of Procedures

We began the process of analyzing the Difficult Run watershed with retrieving, compiling, managing, and refining secondary data. Using these data, we created a Geographic Information Systems (GIS) and a water quality simulation model using EPA's Storm Water Management Model 5.1 (SWMM) to produce additional data pertaining to water quality and the geospatial attributes of the watershed (EPA, 2015). Nutrient loading data for the two time periods in question were tested for normality in order to determine which previously discussed mathematical risk programming model is best suited for the study. Then, we summarized the data to construct a cost minimization mathematical programming model that calculates the cost of controlling for interannual mean nutrient loading for current and altered climate conditions. We used the cost minimization's framework for the development of the Safety First programming model as outlined by Qui et al. (2001). We further modified the Safety First programming model to analyze how the cost of controlling for average interannual nutrient loading differs from the costs of controlling for interannual nutrient loadings variability. Lastly, we conducted sensitivity analysis where the nutrient loading cap and probability of not achieving the cap are extensively explored for both current and future climates.

3.2 Data Overview

We began our analysis by compiling a database for the Difficult Run watershed. We selected BMPs for the watershed based on criteria in accordance with Virginia stormwater regulations. We then compiled the BMPs' key parameters including construction specifications, land requirements, cost estimates, and nutrient loading reduction coefficients. To add geospatial and hydrogeomorphic properties to the mathematical programming models, we compiled, analyzed, and distilled watershed characteristics and geospatial information using GIS and the Difficult Run Watershed Management Plan (Fairfax County DPWES, 2007). Lastly, watershed nutrient loadings were simulated using EPA's Storm Water Management Model (SWMM) 5.1.010 (EPA, 2015). These simulated loadings utilized weather input data drawn from historical climate data spanning from 1971-1998, simulated climate data spanning from 2040-2068, and watershed hydrogeomorphic properties.

3.2.1 Watershed Characteristics

The Difficult Run watershed is a highly urbanized watershed located almost entirely within Fairfax County, Virginia (Figure 1). The watershed drains 58.4 square miles, or some 37,924 acres. Low, medium, and high-density residential land area is the predominant land use accounting for roughly 62.79 percent of the total area. See Table 1 for all existing land use compositions and Figure 2 for visual context. Land use definitions can be found in Table 2. Roughly 18.4 percent of the total area within the watershed is considered impervious surface, as displayed by Figure 3. Some 5,783 acres within the watershed are designated as Chesapeake Bay preservation area - illustrated by Figure 4. According to Fairfax County, the ordinance protecting these areas was adopted to protect the sensitive areas along stream fronts from drastic land use change (Fairfax County, 2016). In that the majority of the watershed was already developed before Virginia's Chesapeake Bay Preservation Act was enacted in 1988, lands protected by the preservation ordinance are dispersed amongst the many different land categorizations present within the watershed. Figure 4 further illustrates how the majority of the watershed's waterbodies with perennial flow are dispersed throughout the watershed's many land uses.

Table 1. Existing Land Use, Difficult Run Watershed

Land Use Type	**Acres**	**Percent**
Agricultural	16.8	0.04%
Commercial	1677.38	4.37%
High-density Residential	769.37	2.00%
Medium-density Residential	841.84	2.19%
Low-density Residential	22,512.54	58.60%
Institutional	1400.98	3.65%
Industrial, light and heavy	143.19	0.37%
Open land, not forested or developed	5834.27	15.19%
Public	256.39	0.67%
Recreation	4872.52	12.68%
Utilities	93.47	0.24%
Total	38,418.75	100%

Figure 1. Difficult Run Watershed Boundary

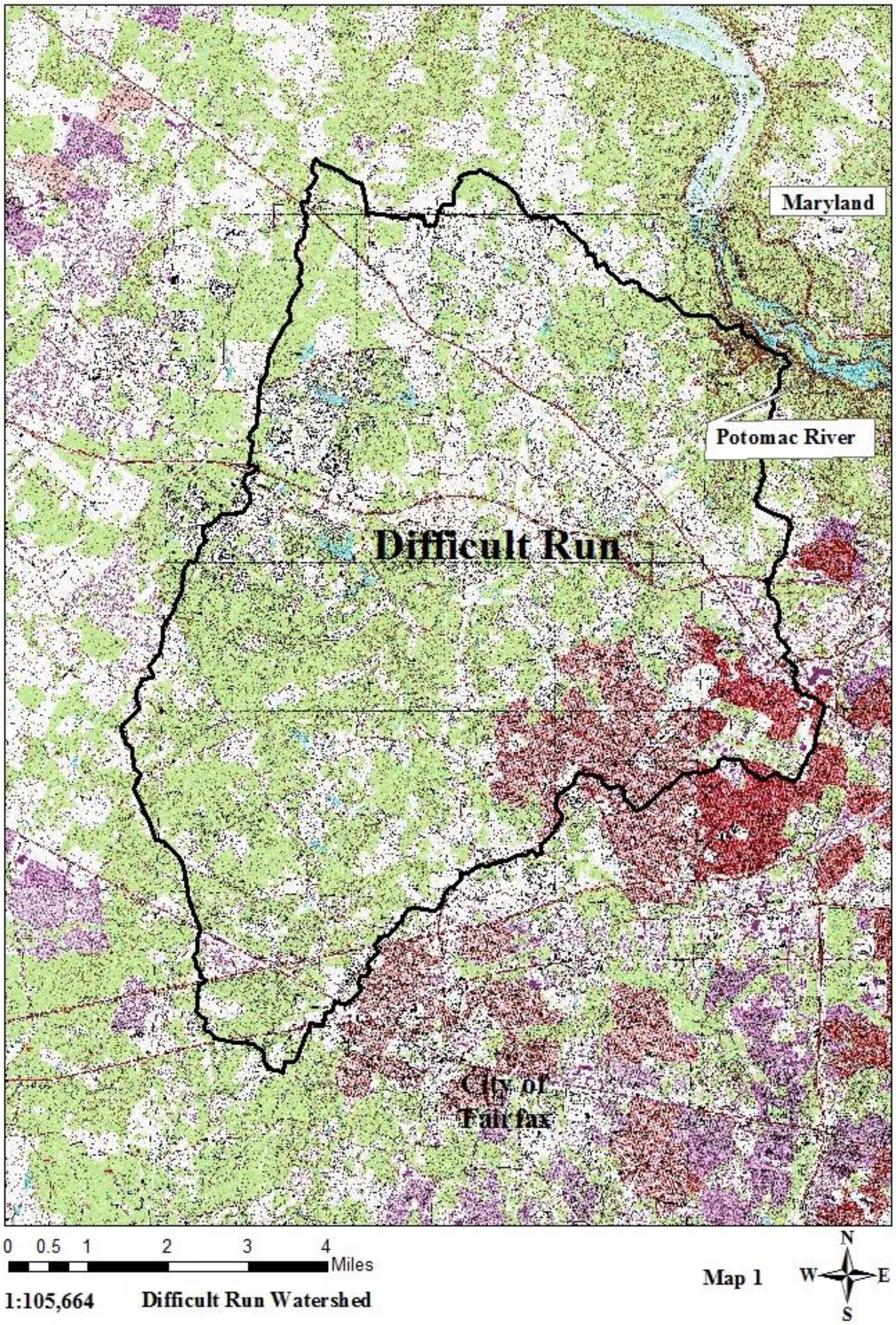


Figure 2. Difficult Run Land Use

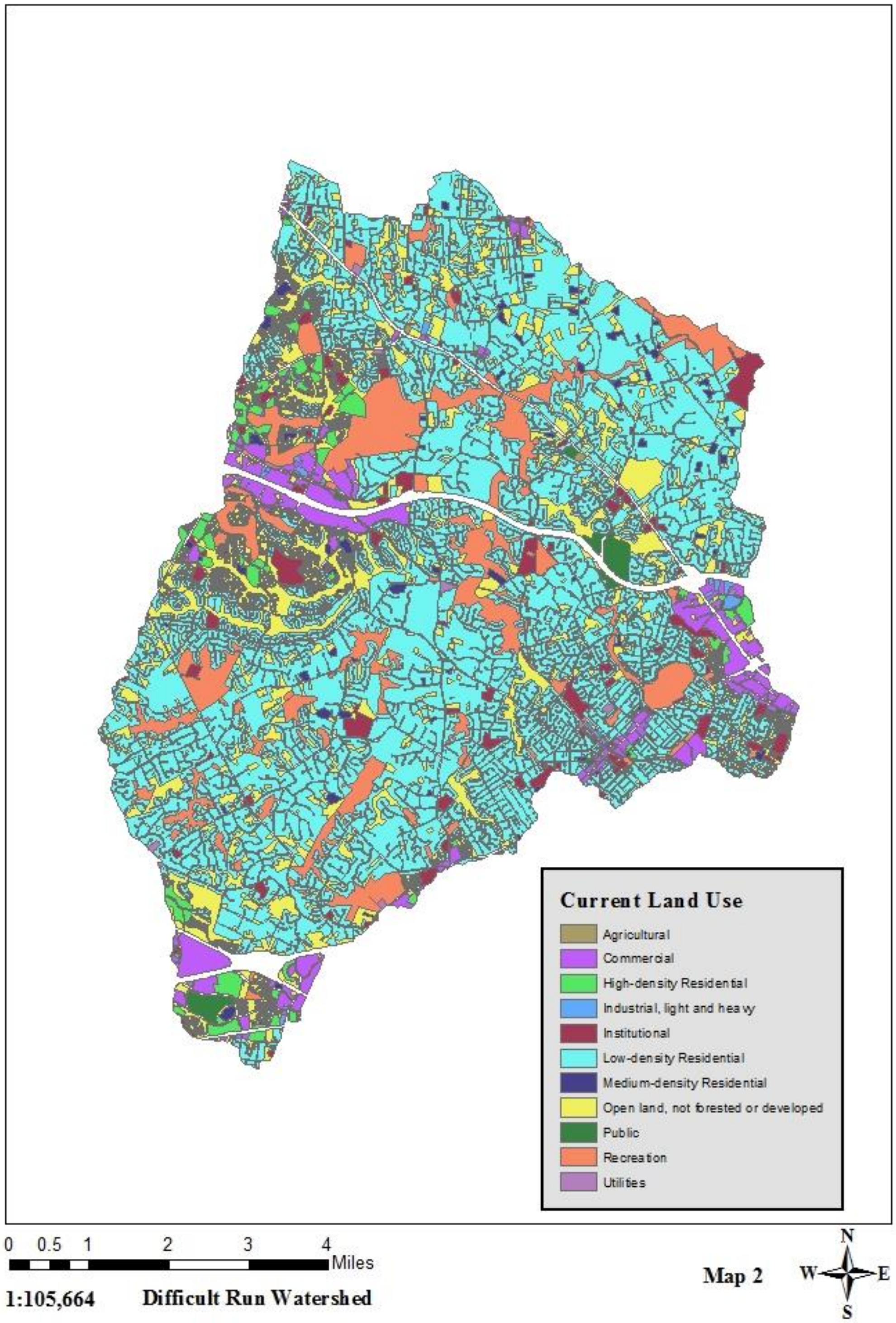


Figure 3. Difficult Run Percent Impervious Surface

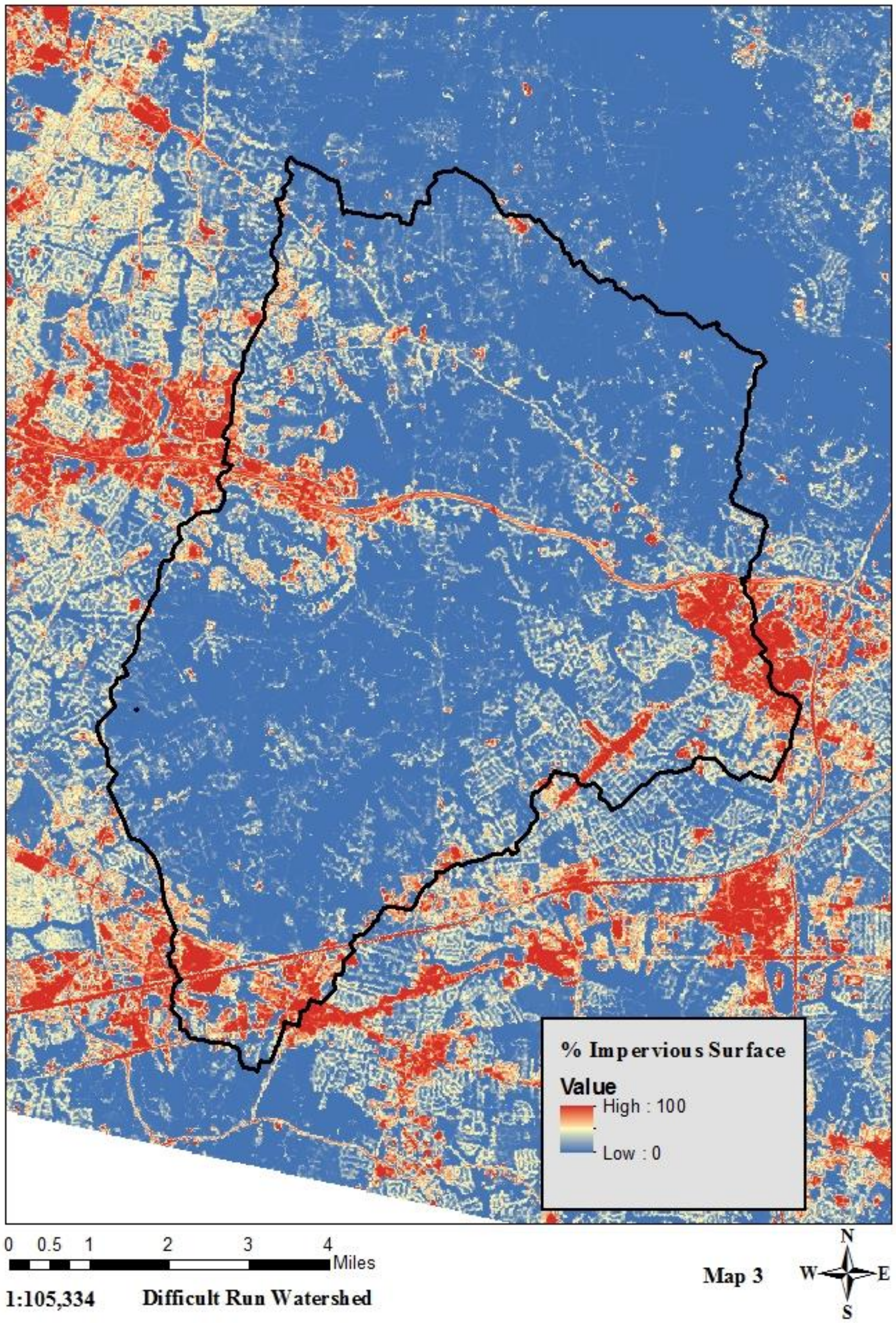


Figure 4. Difficult Run Digital Elevation Model

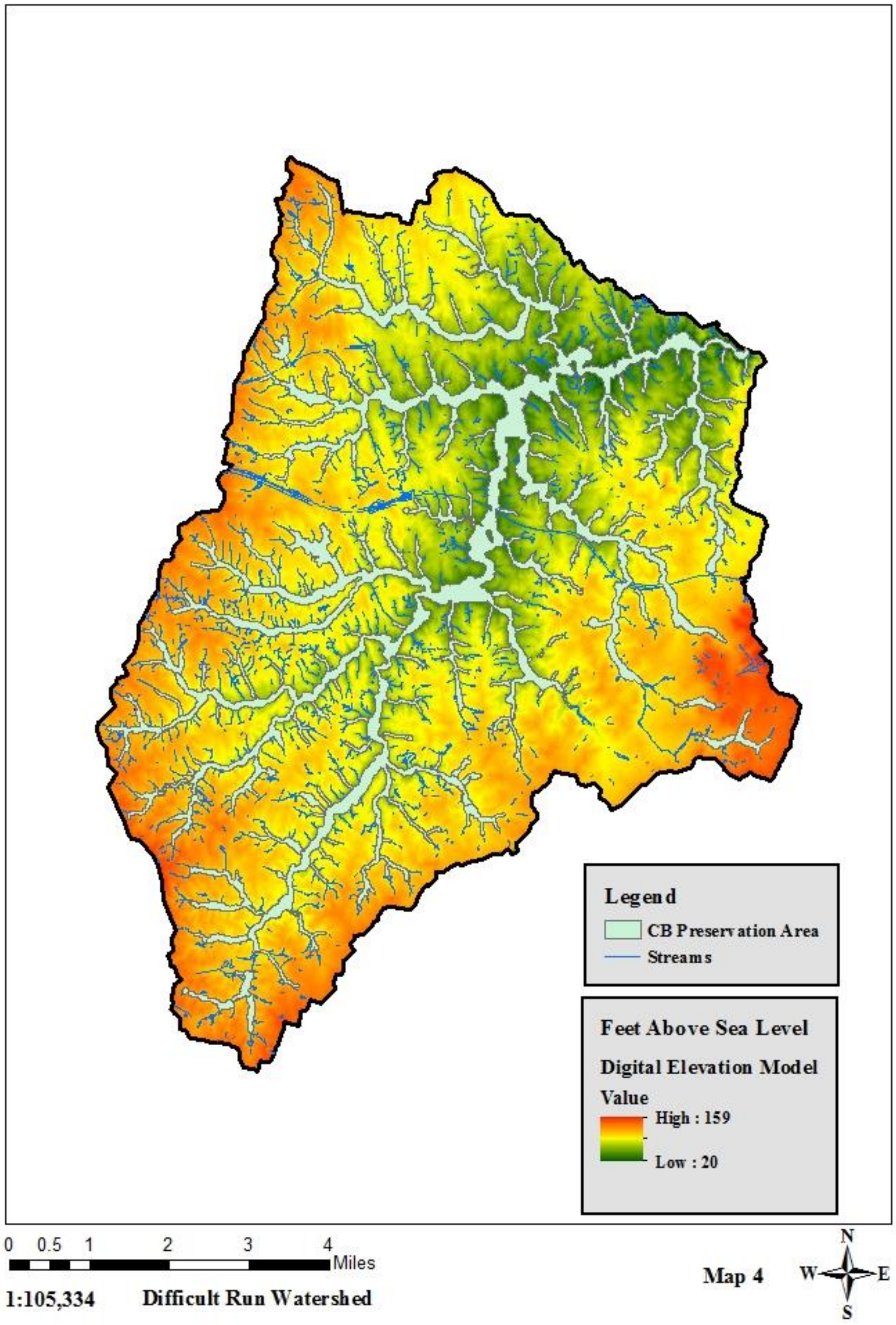


Table 2. Generalized Land Use Categories

Land Use Type	**Description**
Agricultural	Land in agricultural production
Commercial	Office parks, commercial buildings, office complexes, shopping centers, strip malls, automobile dealerships, restaurants, and other facilities considered highly impervious
High-density Residential	Single-family and multi-family residential with more than eight dwelling units per acre
Medium-density Residential	Single-family detached homes with less than 0.5 acres per residence and attached multi-family residential with fewer than eight dwelling units per acre
Low-density Residential	Single-family detached homes with more than two acres per residence
Institutional	Facilities open to the public, including churches, schools, libraries, and county office buildings
Industrial, light and heavy	Industrial land use including industrial parks
Open land, not forested or developed	Parkland, privately owned space, and vacant developable land. Extensive parking areas or buildings associated with parkland are included as industrial
Public	Land including parks and specific county offices
Recreation	Land deemed specifically for parks and recreation
Utilities	Owned by utility companies for the production and distribution of utilities throughout the county

The watershed contains roughly 130 miles of streams and tributaries. In 2002 and 2003, Fairfax County commissioned a study to develop a stream protection program (Fairfax County DPWES, 2007). Of the 130 miles that were assessed, 34 percent were assessed as poor and one percent were assessed as very poor. The majority of stream classifications, 48 percent, were assessed as fair. The mainstem of the Difficult Run includes 39 miles of stream and flows in a northeasterly direction to a confluence with the Potomac River. Tributaries make up the remaining 106 miles of stream within the watershed. The predominant nutrient exported from the watershed is sediment or TSS. Much of the land surrounding the streams has since been put into conservation via Chesapeake Bay preservation land classification.

The hydrogeomorphic region in which Fairfax County lies is the Piedmont Crystalline Non-tidal region. This region is typically comprised of rolling topography with low to moderate slopes. There are 41 different soil types found within the watershed, although only seven soil types comprise roughly 90 percent of the watershed area. The two major soil groups present are the Glenelg-Elioak-Manor association and the Manor-Glenelg-Elioak association. The Glenelg soil type makes up 40.5 percent of the watershed area and is found throughout the watershed, primarily on hilltops and sideslopes. Glenelg soils are highly susceptible to erosion. Manor soils are silty and sandy and make up almost 11 percent of the watershed. This soil type is commonly found on the floodplain fringe. Manor soils are also highly susceptible to erosion. When grouping these soils to Hydric Soil Groupings (HSG), 17,440 acres are majority type A/B soils, 14,254 acres are majority type C/D soils, and 6,187 acres are unknown due to missing data. HSG A/B soil types are characterized as having better drainage and more infiltration, which ultimately translates to less nutrient transport than type C/D soils. In step with the Upper Piedmont's hydrogeomorphology, the average percent slope of the watershed is 7.15 with a standard deviation of 4.78 percent.

The Difficult Run watershed has been the topic of much analysis over the last twenty years. USGS maintains three stream gages draining 7 km^2, 14 km^2, and 150 km^2, where the last stream gage can be labeled as an end of stream gage. These gages serve multiple purposes, measuring among other factors, continuous flow and nutrient concentrations. These data are used for the hydrodynamic and water quality models which were initially developed by Fairfax County for compliance assessment and future planning purposes. Currently, there are over 900 existing BMPs within the watershed. In conjunction with the highly detailed watershed management plan that Fairfax County commissioned (Fairfax County DPWES, 2007), these additional data and water quality models were crucial for advancing the hydrodynamic water quality model used in this study.

3.2.2 BMP Selection and Information Gathering

To select applicable urban BMPs for controlling nutrient transport within the watershed, we extensively reviewed VA government documents, manuscripts, and Chesapeake Bay organizations' recommendations. Low-Impact Development (LID) is gaining support in urban environments where these innovative stormwater control practices mimic predevelopment hydrologic regimes (Bullock & Merkel, 2005). LID consists of methods such as bioretention, green roofs, bioswale, and permeable pavement.

The Chesapeake Bay Program strongly advocates for continued adoption of LID practices within urban watersheds (2015). Fairfax County has recognized the need for LID to control for its nutrient loading (Walker, 2006).

VA land holders, both public and private, may be subject to obtaining stormwater permits for their nutrient export contribution. These costly permits, however, may be mitigated by implementing BMPs. VA Municipal Separate Storm Sewer System (MS4) and VA Pollutant Discharge Elimination System (VDPES) Permit Program documents extensively outline which BMPs may be used and their specification in order to receive off-setting nutrient reduction credits. Using these Commonwealth-specific recommendations, we selected 13 BMPs for use in the Difficult Run watershed. The complete list of BMPs can be found in Table 3.

This study sought to calculate and compare optimal cost estimates for controlling nutrient loading within the watershed, therefore cost estimates for each BMP were required. We used BMP cost estimates developed by King & Hagan (2011) because they provided explicit explanation of how each cost estimate was generated. The cost estimates are comprehensive in that they include pre-construction costs, land costs (where applicable), construction costs, maintenance costs, and opportunity costs. Costs are expressed as the annual cost per acre of impervious acre treated, acre treated, and 100-foot linear stream feet restored. The project lifespan for each BMP is 20 years where initial costs occur at year T=0 and are incurred from year T=1 through year T=20. The BMP costs and maintenance costs are amortized over the project lifespan at 3% to arrive at the final annualized cost estimate. BMPs may be retrofitted or retired upon project maturity. The study gave specific cost adjustments for every county in Maryland. We used Montgomery County as a reference for adjusting the cost estimates in that it borders Fairfax County and shares many characteristics, such land and construction costs. It is important to note, however, that these cost estimates did not produce much variation in opportunity costs among the counties in Maryland. Lastly, we adjusted the cost estimates to 2016 dollars using the Consumer Price Index Calculator in order to account for inflation.

As runoff passes through a BMP, nutrient loadings are stored, filtered, assimilated by plant matter, and/or slowly discharged into water systems downslope. The percentage value by which a BMP reduces nutrients transported in runoff is known as its effectiveness value. For example, if a BMP has an 80% effectiveness value for TN reduction, the BMP reduces 80% of the known TN transport present within the runoff channeled through it. An alternate measure of nutrient loading reductions is the pass-through factor. The pass-through factor measures percent value of nutrients *not* abated by the BMP. Using the previously exemplified BMP, the pass-through factor would be 20%. According to the VA MS4 documents, BMP effectiveness values are how cumulative nutrient loading reduction credits are calculated for stormwater permittees.

Effectiveness values vary across BMPs and across each respective nutrient. The design of a BMP is the primary driver of its effectiveness value. However, many other environmental factors can affect the effectiveness of a BMP. More specifically, the uncertainty in the effectiveness estimates may be due to factors including, but not limited to, variability in precipitation, local hydrogeomorphic characteristics, soils, geology, lag time between nutrient arrival and nutrient export, human errors in BMP implementation and maintenance, and the influence of slope and soil cover. Although these are important variables to consider, the resources and time required to estimate specific geospatial BMP effectiveness values are enormous and, for most stormwater permittees, infeasible. In an effort to alleviate these obstacles, Virginia standardized average effectiveness values specific to all BMPs for which stormwater permittees may receive nutrient reduction credits. In other words, when a municipality applies for stormwater credits through the Virginia Stormwater Management Program, the municipality will calculate how much nutrient export was reduced using the amount and type of BMPs implemented along with the BMPs' corresponding defined effectiveness values as described in the Virginia MS4 guidelines. However, it is not uncommon for the regulatory entity to change the effectiveness value of a BMP even after the BMP has been implemented, which would ultimately affect the number of stormwater credits a municipality or nutrient loading contributing actor must secure.

3.2.3 Geospatial Information Assembly & Modeling

We formulated a GIS in order to distil available acreage to which BMPs may be applied. To understand how the GIS was constructed and further used, it is important to understand the specific geospatial considerations in question regarding the study area.

Each BMP has a set of construction specifications and technical requirements that must be met in order to receive nutrient reduction credits issued by the Virginia Stormwater Management Program. Using the Virginia Stormwater BMP Clearinghouse's structural BMP construction specifications (VADEQ, 2014), the following six BMP parameters were considered adequate geospatial limitations for the implementation for Urban Forest Buffer under A/B soils and under C/D soils, Permeable Pavement under A/B soils and under C/D soils, Infiltration Practices, Bioretention under A/B soils and under C/D soils, Bioswale, Vegetated Open Channels under A/B soils and under C/D soils, Filtering Practices, Wet Ponds and Wetlands, Constructed Wetlands, and Dry Extended Detention Pond under A/B soils and under C/D soils:

1) Mean Water Table Separation Depth – the average depth per acre at which the predominant soil becomes saturated; measured in ft.
2) Average Percent Slope – the average percent slope per acre calculated using ESRI's default slope method, the Horn (1975) algorithm.
3) Minimum Contributing Drainage Area – the minimum amount of acreage which must drain into any given BMP.
4) Maximum Contributing Drainage Area – the maximum amount of acreage that can drain into any given BMP.
5) Average Percent Impervious Surface – the average percent impervious surface in the area to which any given BMP is applied.
6) Hydric Soil Grouping (HSG) – The average HSG present in the area to which any given BMP is applied.

The three remaining BMPs, urban stream restoration (USR), mechanical street sweeping (MSS), and urban nutrient management (UNM), required additional parameters. The construction specifications and requirements are outlined in each BMP's respective Expert Panel Report (Berg et al., 2013; Donner et al., 2015; Aveni et al., 2013) approved by the Chesapeake Bay Program. Required information for USR, MSS, and UNM are outlined below:

1) Linear Stream ft – the length in linear stream ft that can be restored to be considered a functioning, viable BMP.
2) Stream Health – a compilation of environmental factors which gage overall stream health, benthic richness and abundance being an example.
3) Existing Land Use – land use as defined by Table 2.
4) Roadway Distance – roadway distance measured in ft
5) Roadway Lane Count – number of lanes in each roadway that can be calculated into foot width per lane
6) Street Service Provider – the government entity charged with maintaining the roadway in question, VDOT or Fairfax County being examples.

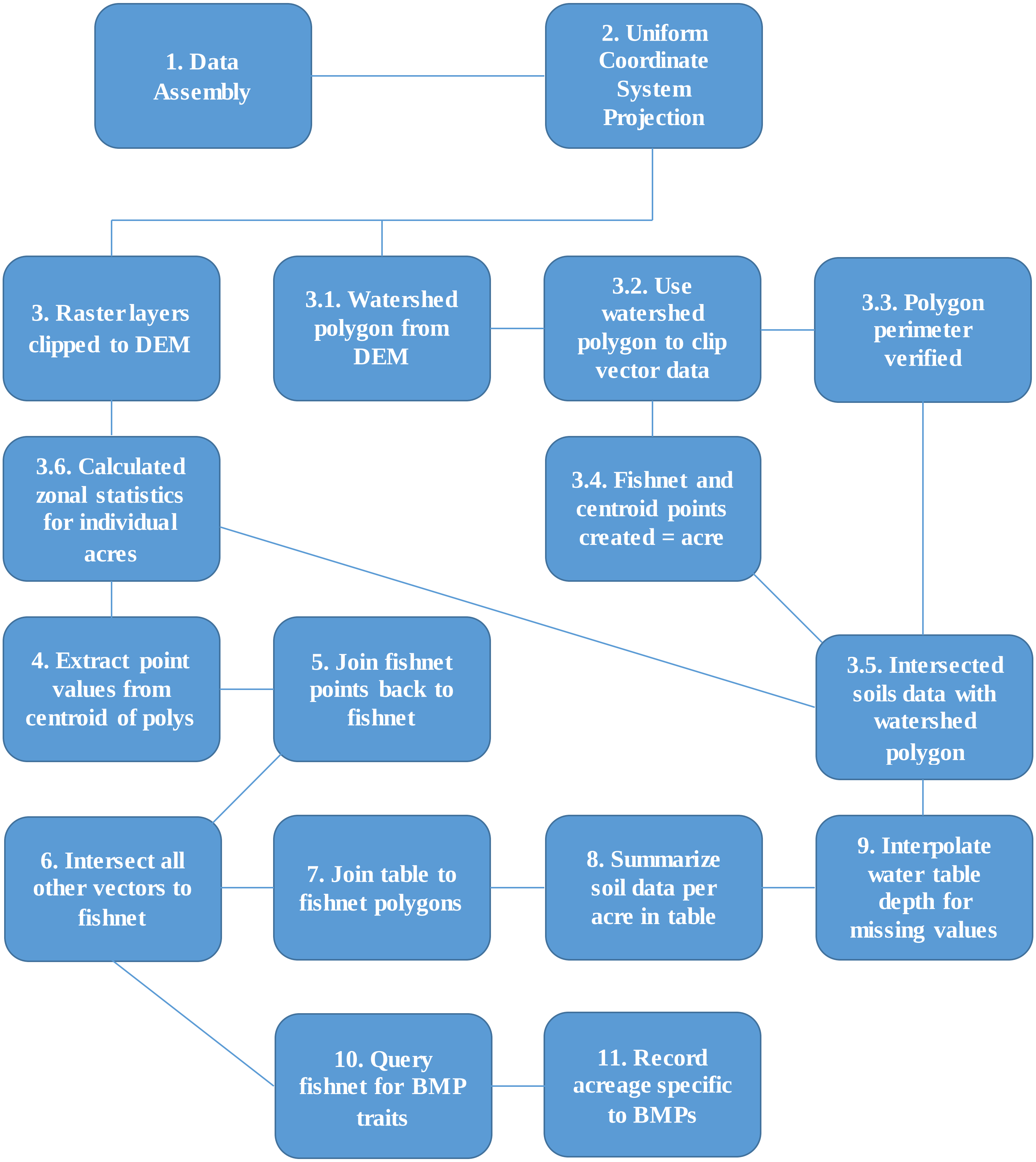
Utilizing these spatial considerations in conjunction with hydrogeomorphological concepts outlined by the Difficult Run Watershed Management Plan (Fairfax County DPWES, 2007), the GIS yields specific acreage and area counts particular to each considered BMP, applicable stream restoration sites, streets to be remediated, and areas to which urban nutrient management may be applied.

Constructing the GIS began with generating a geodatabase robust enough to calculate the required BMP geospatial requirements. To calculate percent slope and differentiate land by upland, midland, and lowland area, we used a 30x30 Digital Elevation Model (DEM) of the watershed, which was provided by David Sample, an active collaborator on this project. We collected county-level soils data to calculate average Water Table Separation Depth and predominant Hydric Soil Grouping (Soils, 2011). Minimum and Maximum Contributing Drainage Area were calculated using watershed vector and DEM data (Watersheds – 2011). We used the most recent version of the National Land Cover Database's Impervious Developed Surface continuous raster to calculate Average Percent Impervious Surface (USGS, 2011; USGS, 2014). Calculating applicable Linear Stream ft required the use of the DEM, Waterlines (2011), and the Difficult Run Watershed Management Plan (Fairfax County DPWES, 2007). We gathered Stream Health data from the Stream Protection Strategy Baseline Study (SPS), commissioned by Fairfax County (Fairfax County DPWES, 2007). We used an Existing Land Use vector data set to distill acreage by existing land use (Existing Land Use – Generalized, 2011). Roadway Distance, Roadway Width (measured in ft), and the Street

Service Provider were derived using Roadway Centerlines (Roadway-Centerlines, 2015) provided by Fairfax County's open GIS database

The GIS methodology can be broken down into several key components. Calculating the available acreage to which BMPs may be applied began with data management. Data management was crucial in that the data sets were originally in different coordinate systems, sometimes incomplete, or not of the same perimeter. Data management procedures help ensure accuracy with respect to GIS attribute queries and calculations. After the geodatabase was constructed, the aforementioned vector layers were seamlessly matched with the Difficult Run watershed polygon. More specifically, the relevant data sets containing information regarding BMP construction parameters, such as slope and soil type, were joined together to form one uniform map of the watershed. We further manipulated these data and generated additional data sets using statistical calculations in GIS. As we are interested in discovering specific acreage and area counts to which BMPs may be applied, we then divided the watershed into acres. Like the larger map from which the acreage map was created, all of the relevant BMP geospatial parameters were added into the individual acres. We performed a series of attribute queries on the acres, which allowed us to distill specific acreage and area counts containing the desired geospatial attributes for any given BMP. The steps outlining these procedures are illustrated in flowchart format by Figure 5 and are explained further afterward.

Figure 5. GIS Methodology



The statistics regarding slope and average elevation and the categorization of land into lowland, midland, and highland, were created from USGS DEM measured at a 30-meter resolution. Referring to the boxes in Figure 5, the polygon layer outlining the watershed was generated from the DEM (box 3.1). We then clipped the impervious surface raster to the DEM (box 3). Using a Fishnet procedure, which creates a new feature class of rectangular cells, we were able to create a new map layer equivalent to the area, perimeter, and extent of the Difficult Run watershed split into acres. Completing this procedure required us to draw the extent of the Fishnet to the Difficult Run watershed polygon and specify that width and length of each grid cell to be equal to 63.35 meters (box 3.4), which is the square root of 4046.856 meters (the meters in an acre). We cast the 1-acre polygons with accompanying centroid points over the watershed polygon. Fairfax County notes that the Difficult Run watershed contains 37,924 acres while we calculated the watershed to have 37,881 acres. The 0.1 percent difference is likely due to rounding errors in the conversion from meters to acres and the loss of boundary raster grid cells when converting into a polygon. By calculating zonal statistics with the newly created acre polygons defining the zonal boundaries for the statistical calculations, we generated the mean level of impervious surface per acre in addition to the average slope per acre (box 3.6). We then extracted the values of each centroid point to a table, which was joined back to the fishnet (boxes 4 and 5). This allows each acre to display information regarding its average slope and percent imperviousness. Using this layer, we intersected the county-level soils map to add soil information (box 6). We summarized the mean water-table separation distance and predominant Hydric Soil Grouping within each acre, and joined the resulting estimates back to the fishnet (boxes 7 and 8). Even among the county-level data sets, water-table separation data are often incomplete. To account for these missing data, we used an Inverse-Distance Weighting interpolation in ESRI to estimate the missing values (box 9). As there were no recorded observations shallower than 23 ft, the predicted values were truncated before 23 ft. Because the maximum water-table separation depth needed for any one of the selected BMPs is less than 10 ft, we conclude that water-table separation will not affect BMP placement in the Difficult Run watershed. Each acre now contains information regarding slope, predominant HSG, and average percent impervious surface. Using the existing the land-use categories vector, roadway centerlines vector, Chesapeake Bay preservation area vector, waterlines vector, DEM, and the created Difficult Run fishnet polygon, we were able to distill geospatial information into specific acreage and area counts for all thirteen BMPs (boxes 11 and 12). The resulting area and acreage count distillation for all BMPs is shown in Table 3[4].

Table 3. Area for BMP treatment

BMP Name	**BMP Code**	**Available Acreage and Area**
Urban Forest Buffer – AB Soils	CAAB	858
Urban Forest Buffer – CD Soils	CACD	2,511
Permeable Pavement – AB Soils	PP1AB	1,682
Permeable Pavement – CD Soils	PP1CD	4,213
Infiltration Practices	MI1	8,623
Bioretention – AB Soils	BRE1AB	639
Bioretention – CD Soils	BRE1CD	1,921
Bioswale	DS1	2,831
Vegetated Open Channels – AB soils	WS1AB	44
Vegetated Open Channels – CD soils	WS1CD	345
Filtering Practices	F1	8,623
Wet Ponds and Wetlands	CW1	8,715
Constructed Wetlands	CP1	8,715
Dry Extended Detention Pond – AB Soils	EPD1AB	639
Dry Extended Detention Pond – CD Soils	EPD1CD	1,921
Mechanical Street Sweeping	MSS	42.11
Urban Nutrient Management	UNM	24,123.75
Urban Stream Restoration	USR	29

3.2.4 Nutrient Loadings Calculation

Nutrient loadings for the Difficult Run watershed were calculated by collaborators Nasrin Alamdari and David Sample of the Department of Biological Systems Engineering at Virginia Tech. To simulate nutrient loadings, a modified version of EPA's SWMM 5.1 (EPA, 2015) was used. SWMM is commonly used for a variety of planning procedures related to runoff, sanitary systems, and other drainage systems in urban areas. Like many hydrology-hydraulic water quality simulation models, it is dynamic and can

[4] The full list of BMPs along with their respective definitions can be found in Table A.1, Appendix A.

be used for a single event or continuous simulation of runoff quality and quantity for a defined area.

SWMM is appropriate for modeling water quality and runoff in urban environments due to the process by which it calculates water quality and runoff. First, a runoff component is constructed which operates by implementing a collection of sub catchment areas that receive precipitation and generate runoff and pollutant loads (EPA, 2015). Second, the runoff is channeled through a system of pipes, channels, storage or treatment devices (such as BMPs), pumps, and regulators by the creation of a routing component. Since urban environments are known as “built environments”, it is important to use a water quality simulation model that captures the built characteristics of urban watersheds.

Water quality models are enhanced by spatial specificity, be it by using hydrological response units or sub catchments. In the case of SWMM, models that have many sub catchments have the potential to better simulate water quality dynamics. Having multiple sub catchments can better predict runoff and water quality in that irregularities and differences on the field or sub catchment level are accounted for. For the purposes of this study, however, the sub catchments were aggregated into a single sub catchment, the Difficult Run watershed. Although some accuracy is lost, the aggregation resolves a mathematical modeling issue related to the dynamics of runoff flow, which is discussed in further detail in the following section. The important thing to note is that SWMM is modeled such that the flow of nutrient loadings and runoff are routed to the end of stream, in this case the Potomac River, as a singular confluence across the entire watershed.

We used SWMM to simulate nutrient loadings for current climate conditions and altered climate conditions forecasted for CC. SWMM was constructed using the watershed’s hydrogeomorphic properties, precipitation data, and spatial inputs. The model was calibrated and validated using USGS stream gauge data from 1970-1998. The resulting simulated nutrient loading closely mimicked the actual loading observed within the watershed. We then used the functioning SWMM model to simulate nutrient loading for altered climate conditions. The main difference in each model is the precipitation input data. For the model simulating nutrient loading for historical conditions, precipitation data were pulled from years 1971-1998; however, precipitation data for the CC model are simulated weather input data from the North American Climate Change Assessment Program's (NARCCAP) regional climate model (RCM), MM5I_cssm, modeled by Andrew Ross and Raymond Najjar of the Department of Meteorology at Penn State. NARCCAP follows the CC narrative proposed by the Intergovernmental Panel on Climate Change's (IPCC) A2 Special Report Emissions Scenario (SRES). The A2 scenario follows an underlying theme of heterogeneity throughout the world where technological innovation is fragmented, global population is still quickly increasing, and economic growth per-capita is regionally oriented (IPCC, 2000). Therefore, it can be deduced that if anthropogenic influences contributing to CC are reduced at a faster rate than the A2 scenario assumes, then nutrient loading, and subsequent water quality policy costs, are likely to be lower than this study's CC estimates.

Nutrient loading data were simulated for two separate time-series lasting twenty-eight years each. Within each time-series there is an underlying distribution of nutrient loadings. As previously discussed in Chapter 2, the underlying distribution of an environmental variable greatly influences the accuracy of estimates produced by risk programming models. CCP models assume that the stochastic data are normally distributed, although the Safety First programming does not. Therefore, it was necessary to test the nutrient loadings for normality such that we may select the model that produces the more accurate estimates. We tested for normality by analyzing the Skewness and Kurtosis of the nutrient loading data sets. Skewness measures the asymmetry of the probability distribution of real-valued variables about its mean. Data that are normally distributed have a Skewness of 0.0. Data with asymmetrical distributions skewed to the right have positive values whereas the opposite holds true for data with asymmetrical distributions skewed to the left. Kurtosis quantifies the shape of the distribution's peak. Normal distributions have a Kurtosis of 0.0. Negative Kurtosis indicates flatter peaks whereas positive Kurtosis indicates sharper peaks – both of which indicate that the data are not normally distributed. The results of the normality tests and summary statistics of the nutrient loadings data are shown in Table 4.

Table 4. Nutrient Loadings Summary Statistics

	Historical Climate (1971-1998)			**Climate Change (2041-2068)**		
	TN Loading	*TP Loading*	*TSS Loading*	*TN Loading*	*TP Loading*	*TSS Loading*
Mean	40310	1539	431678	43330	1673	464544
Std. Error	1317	54	14160	1370	57	14742
Sample Variance	48530523	81559	5613794453	52517502	90249	6084880633
Std. Deviation	6966	286	20295	7247	300	78006
Kurtosis	0.35	1.05	0.41	-0.80	-0.77	-0.81
Skewness	0.56	.77	0.57	0.25	0.23	0.25
Minimum	29769	1107	318284	29171	1085	312103
Maximum	59130	2367	635391	57872	2282	621129
Coeff. of Variation	0.17	0.19	0.17	0.162	0.18	0.167

The results of the Skewness and Kurtosis tests indicate that the nutrient loadings data are not normally distributed. For altered climate conditions, we find that the data have a positive Skewness, which indicates that the distribution of loadings is asymmetrically skewed to the right of its mean. The positive Kurtosis indicates that nutrient loadings' distribution is sharper than that of a normally distributed set. For altered climate conditions, we find that the Skewness of the data is less severe, although the loadings data remain slightly skewed to the right. However, the loadings' Kurtosis results indicate that the loadings data have flatter peaks than data that are normally distributed. Annual loading for TN, TSS, and TP are plotted in Figures 6 and 7 to visually display the variability in nutrient loading over time.

Figure 6. Nutrient Loadings Simulated for Historical Climate

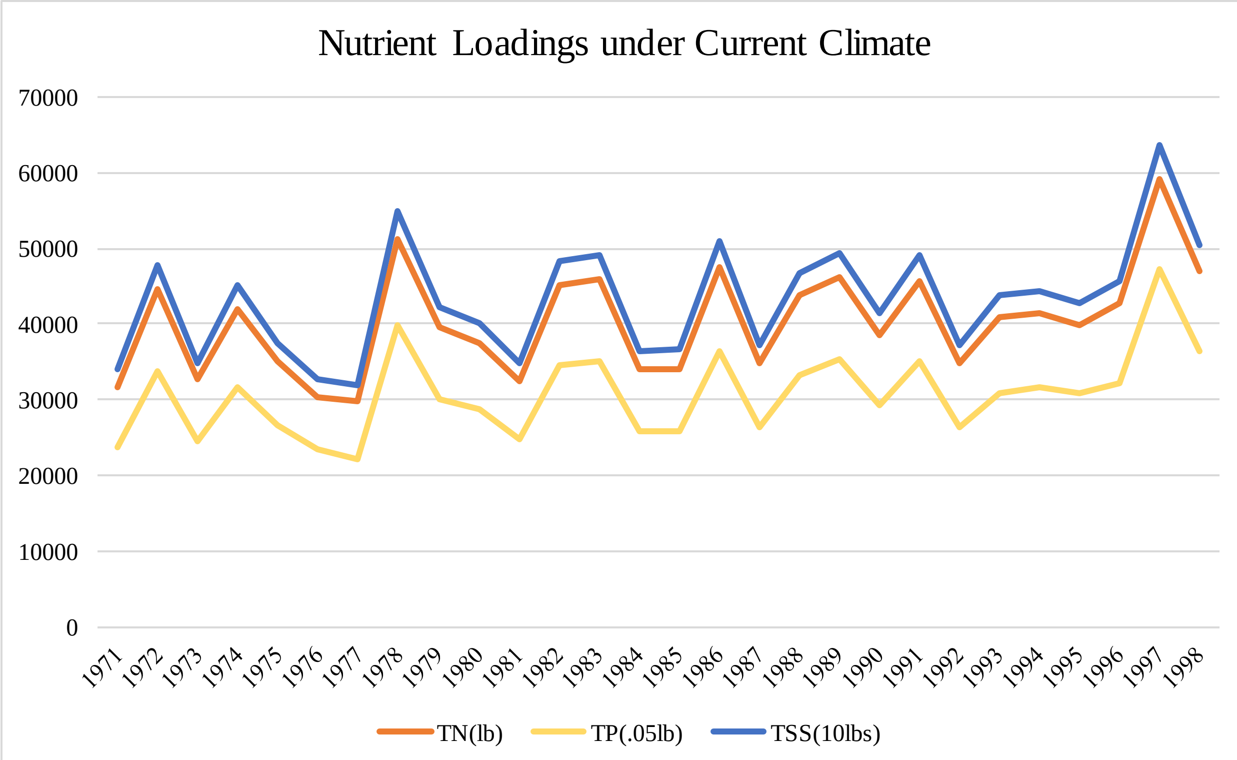
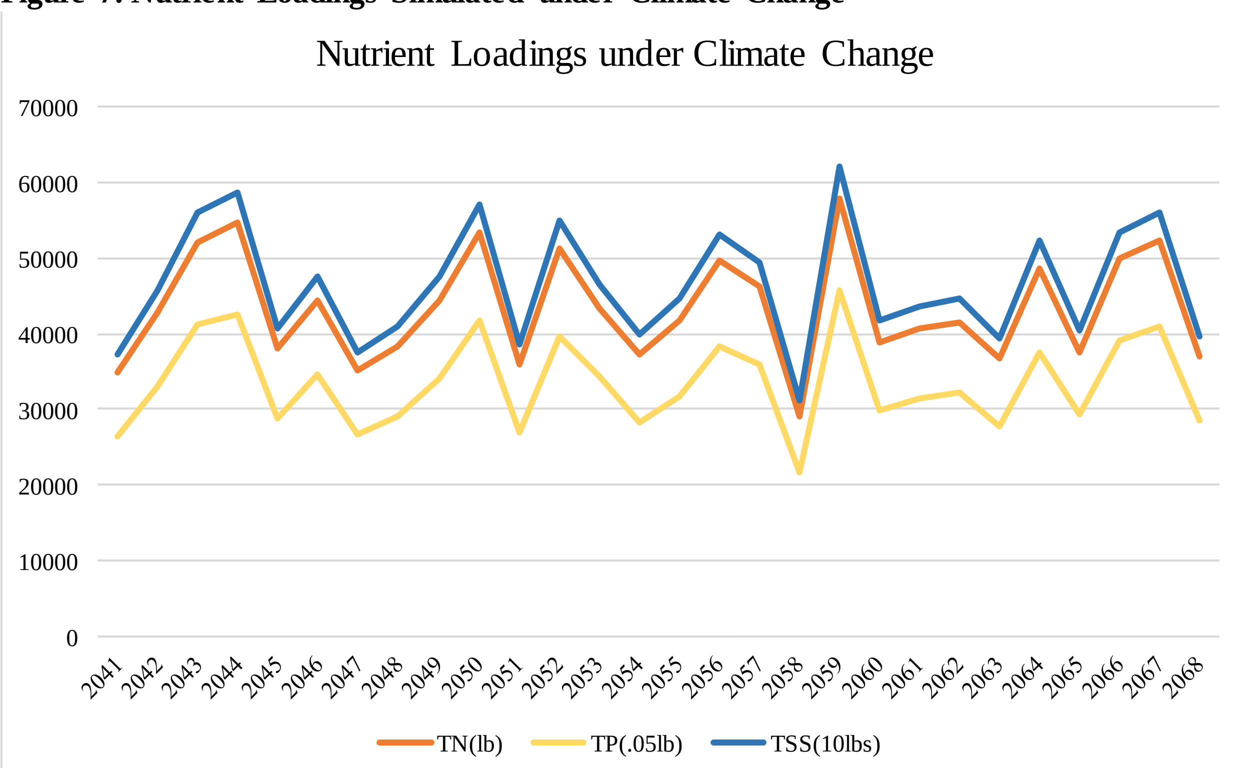


Figure 7. Nutrient Loadings Simulated under Climate Change



Knowing that the data are not normally distributed, it can be assumed that the Safety First programming model will yield more accurate cost estimates than the CCP model. Therefore, we use a modified Safety First programming model, as outlined in the following section, to analyze the environmental risk within the watershed.

Lastly, we tested these two time-series for trends such that we may better understand each time periods coefficient of variation. The total variance for each time series of nutrient loading is greater for altered climate conditions than it is for historical conditions. However, the coefficient of variation is slightly larger for the nutrient loadings for current climate conditions. The larger coefficient of variation for the nutrient loadings for current climate conditions is due to the larger respective range and smaller averages. Thus, we tested each time series of nutrient loading for trends using an Ordinary Least Squares regression to better understand why that might be. The independent variable, or trend variable, is the year in which the dependent variable, the watershed nutrient loading simulated in SWMM, occurred. The linear model is specified below

(8) $Simulated\ Nutrient\ Loadings = \propto_1 + \ \beta_1 year + \ \epsilon$

where $\propto_1$ is the intercept term, β_1 is the estimated marginal effect of each year on simulated nutrient loadings, and ϵ is the error term. Tables 5 and 6 show the respective results.

Table 5. Historical Nutrient Loadings Trend Analysis

		Coefficients	*Std. Error*	*T-stat*	*P-value*	R^2
TN	$\propto_1$	-701771.064	295729.825	-2.373	0.025	0.195
	β_1	373.938	149.019	2.509	0.019	
TP	$\propto_1$	-29282.908	12084.384	-2.423	0.023	0.200
	β_1	15.531	6.089	2.551	0.017	
TSS	$\propto_1$	-7554572.304	3180168.965	-2.376	0.025	0.195
	β_1	4024.314	1602.491	2.511	0.019	

The results for the historical nutrient loadings trend analysis show positive, statistically significant estimated coefficients for the trend variable, β_1. The R^2 indicates that little of the variation in nutrient loadings is explained by the model, although it is important to note that the R^2 is adversely affected by small sample size in which this model's observation count is 28.

Each additional year along the progression of the historical time series of data results in a slightly upward trend in nutrient loadings. As land use, land cover, and percent impervious surface are held constant over the both time series, it is not easily discernable why there is a positive linear trend observed within these data. However, from 1981 to 1997, Fairfax County consistently endured hotter than average temperatures and saw a moderate increase in drier than average precipitation patterns. As the years associated with below average precipitation occur less frequently than the years with higher than average temperatures, the latter meteorological phenomenon may be to blame for the higher simulated nutrient loading estimates on the latter end of the time series, which may explain why there is a positive, linear trend in the data.

Table 6. Climate Change Nutrient Loadings Trend Analysis

		Coefficients	*Std. Error*	*T-stat*	*P-value*	R^2
TN	$\propto_1$	32194.778	354959.864	0.091	0.928	0.000
	β_1	5.420	172.771	0.031	0.975	
TP	$\propto_1$	400.009	14712.785	0.027	0.979	0.000
	β_1	0.620	7.161	0.087	0.932	
TSS	$\propto_1$	313960.151	3820748.889	0.082	0.935	0.000
	β_1	73.295	1859.683	0.039	0.969	

The results for the CC trend analysis test show that there is no linear trend present within the simulated nutrients loading data for altered climate conditions. For all three nutrients, the estimated coefficient for the yearly marginal effect on simulated nutrient loading, β_1, is not statistically significant. Additionally, the R^2 shows that zero percent of the variation in the models is explained by the year in which the nutrient loadings were simulated. These results indicate that nutrient loadings are not increasing over time unlike the nutrient loadings simulated for the historical climate. Consequently, the range in nutrient loadings for altered climate conditions is slightly smaller than the range of nutrient loadings for current climate conditions.

3.3 Methods

We use mathematical programming to perform the calculations necessary to better understand the costs of nutrient loading abatement policies for current climate and for altered climate conditions. Beginning with the first objective, we develop a cost minimization model to compare the costs of reducing average interannual nutrient loading in the watershed based on historical conditions to those predicted for altered climate conditions. Following the second objective, we use the modified Safety First programming model to compare the costs of reducing interannual nutrient loading export variability in the watershed to the interannual nutrient loading export variability predicted for altered climate conditions.

The first mathematical programming model is a cost minimization, linear programming model which minimizes the total cost of BMP placement subject to a user-defined nutrient loading target reduction. Let k be the number of resources to allocate to activities n; BMP_j be the level of activity j where j =1, 2,…, n; $\propto_j$ be the rise in Z resulting from a marginal increase in the level of activity j; Z be the annualized cost estimate for the 20 year project life span for a chosen percent reduction in the average physical nutrient loading; θ_k be the amount of resource k available for allocation to activities j where k = 1, 2,… m; β_{kj} be the marginal amount of resource k taken by activity j; ρ_j be the average physical nutrient loading reduction made by BMP_j in the watershed; and μ_{NL} be the total simulated annual average nutrient loading (NL) for the watershed. Knowing that BMP_j represents the decision making variables and that $\propto_j$, β_{kj}, and ρ_j, are parameters within the model, the cost minimization model is mathematically expressed below:

$$(9a) \quad min\, Z = \sum_{j=1}^{n} \propto_j BMP_j$$

$subject\ to$:

$$(9b) \quad \sum_{j=1}^{n} \beta_{kj} BMP_j \leq \theta_k \qquad\qquad k = 1,2,\dots,m$$

$$(9c) \quad \sum_{j=1}^{n} \rho_j BMP_j \geq (\mu * target\ \%\ NL\ loading\ reduction)$$

$$(9d) \quad BMP_j \geq 0$$

where equation (9a) represents the objective function, equation (9b) represents the resource, or functional, constraints imposed on the model, equation (9c) represents the pollution goal that must be realized, and equation (9d) is a non-negativity constraint.

The second mathematical programming model is modeled after Qui et al. (2001) Safety-First risk analysis model, which pulls its core construction from the Target MOTAD construction. Rather than arbitrarily setting the level of nutrient loading variability, hereby defined as environmental risk, like that of traditional Target MOTAD approaches, this model endogenously chooses the level of environmental risk subject to a user-defined allowable probability of exceeding the Target. The interest now falls on the probability of exceeding a pollution cap rather than falling short of making a specific percent reduction. Let ϕ be the average nutrient loading per acre in the watershed across the time series; T be the endogenously determined nutrient loading per year to be drained from the watershed; δ_{rj} be the remaining nutrient loading for BMP_j in year r expressed as lbs/acre/year; ϕ_{r} be the interannual average nutrient loading per acre in the watershed for year r; G_e be the nutrient loading goal hereby defined as the environmental goal; and L be the inverse of the acceptable probability of environmental pollution greater than the environmental goal G_e. The economic model employing safety-first constraints is mathematically expressed below:

$$(10a)\ \ Min\ E(Z) = \sum_{j=1}^{n} \propto_j BMP_j + 0 * \phi$$

$subject\ to$:

$$(10b)\ \ \sum_{j=1}^{n} \beta_{kj} BMP_j \leq \theta_k \qquad\qquad k = 1, 2, \dots, m$$

$$(10c)\ \ T - \sum_{j}^{n} \delta_{rj} BMP_j - \phi_r + y_r \geq 0 \qquad\qquad r = 1, 2, \dots, s$$

$$(10d)\ \ \sum_{r=1}^{s} p_r d_r - \theta(t) = 0$$

$$(10e)\ \ T + L^{*}\theta(t) \leq G_e$$

$$(10f)\ \ BMP_j \geq 0\ \forall\ BMP_j$$

$$(10g)\ \ d_r \geq 0\ \forall\ d_r$$

where d_r is zero or the deviation above T for state or year r, and $\theta(t) = \theta(1,t) = \rho(1,t)$ is the expected deviation above T, the endogenously determined environmental risk target. All other variables were previously defined in equation set (9).

The way in which the Safety First programming model operates is fundamentally different from the cost minimization model. This difference stems from how the Safety First programming model calculates nutrient loading reductions, how its associated nutrient loading pollution goals are set, and how frequently its nutrient loading pollution goal is met. δ_{rj} is calculated using the previously mentioned pass-through factor, which is mathematically expressed below:

$$10h)\ \delta_{rj} = \left(1 - BMP_{effectivenessvalue}\right) * \left(\frac{\frac{avglb}{acre}}{year}_{NL}\right)$$

δ_{rj} is the average physical nutrient loading per acre per year *after* a BMP has been applied. Policy makers and watershed managers set an environmental goal within the watershed, which is the Target. The sum of nutrient loadings stemming from BMP treated acres and non-treated acres must be less than or equal to the endogenously determined Target. However, as there is variability in nutrient loading over time, it can be expected that there will be years in which the Target nutrient loading is exceeded. Unlike the cost minimization model, the Safety First programming model allows for positive deviations above the Target. Formulated by equations 10d and 10e, the sum of the positive deviations weighted by the user-defined probability of exceeding the environmental goal plus the endogenously determined Target must be less than or equal to the environmental goal. Thus, policy makers and watershed managers must decide on the environmental goal and the probability of failing to meet the environmental goal in order to carry out this analysis.

For both mathematical programming models, we treat the watershed as a singular subcatchment. This aggregation was performed to avoid errors in nutrient transport calculations caused by "treatment trains". In other words, the treatment of one subcatchment affects the water quality received by at least one other subcatchment downstream. As water quality is altered by the subcatchment up stream, the water and associated nutrient loading are now different than the simulated nutrient loading and BMP nutrient loading reduction coefficient predict them to be. The water and associated nutrient transport continues to flow downstream until it reaches its point of confluence – in the case of the Difficult Run, the Potomac River. Because the models presented in this research paper do not account for the dynamic interactions amongst subcatchments, also known as the cascade of water flows, the aggregation of subcatchments to a single subcatchment were justified.

We conduct extensive sensitivity analysis for added robustness and flexibility of solutions on behalf of interested stakeholders. We begin by parametrically varying the desired nutrient loading reduction goals in the watershed. The results give policy makers additional information about the way in which costs behave for increased levels of nutrient loading abatement. To analyze the cost of mitigating environmental risk, we calculate how the costs of nutrient loading abatement change as the probability of success for the environmental goal is varied. The sensitivity analysis is conducted for the current climate and for CC. The results of the above analyses are displayed in the following chapter.

CHAPTER 4: RESULTS

4.1 Cost Minimization Results

This section presents the main findings for abating mean interannual nutrient loadings under historical conditions and under CC. The percent nutrient loading reductions were parametrically varied from 1-50% for each nutrient under both scenarios in order to develop an optimal cost frontier as shown in Figures 8-23. BMPs selected by the modeling are presented in Tables 7-22. Relevant shadow prices[5] for each model are also discussed to give stakeholders information regarding suggested field and stream assessment. We briefly examine the relationship of nutrient loadings abatement costs for all three of the nutrients under each climate scenario. Lastly, we compared the costs of nutrient loading abatement calculated for historical conditions to those calculated under CC in order to determine the effects of CC on nutrient loading abatement costs, *ceteris paribus*.

4.1.1 Cost Minimization under Historical Climate

We analyzed each of the nutrients of interest individually. The order goes as follows: TN, TP, and TSS. We choose to analyze the nutrients individually due to the characteristics of TN loading abatement. TN loading reduction coefficients for BMPs are lower than those of TP and TSS's, therefore the TN loading reduction goal would drive the mathematical model to produce a solution satisfying the TN loading reduction goal and over satisfying the reduction goals for TP and TSS. Analyzing all three nutrients simultaneously would yield little information about the number and types of BMPs and respective cost estimates for specifically meeting TP and TSS loading reduction goals. The cost comparison amongst all three nutrients is provided in this section.

TN loading abatement costs rise in a nearly linear fashion until 23% where the costs then begin to increase at an increasing rate. This is indicative of the model selecting

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[5] Shadow prices for all individual BMPs were not available. Urban nutrient management, mechanical street sweeping, and urban stream restoration have individual shadow prices due to the type of area to which they may be applied. More specifically, no other BMPs can compete for that area because it is specific to just those BMPs. Other BMPs, however, must compete for the same land, thus the shadow price represents the shadow price for the land type. As an example, the shadow price for land type AB2 may be positive and increasing, therefore acres with type AB soils on average slopes of two percent or less have a positive and increasing shadow price.

less and less cost effective BMPs in order to meet the watershed goal. TN loadings abatement became infeasible beyond a 31% TN loading abatement goal. Model infeasibility signifies that the model cannot meet the water quality goal given the constraints imposed on the model. The full cost schedule is displayed by Figure 8. Favored BMPs are infiltration practices, bioretention practices, bioswale, wet swale, and urban stream restoration. Urban stream restoration is the most cost-effective BMP. Urban stream restoration's shadow price ranges from negative $83,093 to negative $1,379,371; in other words, by increasing a single 100+ ft. segment of stream available to be restored, the total cost estimate will decrease by $83,093 at the minimum and $1,379,371 at the maximum[6]. Although there are a finite number of applicable streams to be restored within the watershed, field and stream level assessment may reveal additional streams that may be restored. Thus, a large shadow price may warrant field-level assessment, which could reveal more sites available for restoration. Less cost-effective BMPs such as urban nutrient management and mechanical street sweeping are incorporated when the nutrient loading goal is raised beyond a 23% watershed wide reduction. The pattern in BMP selection is echoed for TP and TSS loading abatement[7]. Table 7 below shows the acres treated by selected BMPs for 5, 10, 15, 20, 25, and 30 percent TN loading reductions.

[6] The full list of shadow prices for each model can be found in Appendix C.
[7] The full list of BMPs for each model can be found in Appendix B.

Figure 8. Mean Annual TN Cost Pathway under Historical Climate

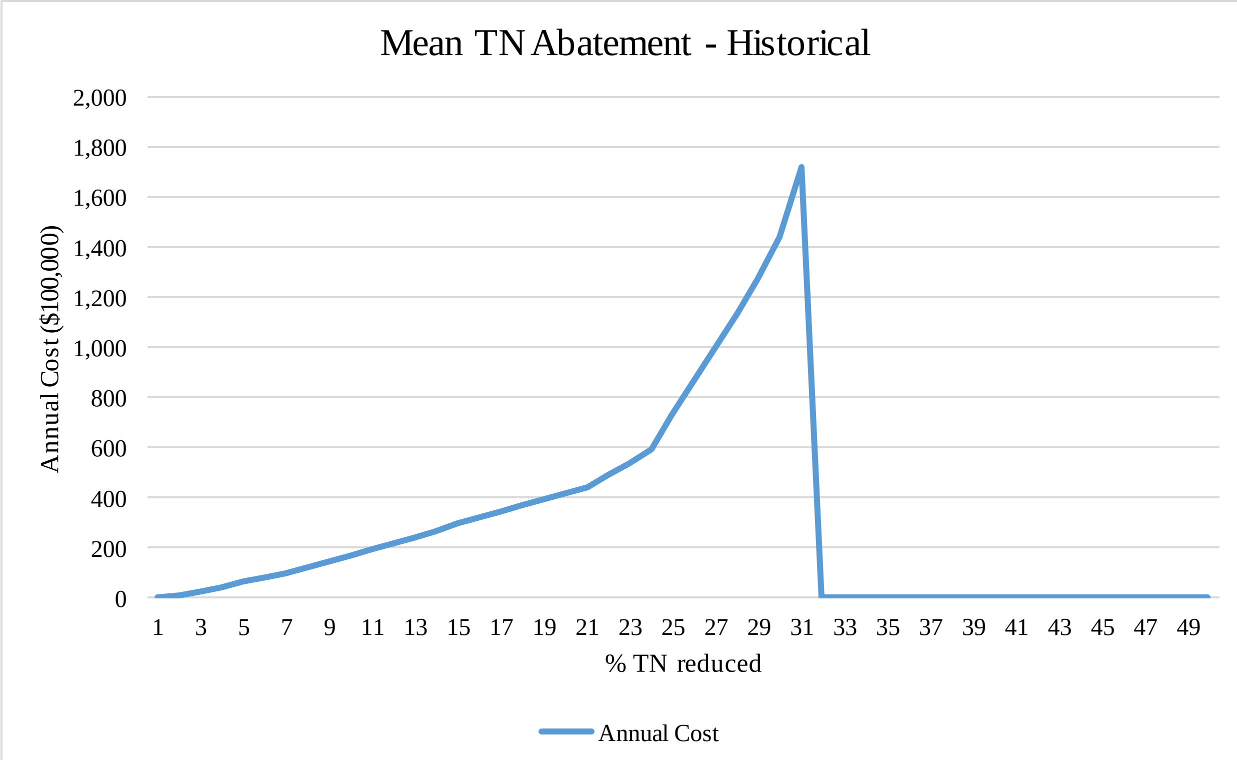


Table 7. Area Treated by BMPs Employed for TN Cost Minimization Model under Historical Climate

%	CAAB	CACD	PP1AB	MI1	BRE1AB	DS1	WS1AB	WP1	MSS	UNM	USR
5						1899	44				29
10				883	639	2831					29
15				3111	639	2831					29
20				5339	639	2831					29
25	219	2511		8623	639			92	42	4243	29
30	219	2511	524	8623	639			92	42	24124	29

See footnote for BMP definitions and units[8]

The first sharp increase in TP loading reduction costs occurs beyond the 13% due to the constraint on urban stream restoration (Figure 9). Due to the scale of the graph and the dramatic increase in costs beyond the 13% reduction, it is difficult to discern the costs of mean TP loading reductions before the 13% reduction. These costs are positive and

[8] BMP units are in acres treated. USR units are in 100+ft stream segments restored. CAAB/CD = urban forest buffer under AB/CD soils, PP1AB = permeable pavement under A/B soils, MI1 = infiltration practices, BRE1AB = bioretention under A/B soils, DS1 = bioswale, WS1AB = vegetated open channels under A/B soils, WP1 = wet ponds and wetlands, MSS = mechanical street sweeping, UNM = urban nutrient management, and USR = urban stream restoration.

rising incrementally. Urban stream restoration is the sole BMP employed for each percent increase in TP loading reductions until the 12% reduction, thus the cost of achieving these early reductions is significantly less expensive than the cost of achieving reductions beyond 12% percent. TP loading abatement costs rise in a nearly linear fashion until 37% where they then begin to follow a similar cost schedule to TN's. The constraints imposed upon the model were less constricting than that of those on the TN model in that the TP abatement became infeasible at a greater pollution reduction target, beyond a 42% TP loading abatement goal. The full cost schedule is displayed by Figure 9. Favored BMPs are infiltration practices, bioretention practices, bioswale, wet swale, and urban stream restoration. Urban stream restoration remains the most cost-efficient BMP. Urban stream restoration's shadow price ranges from negative $636,488 to negative $11,905,775. For reducing TP loading, the urban stream restoration's shadow price is substantially higher than TN loading abatement, which reflects that urban stream restoration is relatively more cost-efficient for removing TP loading than TN loading. Less cost-effective BMPs such as urban nutrient management and mechanical street sweeping are incorporated when the nutrient loading goal is raised beyond a 39% watershed wide reduction. BMPs employed for five percent intervals in TP loading reductions are provided in Table 8.

Figure 9. Mean Annual TP Cost Pathway under Historical Climate

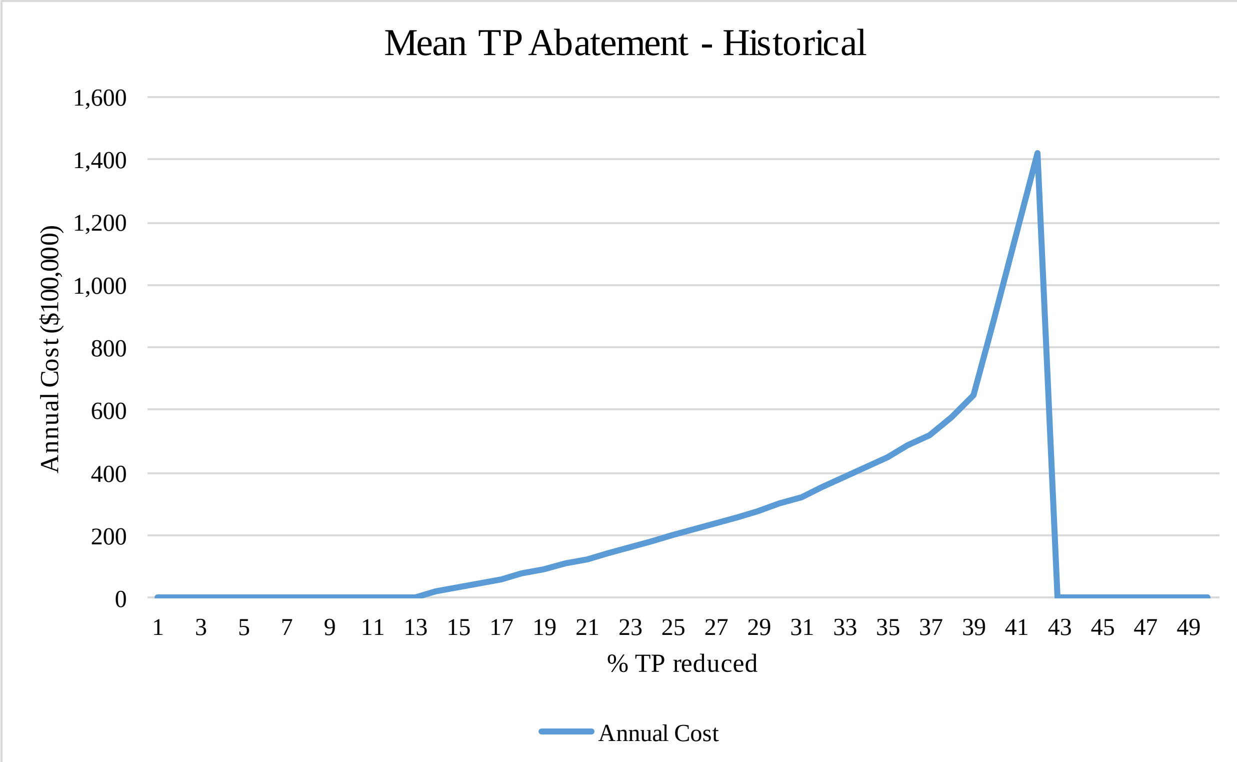


Table 8. Area Treated by BMPs Employed for TP Cost Minimization Model under Historical Climate

%	CAAB	CACD	PP1AB	MI1	BRE1AB	DS1	WS1AB	WP1	MSS	UNM	USR
5											11
10											23
15						974					29
20						2831	44	658			29
25						2831	44	4867			29
30	1826				639	2831		5884			29
35	2140	590		3605	639	2831		2279			29
40	1921	590	1043	5792	639	2831		92	42	6505	29

See footnote for BMP definitions and units[9]

The costs of TSS loading reductions share many of the same characteristics as TP's. However, the slow, incremental rise in cost continues until 20% rather than 13%

[9] BMP units are in acres treated. USR units are in 100+ft stream segments restored. CAAB/CD = urban forest buffer under AB/CD soils, PP1AB = permeable pavement under A/B soils, MI1 = infiltration practices, BRE1AB = bioretention under A/B soils, DS1 = bioswale, WS1AB = vegetated open channels under A/B soils, WP1 = wet ponds and wetlands, MSS = mechanical street sweeping, UNM = urban nutrient management, and USR = urban stream restoration.

(Figure 10). Urban stream restoration abates more TSS loadings than TP loadings, respectively. It is difficult to discern the costs of mean TSS loading reductions before the 20% reduction due to the scale of the graph and the large range of costs across percent TSS loading reductions. The mean TSS loading abatement model does not yield an infeasible solution up to the 50% reduction. Favored BMPs are infiltration practices, bioretention practices, bioswale, wet swale, and urban stream restoration. Urban stream restoration is extremely cost effective with respect to removing TSS loading. Urban stream restoration's shadow price ranges from negative $1,075,714 to negative $7,278,090. Urban stream restoration's shadow price is the highest amongst all nutrients for TSS loadings abatement, although it rises slower than with the previously discussed two nutrients. This observation is a product of BMPs, in general, being more effective at removing TSS loadings than TN and TP loadings. Less cost-effective BMPs such as dry extended detention ponds and mechanical street sweeping are incorporated when the TSS loadings reduction goal is raised beyond a 46% watershed wide reduction. The list of acres and area treated by selected BMPs are displayed in the same fashion as for TP's BMPs in Table 9.

Figure 10. Mean Annual TSS Cost Pathway under Historical Climate

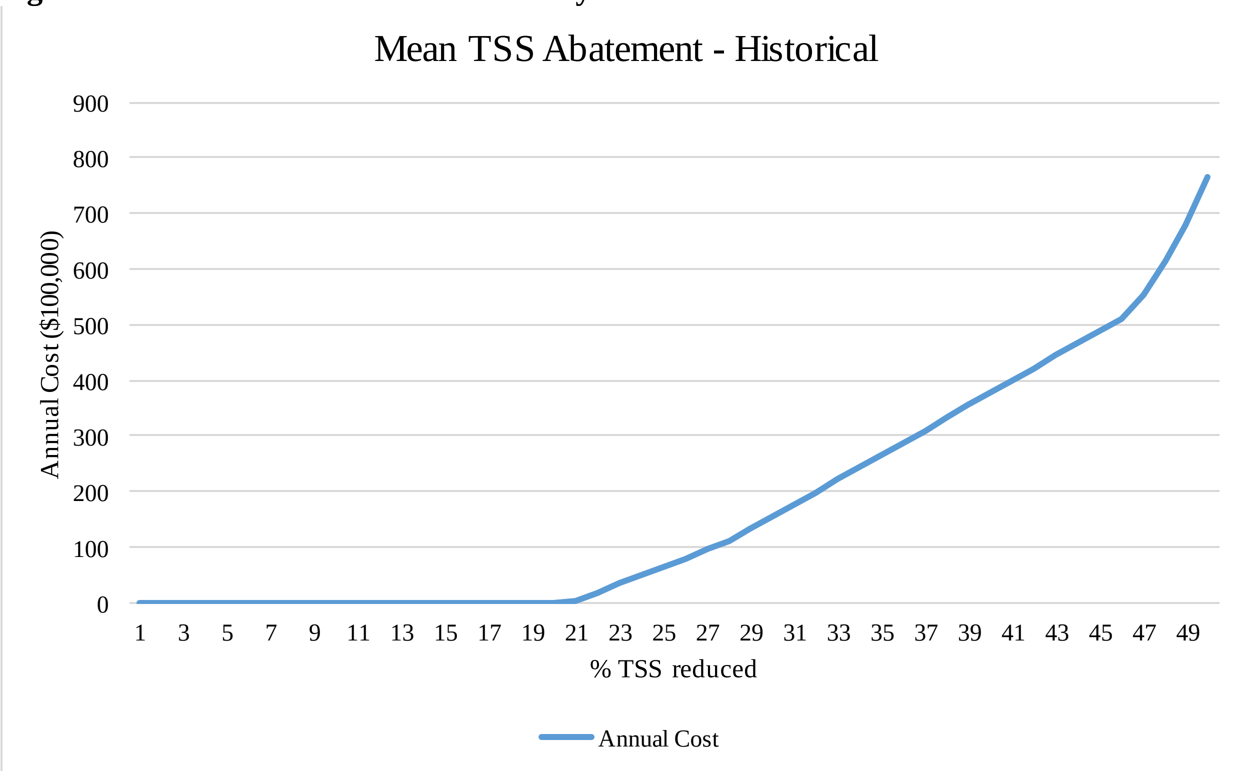


Table 9. Area Treated by BMPs Employed for TSS Cost Minimization Model under Historical Climate

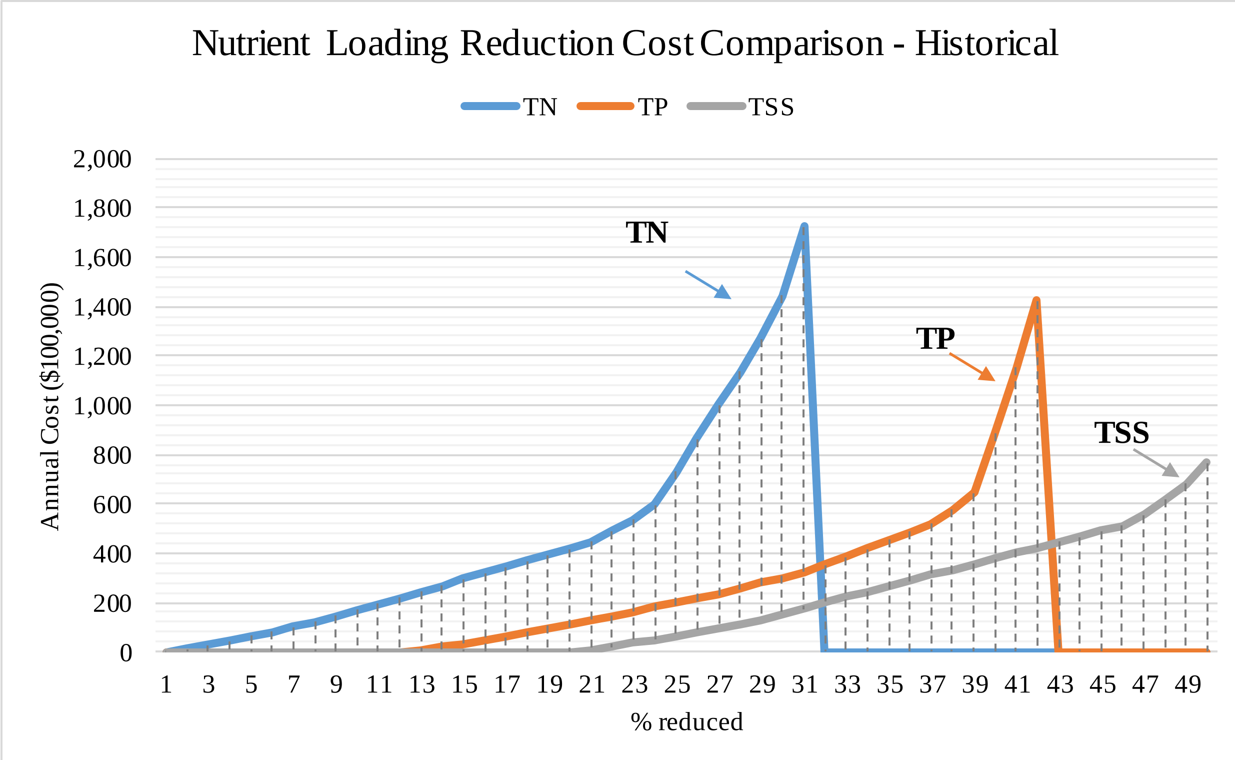
%	CAAB	CACD	PP1AB	PP1CD	MI1	BRE1AB	DS1	WS1AB	WS1CD	WP1	MSS	USR
5												7
10												14
15												21
20												28
25							1723	44	345			29
30					497	595	2831	44	345			29
35					2490	595	2831	44	345			29
40					4484	595	2831	44	345			29
45	219	1084			5792	595	2831	44	345			29
50	219	2166	824	357	8623	639			345	92	42	29

See footnote for BMP definitions and units[10]

As summarized in Figure 11, TN loadings abatement is costlier than other nutrient loading abatement procedures. The second costliest is TP loading reductions. TSS abatement is substantially less expensive than the TN and TP abatement. The cost curves follow similar trends of BMP efficiency with respect to each nutrient. The cost curves of all three abatement solutions are convex where TN and TP cost curves have a steeper slope than TSS abatement.

[10] BMP units are in acres treated. USR units are in 100+ft stream segments restored. CAAB/CD = urban forest buffer under AB/CD soils, PP1AB/CD = permeable pavement under AB/CD soils, MI1 = infiltration practices, BRE1AB = bioretention under A/B soils, DS1 = bioswale, WS1AB/CD = vegetated open channels under AB/CD soils, WP1 = wet ponds and wetlands, MSS = mechanical street sweeping, and USR = urban stream restoration.

Figure 11. Nutrient Loading Abatement Costs under Historical Climate



4.1.2 Cost Minimization under Climate Change

In the same manner as the cost minimization models above, percent nutrient loading reductions were parametrically varied from 1-50% for the CC cost minimization analysis. TN, TP, and TSS were analyzed individually. We conclude this section by drawing comparisons among the cost schedules of all three nutrients.

Beginning with TN loadings abatement, the costs rise in a linear fashion until 22% where the costs begin to sharply increase. TN abatement became infeasible beyond a 30% TN loading abatement goal. The full cost schedule is displayed by Figure 12. The costs associated with TN loadings abatement are slightly higher for altered climate conditions compared to historical climate conditions as the mean interannual loadings for altered climate conditions do not differ from the historical loadings as drastically as we originally predicted. Thus, BMP selection patterns for altered climate conditions closely follow those seen for historical climate. Favored BMPs are infiltration practices, bioretention practices, bioswale, wet swale, and urban stream restoration. Urban stream restoration is the most cost-efficient BMP. Urban stream restoration's shadow price ranges from negative $77,002 to negative $1,282,915, which is slightly less than those seen for historical climate conditions. Less cost-effective BMPs such as urban nutrient management and mechanical street sweeping are incorporated when the nutrient loading goal is raised beyond a 22% watershed wide reduction. Table 10 shows the selected BMPs for 5, 10, 15, 20, 25, and 30 percent TN loading reductions.

Figure 12. Mean Annual TN Cost Pathway under Climate Change

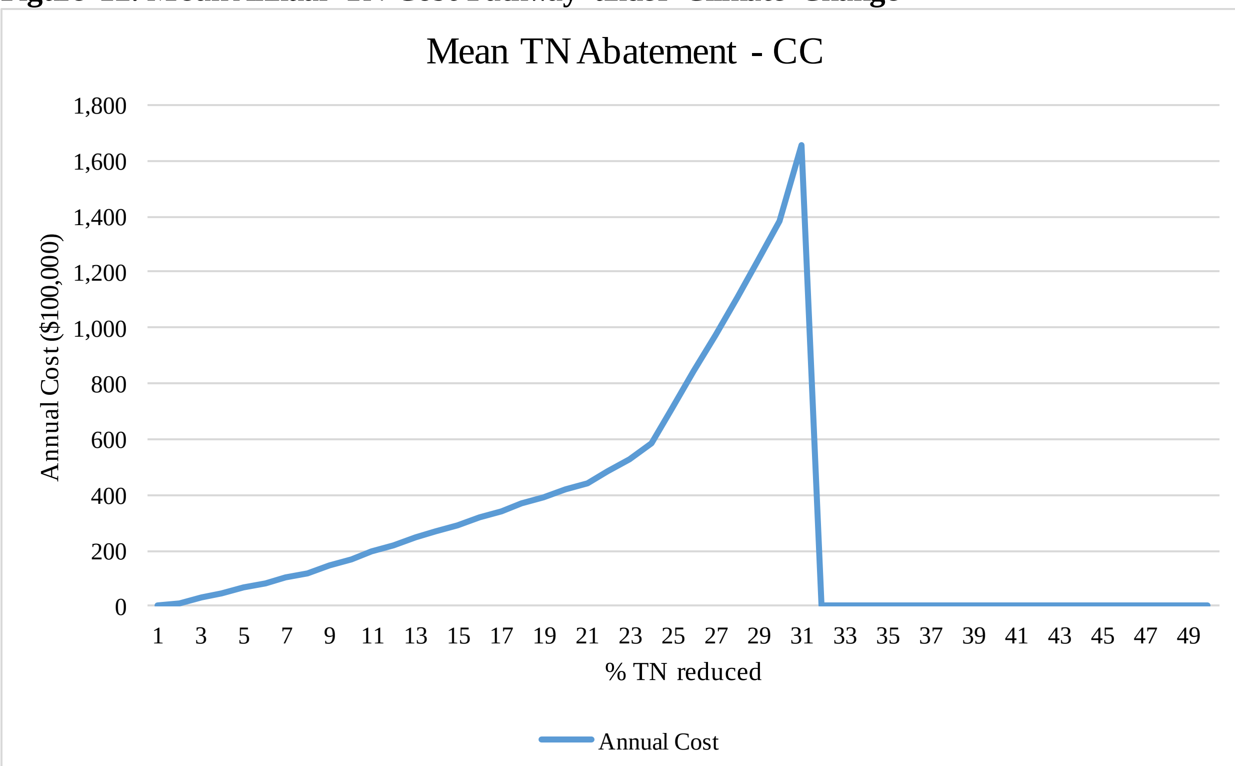


Table 10. Area Treated by BMPs Employed for TN Cost Minimization Model under Climate Change

%	CAAB	CACD	PP1AB	MI	BRE1AB	DS1	WS1AB	WP1	MSS	UNM	USR
5						1924	44				29
10					639	2831					29
15					639	2831					29
20					639	2831					29
25	219	1921		2831	639			92	42	3546	29
30	219	1921	110	2831	639			92	42	24124	29

See footnote for BMP definitions and units[11]

Similar to the cost schedule seen for historical climate, TP loading abatement costs rise slowly until the 12% loading reduction is initiated (Figure 13). Beginning at the 12% loading reduction, costs sharply increase, which, in addition to the graph's scale, made it difficult to discern the costs prior to the 12% loading reductions. TP abatement became infeasible beyond a 41% TP loading abatement goal, a one percent difference from the same model drawing from historical nutrient loading data. The costs associated with TP loading abatement are substantially higher for altered climate conditions opposed to historical climate due to the large relative increase in mean interannual TP loading. BMP selection patterns for altered climate conditions closely follow those for historical climate conditions. Favored BMPs are infiltration practices, bioretention practices, bioswale, wet swale, and urban stream restoration. Urban stream restoration remains the most cost-efficient BMP. Like that of the TN loading abatement model, urban stream restoration's shadow price decreased slightly ranging from negative $585,065 to negative $10,949,960. Less cost-effective BMPs such as urban nutrient management and mechanical street sweeping are incorporated when the nutrient loading goal is raised beyond a 39% watershed wide reduction. BMPs for five percent intervals in TP loading reductions are displayed by Table 11 below.

[11] BMP units are in acres treated. USR units are in 100+ft stream segments restored. CAAB/CD = urban forest buffer under AB/CD soils, PP1AB/CD = permeable pavement under AB/CD soils, MI1 = infiltration practices, BRE1AB = bioretention under A/B soils, DS1 = bioswale, WS1AB = vegetated open channels under A/B soils, WP1 = wet ponds and wetlands, MSS = mechanical street sweeping, UNM = urban nutrient management, and USR = urban stream restoration.

Figure 13. Mean Annual TP Cost Pathway under Climate Change

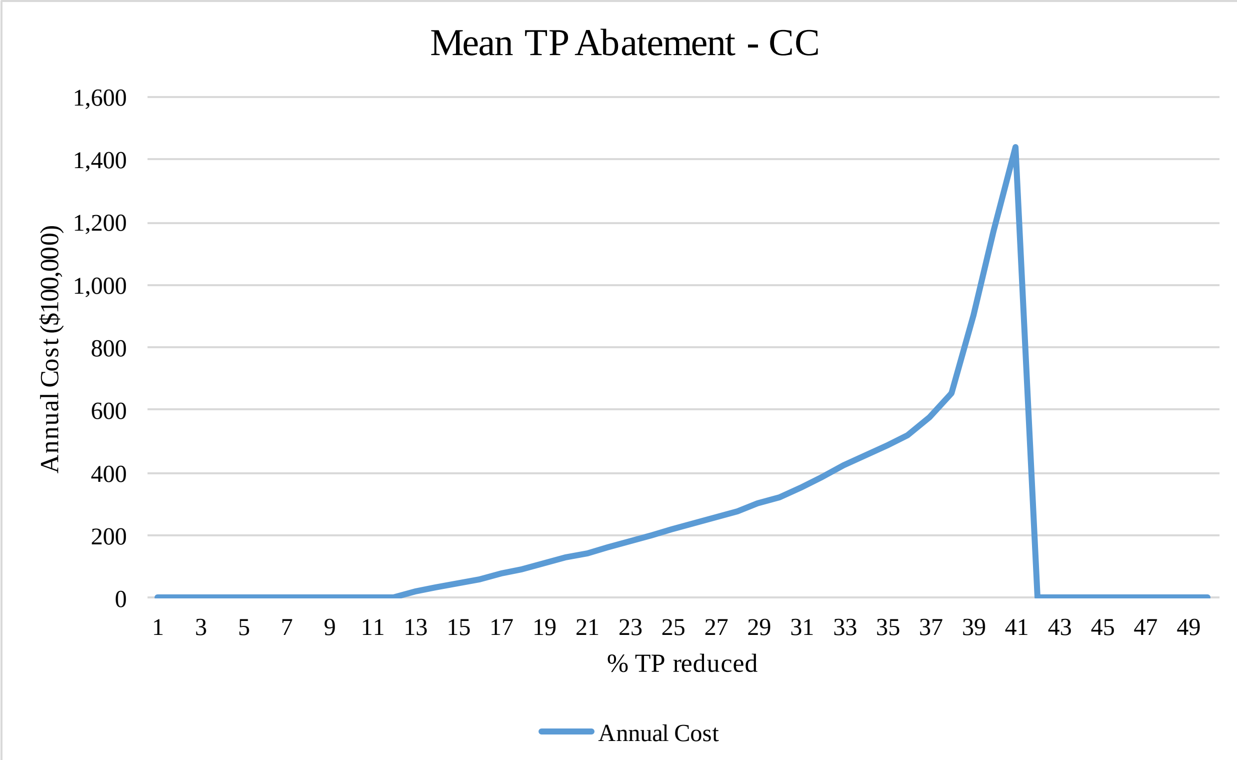


Table 11. Area Treated by BMPs Employed for TP Cost Minimization Model under Climate Change

%	CAAB	CACD	PP1AB	BRE1AB	DS1	WS1AB	WP1	MSS	UNM	USR
5										12
10										25
15					1434					29
20					2831	44	92			29
25					2831	44	92			29
30	219	2411		639	2831		92			29
35	219	2411		639	2831		92			29
40		2411	1043	639	2831		92	42	15528	29

See footnote for BMP definitions and units[12]

TSS loading abatement costs rise slowly until 21% where they begin to sharply increase due to the constraint on urban stream restoration (Figure 14). Urban stream

[12] BMP units are in acres treated. USR units are in 100+ft stream segments restored. CAAB/CD = urban forest buffer under AB/CD soils, PP1AB/CD = permeable pavement under AB/CD soils, MI1 = infiltration practices, BRE1AB = bioretention under A/B soils, DS1 = bioswale, WS1AB = vegetated open channels under A/B soils, WP1 = wet ponds and wetlands, MSS = mechanical street sweeping, UNM = urban nutrient management, and USR = urban stream restoration.

restoration is the sole BMP employed until the 19% loading reduction is mandated, which is the driving force behind the extremely low calculated costs prior to 20% loading reduction. Echoing the model using historical TSS loading data, the mean TSS loadings abatement model yields feasible solutions up to the 50% loadings reduction goal. Favored BMPs are infiltration practices, bioretention practices, bioswale, wet swale, and urban stream restoration. Urban stream restoration's shadow price ranges from negative $999,305 to negative $6,762,868. Like that of historical climate, the shadow price for urban stream restoration starts out highest among all three nutrients, yet rises slower than shadow prices for TN and TP, respectively. Less cost-effective BMPs such as dry extended detention ponds and mechanical street sweeping are incorporated when the nutrient loadings goal is raised beyond a 45% watershed wide reduction. The list of selected BMPs are displayed in the same fashion as TP's BMPs, which are displayed by Table 12.

Figure 14. Mean TSS Cost Pathway under Climate Change

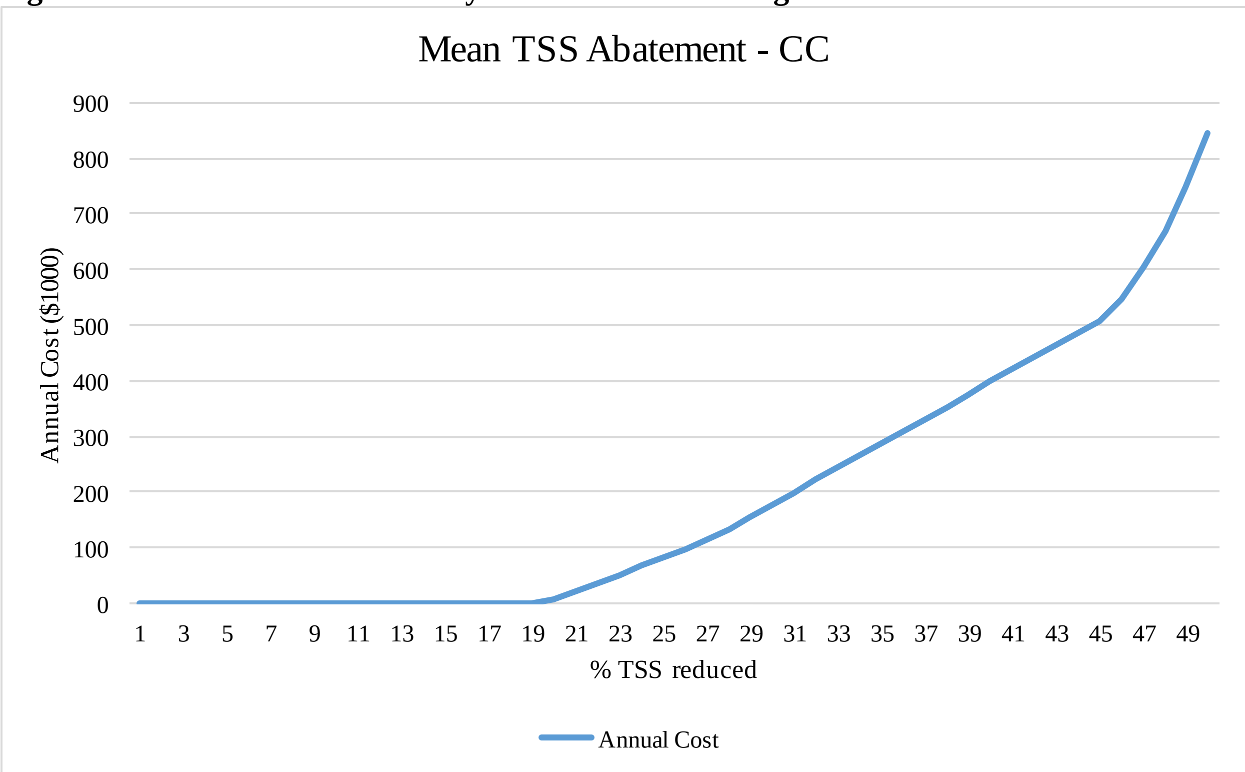


Table 12. Area Treated by BMPs Employed for TSS Cost Minimization Model under Climate Change

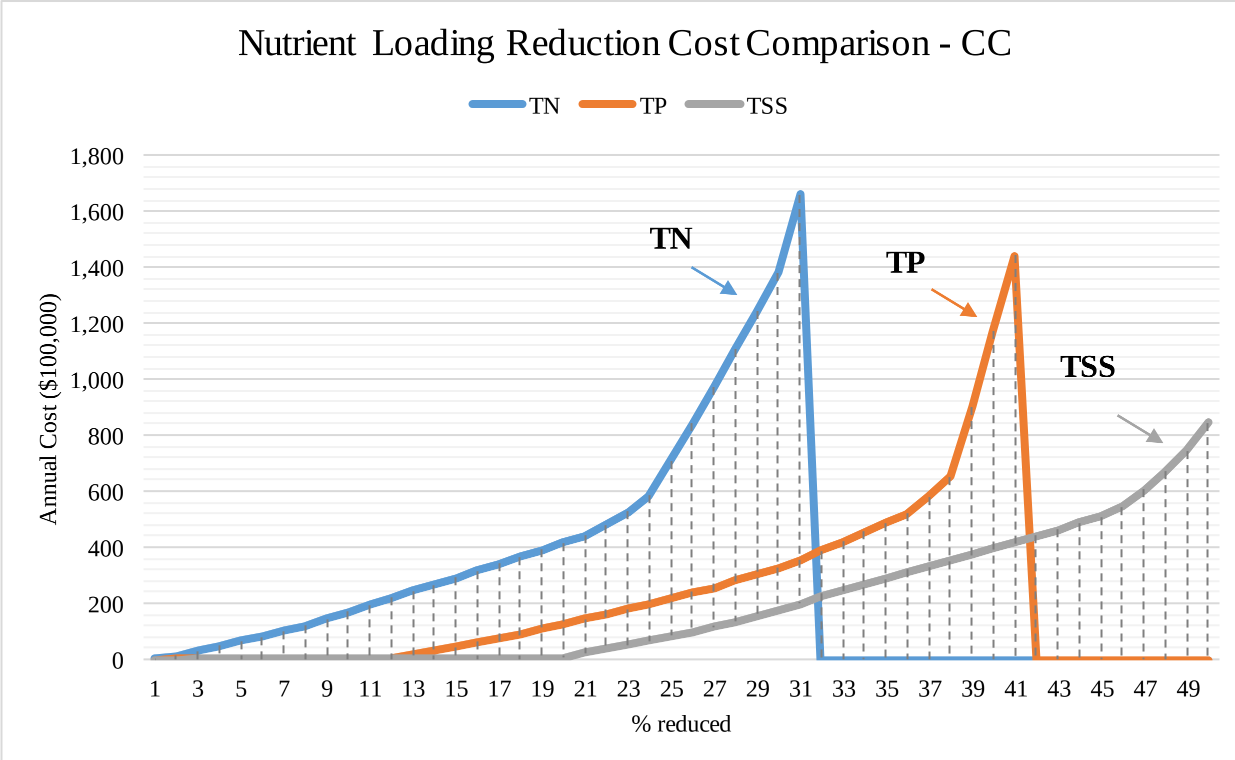
%	CAAB	CACD	PP1AB	PP1CD	MI1	BRE1AB	DS1	WS1AB	WS1CD	WP1	MSS	USR
5												7
10												15
15												22
20								44	227			29
25							2262	44	345			29
30					925	595	2831	44	345			29
35					2892	595	2831	44	345			29
40					4859	595	2831	44	345			29
45	219	1746			5792	595	2831	44	345			29
50	219	2166	824	913	8623	639			345	92	42	29

See footnote for BMP definitions and units[13]

Much like we see for historical climate conditions, TN loadings abatement is costlier than other nutrient loading abatement procedures. The second costliest is TP loadings abatement. TSS abatement is still substantially less expensive than TN and TP loadings abatement. The cost curves of all three abatement solutions are convex where TN and TP cost curves have a steeper slope than TSS abatement. The full cost schedule comparison is illustrated below by Figure 15.

[13] BMP units are in acres treated. USR units are in 100+ft stream segments restored. CAAB/CD = urban forest buffer under AB/CD soils, PP1AB/CD = permeable pavement under AB/CD soils, MI1 = infiltration practices, BRE1AB = bioretention under A/B soils, DS1 = bioswale, WS1AB/CD = vegetated open channels under AB/CD soils, WP1 = wet ponds and wetlands, MSS = mechanical street sweeping, and USR = urban stream restoration.

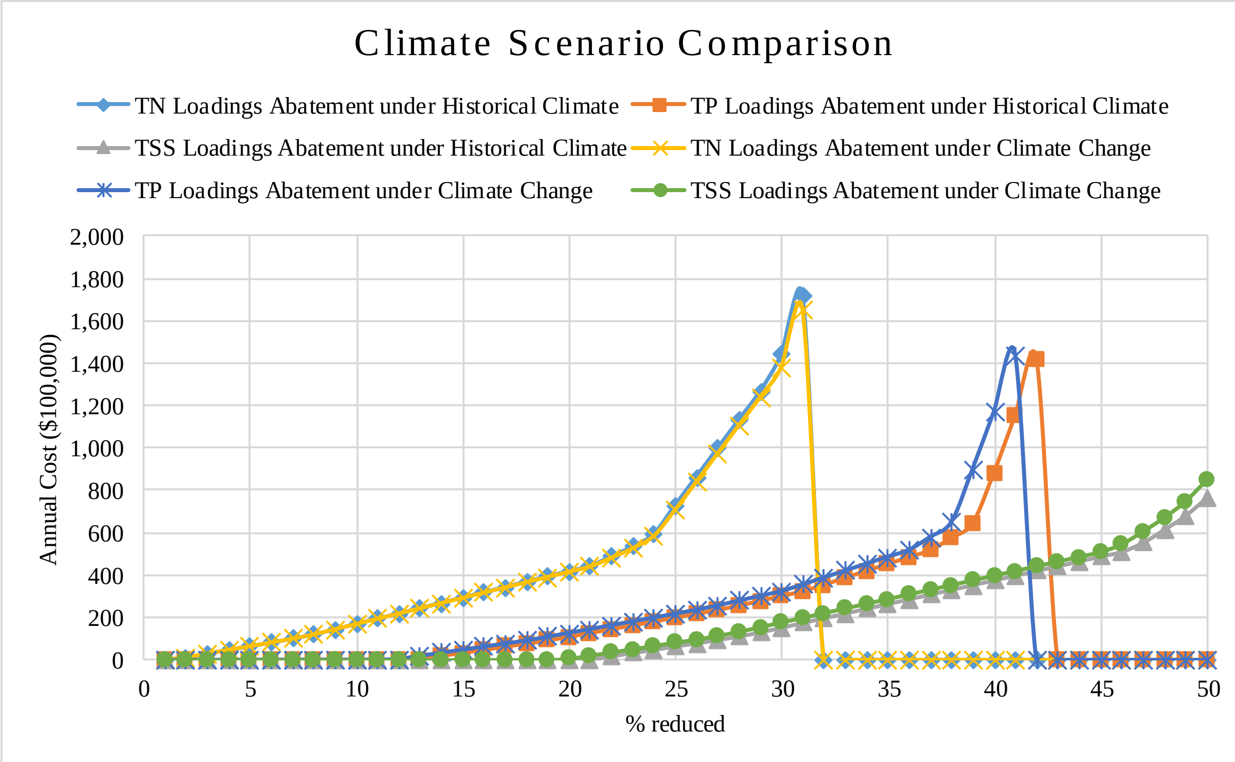
Figure 15. Nutrient Loading Abatement Costs under Climate Change



4.1.3 Cost Minimization Cost Comparison

Holding all else equal, controlling for mean interannual nutrient loadings for altered climate conditions is more expensive than those for current climate conditions (Figure 16). At the lower bound, TN loading abatement results in an average increase of 0.56% in cost. On the upper bound, TP loading abatement programs result in an average increase of 31.75%. Slightly behind TP, TSS mean loading abatement costs increase, on average, by 31.06% for CC. The large increases in TP and TSS nutrient loading abatement cost estimates can be attributed to the respective larger increases in interannual mean nutrient loadings simulated for CC. However, it is important to note that controlling for mean TN loadings remains significantly more expensive than the aforementioned two nutrients for both climate scenarios. Accordingly, if policy makers implemented policies controlling for TN, TP and TSS would be reduced at a greater respective rate. We find similar results with respect to the Safety First programming analysis, which is presented and discussed in section 4.2.

Figure 16. Mean Loading Reduction Cost Comparison among Climates



4.2 Safety First Programming Results

The following tables and charts present the findings for abating nutrient loadings for current climate conditions and for altered climate conditions utilizing the Safety First programming (SFP) framework. For the TN analysis, environmental goals were derived by reducing the mean interannual TN loading by 2, 5, 10, 15, 17, 20, and 22 percent. TP and TSS environmental goals were pushed further where the environmental goals were generated from 2, 5, 10, 15, 17, 20, 22, 28, 35, and 40 percent loading reductions. We analyzed each of the aforesaid environmental goals at three probabilities of success: 0.5, 0.75, and 0.95. In the same format as above, the cost schedules of meeting environmental goals under varying probabilities were graphed in the figures below. However, model infeasibility is graphed differently than the previous Cost Minimization model's graphs due to the decreased number of solutions from which to generate the Safety First programming graphs. Selected BMPs were summarized in tables. We briefly examined the relationship of meeting environmental goals under varying probabilities of success for the three nutrients of interest for both climate scenarios. Lastly, we compared the cost schedules calculated for the historical baseline climate to those calculated for altered climate conditions in order to determine the effects of CC on water quality policy costs, *ceteris paribus*.

4.2.1 Safety First Programming under Historical Climate

Beginning with TN loadings abatement, the cost schedules for TN abatement goals under probabilities of success 0.5 and 0.75 increase at an increasing rate, as illustrated by Figure 17. Both cost schedules continue to rise where they each became infeasible at a 20 and 15% loadings reduction, respectively. Meeting any environmental goal at the 0.95 probability of success is infeasible. Urban stream restoration and LID practices remain the favored BMPs. Less effective BMPs are quickly incorporated as the environmental goal increases, although the probability of success drives the incorporation of all applicable BMPs at a faster rate than the environmental goals. Urban stream restoration's shadow price was lower for all environmental goals under 0.75 probability of success than the shadow price under the 0.5 probability of success As Table 13 shows[14], the number of acres treated by BMPs selected for each environmental goal is higher under the higher probability of success.

[14] The following series of tables showing BMPs employed utilizing the SFP model display the amount of BMPs employed for a specific percent loadings reductions (%) under a specific probability of success (***Prob. B***). This format is continued for all SFP analysis.

Figure 17. TN Variable Loadings Abatement Cost Pathway under Historical Climate

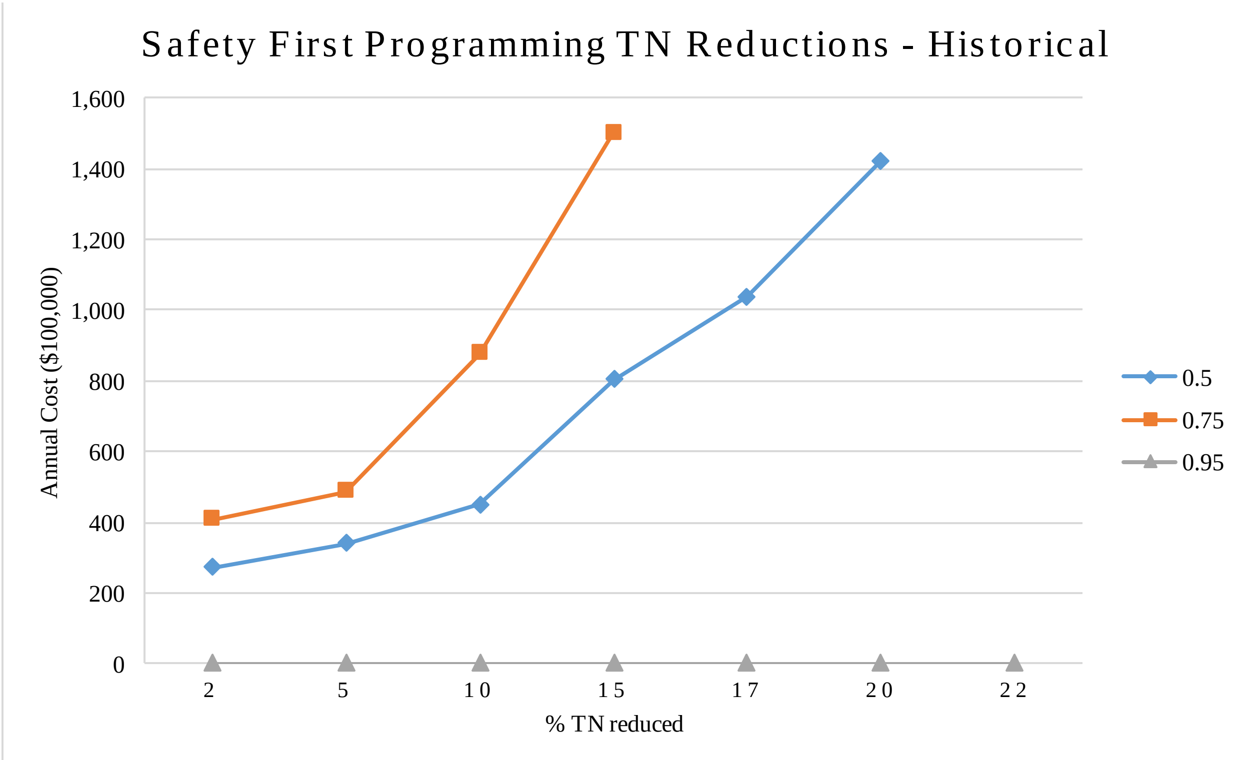


Table 13. Area treated by BMPs Employed for TN Variable Loadings Abatement under Historical Climate

Prob. B	%	CAAB	CACD	PP1AB	MI1	BRE1AB	DS1	WP1	MSS	UNM	USR	Untreated
0.5	2				2723	639	2831				29	31659
	5				3896	639	2831				29	30486
	10	125			5792	639	2831	92			29	28373
	15	219	2511		8623	639		92	42	6489	29	19237
	17	219	2511		8623	639		92	42	13874	29	11852
	20	219	2511	372	8623	639		92	42	24124	29	1230
0.75	2				5122	639	2831				29	29260
	5	219	1170		5792	639	2831	92			29	27109
	10	219	2511		8623	639		92	42	8860	29	16866
	15	219	2511	824	8623	639		92	42	24124	29	676

See footnote for BMP definitions and units[15]

[15]BMP units are in acres treated. USR units are in 100+ft stream segments restored. CAAB/CD = urban forest buffer under AB/CD soils, PP1AB = permeable pavement under A/B soils, MI1 = infiltration practices, BRE1AB = bioretention under A/B soils, DS1 = bioswale, WP1 = wet ponds and wetlands, MSS = mechanical street sweeping, UNM = urban nutrient management, USR = urban stream restoration, and Untreated = untreated acreage.

The cost schedules for TP abatement goals under probabilities of success 0.5 and 0.75 increase at a slower rate than TN abatement goals, as illustrated by Figure 18. Both TP abatement cost schedules continue to rise where they each became infeasible at a 28 and 22% loading reduction, respectively. Meeting the environmental goal at the 0.95 probability of success renders an infeasible solution beyond a 10% loading reduction. The relationship with the costs schedules is interesting in that under the probabilities of success 0.5 and 0.75, the costs rise rather slowly, which is not indicative of impending model infeasibility. The costs associated with meeting environmental goals under the 0.95 probability of success displays a more intuitive relationship prior to model infeasibility. Costs increase substantially before model infeasibility whereas the two other cost schedules do not. Additionally, costs under the 0.95 probability of success are much higher than the two other cost schedules, which is a product of the model meeting the percent reductions objective for the extreme weather years. Urban stream restoration and LID practices remain the favored BMPs. The list of BMPs using selected environmental goals can be found in Table 14 below. As expected, the shadow price for urban stream restoration is substantially higher than other land constraints. Shadow prices for BMPs that can handle versatile Hydric Soil Groupings such as bioswale and wet ponds and wetlands quickly follow those of urban stream restoration.

Figure 18. TP Variable Loadings Abatement Cost Pathway under Historical Climate

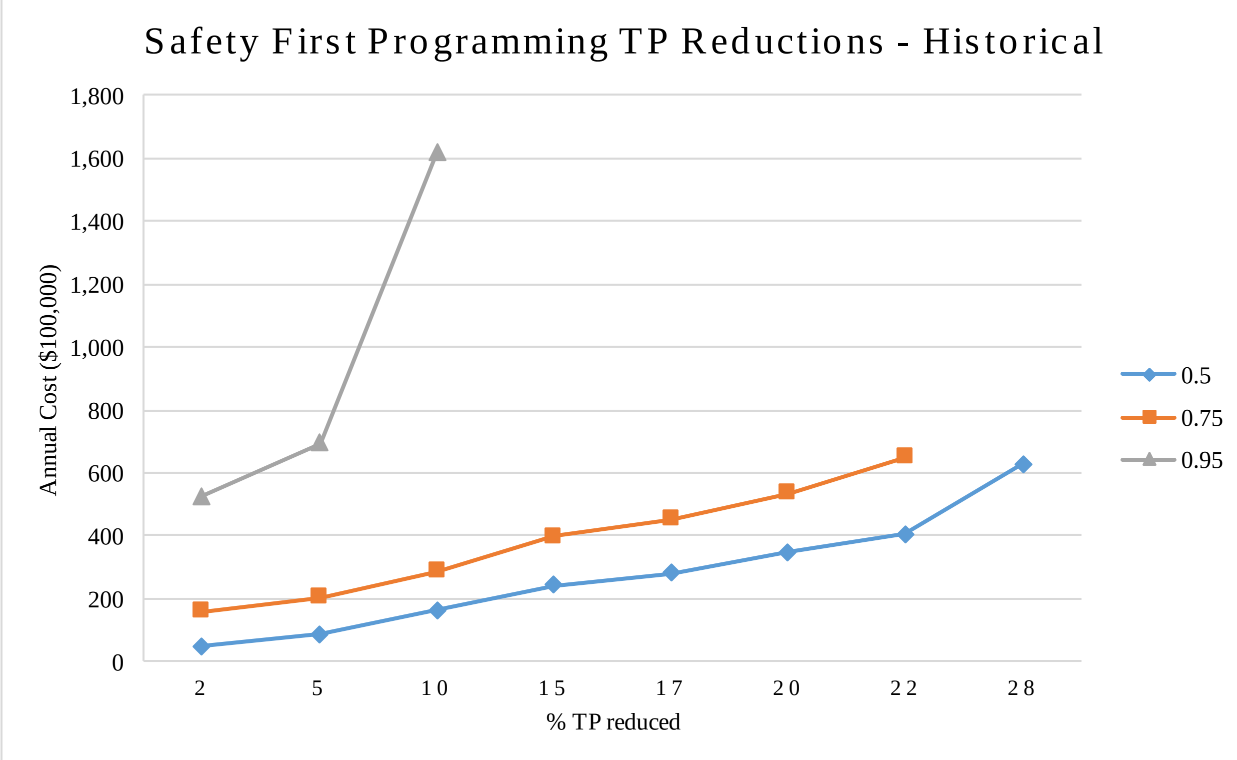


Table 14. Area treated by BMPs Employed for TP Variable Loadings Abatement under Historical Climate

Prob. B	%	CAAB	CACD	PP1AB	PP1CD	MI1	BRE1AB	DS1	WS1AB	WP1	MSS	UNM	USR	Untreated
0.5	5							2604					29	35248
	10							2831	44	3200			29	31777
	15						523	2831	44	5884			29	28569
	20	219	2511			524	639	2831		5359			29	25768
	28	219	2511	671		5792	639	2831		92			29	25097
0.75	5							2831	44	5019			29	29910
	10	219	1073				639	2831		5792			29	27206
	15	219	2511			2045	639	2831		3746			29	25768
	20	219	2511	48		5792	639	2831		92			29	25711
0.95	5		2511	1043		5792	639	2831		92	42.1	572	29	24330
	10		2511	1043	1260.5	5792	639	2831		92	42.1	23641	29	

See footnote for BMP definitions and units[16]

Following the trend displayed in the cost minimization models, TSS loading reductions are substantially less costly than reducing TN or TP loadings. The cost schedules for TSS abatement goals under 0.5 and 0.75 probabilities of success rise similarly to TP's loading reduction costs. Illustrated by Figure 19, we see that the forcing environmental goals of 22% loading reductions or less display approximately linear cost schedules, which then turn into costs schedules resembling exponential relationships. The cost schedule for meeting TSS loading reductions under the 0.95 probability of success is significantly higher than the two other probabilities. This relationship is a result of the sparse, yet extreme weather years that produce large amounts of TSS loadings, which reveal themselves when the model is forced to reach its goal at higher levels of success. In that BMP selection and shadow prices reflect previous trends, thus there is no need for further discussion. A list of selected BMPs can be found in Table 15.

[16] BMP units are in acres treated. USR units are in 100+ft stream segments restored. CAAB/CD = urban forest buffer under AB/CD soils, PP1AB/CD = permeable pavement under AB/CD soils, MI1 = infiltration practices, BRE1AB = bioretention under A/B soils, DS1 = bioswale, WS1AB = vegetated open channels under AB soils, WP1 = wet ponds and wetlands, MSS = mechanical street sweeping, UNM = urban nutrient management, USR = urban stream restoration, and Untreated = untreated acreage.

Figure 19. TSS Variable Loadings Abatement Cost Pathway under Historical Climate

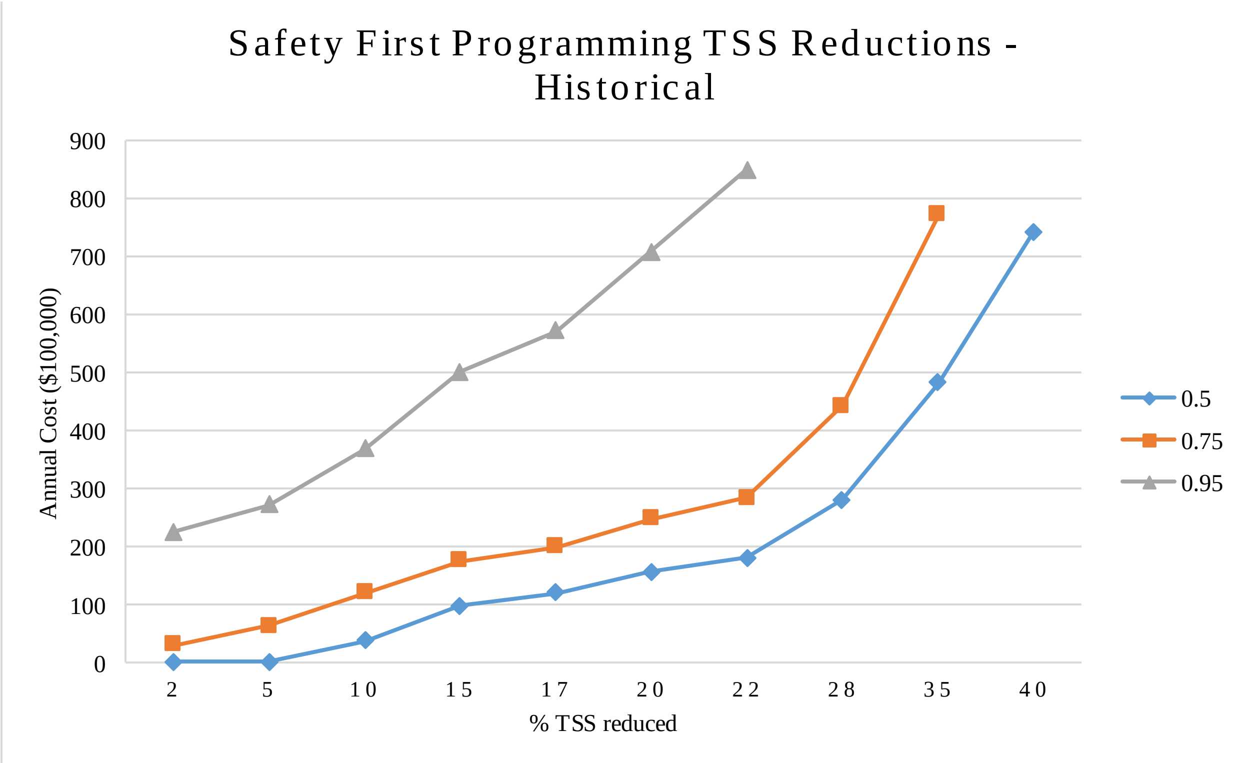


Table 15. Area Treated by BMPs Employed for TSS Variable Loadings Abatement under Historical Climate

Prob. B	%	CAAB	CACD	PP1AB	PP1CD	MI1	BRE1AB	DS1	WS1AB	WS1CD	WP1	MSS	USR	Untreated
	5												26	37855
	10								44		1665		29	36143
	15								44		4434		29	33374
0.5	20								44		7203		29	30606
	28	219	734				595	2831	44	345	5884		29	27200
	35	219	2166			4587	595	2831	44	345	1297	42	29	25726
	40	219	2166	824	192	8623	639			345	92	42	29	24710
	5								44		2898		29	34910
	10								44		5494		29	32314
0.75	15								44		8090		29	29718
	20						595	2373	44	345	6342		29	28153
	28	219	2166			3440	595	2831	44	345	2444	42	29	25726
	35	219	2166	824	407	8623	639			345	92	42	29	24495
	5	219	417				595	2831	44	345	5884		29	27517
0.95	10	219	1007			1313	595	2831	44	345	4571	42	29	25726
	15	219	1007			5136	595	2831	44	345	748	42	29	25726
	20	219	1007	794		8623	639			345	92	42	29	24932

See footnote for BMP definitions and units[17]

4.2.2 Safety First Programming under Climate Change

As in the previous section, we began the Safety First programming analysis with analyzing TN loadings abatement (Figure 20). The cost schedules of meeting the watershed goals under the probabilities of success are higher than the same environmental goals for historical climate conditions. Although, the CC model produces feasible solutions under 0.95 probability of success ranging from zero to five percent loading reductions, whereas no loading reduction goals under the same probability of success were met for historical climate conditions. As discussed in Chapter 3, this may be due to the coefficient of variation being smaller for the CC data than the historical data and the observed positive linear trend in nutrient loading within the historical data set. Urban stream restoration and LID practices remain the favored BMPs. Shadow prices

[17]BMP units are in acres treated. USR units are in 100+ft stream segments restored. CAAB/CD = urban forest buffer under AB/CD soils, PP1AB/CD = permeable pavement under AB/CD soils, MI1 = infiltration practices, BRE1AB = bioretention under A/B soils, DS1 = bioswale, WS1AB/CD = vegetated open channels under AB/CD soils, WP1 = wet ponds and wetlands, MSS = mechanical street sweeping, USR = urban stream restoration, and Untreated = untreated acreage.

follow the same trend that display with respect to historical climate conditions. As Table 16 shows, the number of BMPs selected for each environmental goal is significantly higher under the higher probabilities of success.

Figure 20. TN Variable Loadings Abatement Cost Pathway under Climate Change

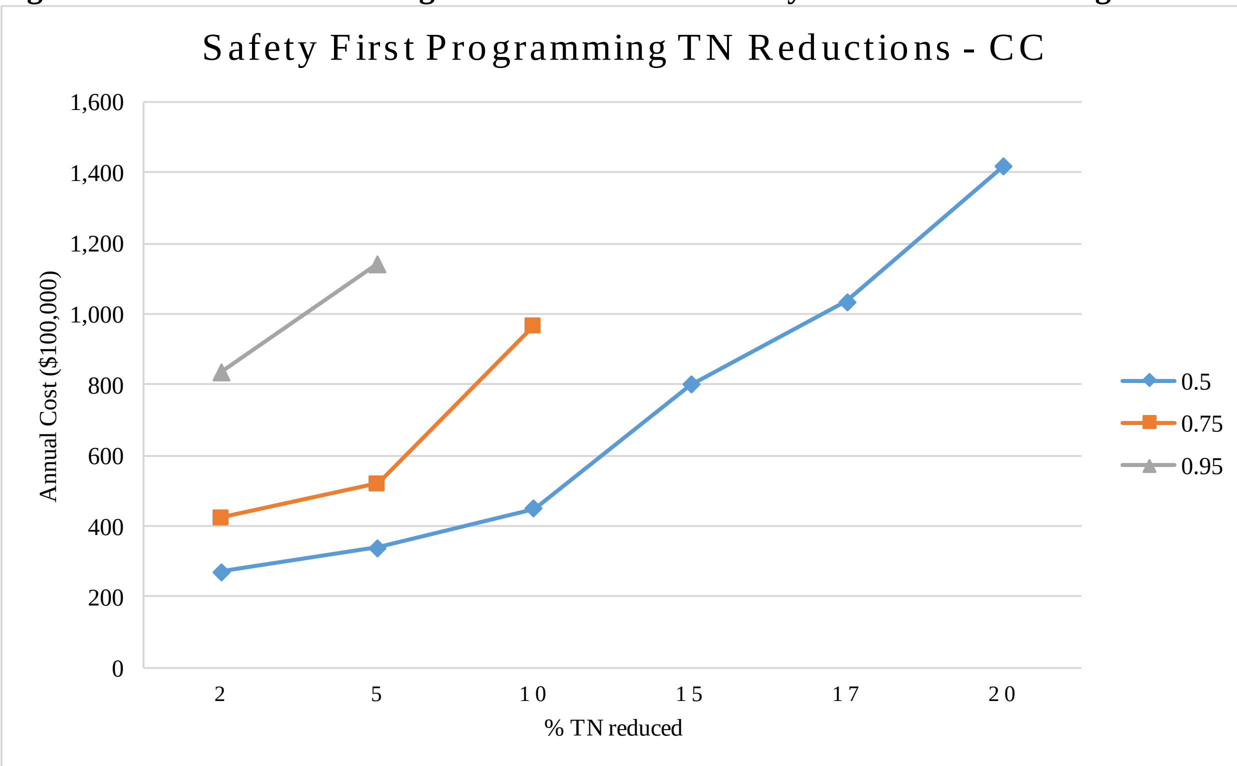


Table 16. Area Treated by BMPs Employed for TN Variable Loadings Abatement under Climate Change

Prob. B	%	CAAB	CACD	PP1AB	MI1	BRE1AB	DS1	WP1	MSS	UNM	USR	Untreated
0.5	2				2709	639	2831				29	31674
	5				3883	639	2831				29	30499
	10	74			5792	639	2831	92	42		29	28382
	15	219	2511		8623	639		92	42	6392	29	19334
	17	219	2511		8623	639		92	42	13787	29	11939
	20	219	2511	340	8623	639		92	42	24124	29	1262
0.75	2				5442	639	2831				29	28940
	5	219	2212		5792	639	2831	92	42		29	26025
	10	219	2511		8623	639		92	42	11639	29	14087
0.95	2	219	2511		8623	639		92	42	7528	29	18198
	5	219	2511		8623	639		92	42	17134	29	8592

See footnote for BMP definitions[18]

The cost schedules for TP loadings abatement for altered climate conditions under CC display some of the previously noted trends observed within the Safety First programming TN loading abatement cost schedules. The Safety First programming model renders infeasibility less often, albeit costs are, on average, higher for each goal under each probability of success as displayed by Figure 21. At the .95 probability of success, the cost schedule rises incrementally until a ten percent TP loading reduction is forced in which the cost schedule then increases at an increasing rate. This relationship indicates that beyond a ten percent reduction, the variability in TP loadings for altered climate conditions is driving the cost schedule. Similar trends are found under 0.75 and 0.5 probabilities of success for 20 and 22 percent TP loading reductions, respectively. Like that of the models for historical climate conditions, urban stream restoration remains the most cost effective BMP. Continuing the same selection patterns of other models, modern LID practices such as bioswale, bioretention, wet ponds, and vegetated open channels are quickly incorporated as the constraint on urban stream restoration became binding. A selected list of BMPs is presented below in Table 17.

[18] BMP units are in acres treated. USR units are in 100+ft stream segments restored. CAAB/CD = urban forest buffer under AB/CD soils, PP1AB = permeable pavement under AB soils, MI1 = infiltration practices, BRE1AB = bioretention under A/B soils, DS1 = bioswale, WP1 = wet ponds and wetlands, MSS = mechanical street sweeping, UNM = urban nutrient management, USR = urban stream restoration, and Untreated = untreated acreage.

Figure 21. TP Variable Loadings Abatement Cost Pathway under Climate Change

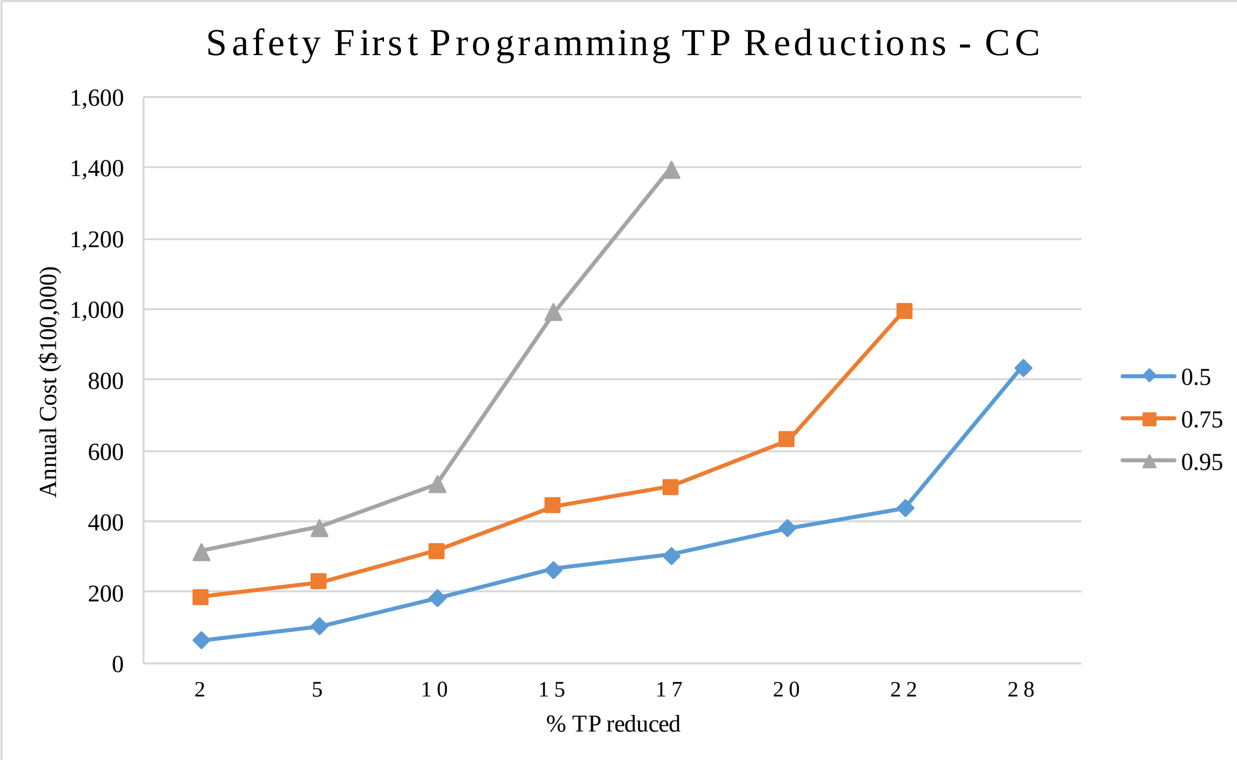


Table 17. Area Treated by BMPs Employed for TP Variable Loadings Abatement under Climate Change

Prob. B	%	CAAB	CACD	PP1AB	MI1	BRE1AB	DS1	WS1AB	WP1	MSS	UNM	USR	Untreated
0.5	5						2831	44	505			29	34472
	10						2831	44	4167			29	30810
	15	219	486			639	2831		5884			29	27793
	20	219	2511		1589	639	2831		4296			29	25768
	28		2511	1043	5792	639	2831		92	42	5089	29	19813
0.75	5					233	2831	44	5884			29	28860
	10	219	2181			639	2831		5884			29	26098
	15	219	2511		3401	639	2831		2483			29	25768
	17	219	2511		4926	639	2831		958			29	25768
	20	219	2511	711	5792	639	2831		92			29	25057
0.95	5	219	2511		1652	639	2831		4232			29	25768
	10	219	2511		5190	639	2831		694			29	25768
	15		2511	1043	5792	639	2831		92	42	9962	29	14940

See footnote for BMP definitions[19]

The resulting cost schedules for TSS loading abatement for altered climate conditions are relatively smoother than the two other analyzed nutrients for altered climate conditions. Like that of TP and TN, TSS loadings abatement for altered climate conditions shows less model infeasibility, especially under the environmental goals set at a 0.95 probability of success. The cost schedules for all three probabilistic scenarios are displayed by Figure 22. These cost schedules support the idea that the variability of nutrient loadings surrounding the mean for altered climate conditions is tighter than those for historical climate conditions. As discussed in Chapter 3, this may be due to the trend in the historical data in addition to the CC data having a slightly smaller coefficient of variation. The pattern of BMP selection closely follows those of the previous Safety First programming models that analyze the other two nutrients of interest, where urban stream restoration model is the first BMP selected and modern Low Impact Development quickly follows – bioswale, wet ponds and wetlands, and vegetated open channels, being examples. The selected list of BMPs is shown below in Table 18.

[19] BMP units are in acres treated. USR units are in 100+ft stream segments restored. CAAB/CD = urban forest buffer under AB/CD soils, PP1AB = permeable pavement under AB soils, MI1 = infiltration practices, BRE1AB = bioretention under A/B soils, DS1 = bioswale, WS1AB = vegetated open channels under A/B soils, WP1 = wet ponds and wetlands, MSS = mechanical street sweeping, UNM = urban nutrient management, USR = urban stream restoration, and Untreated = untreated acreage.

Figure 22. TSS Variable Loadings Abatement Cost Pathway under Climate Change

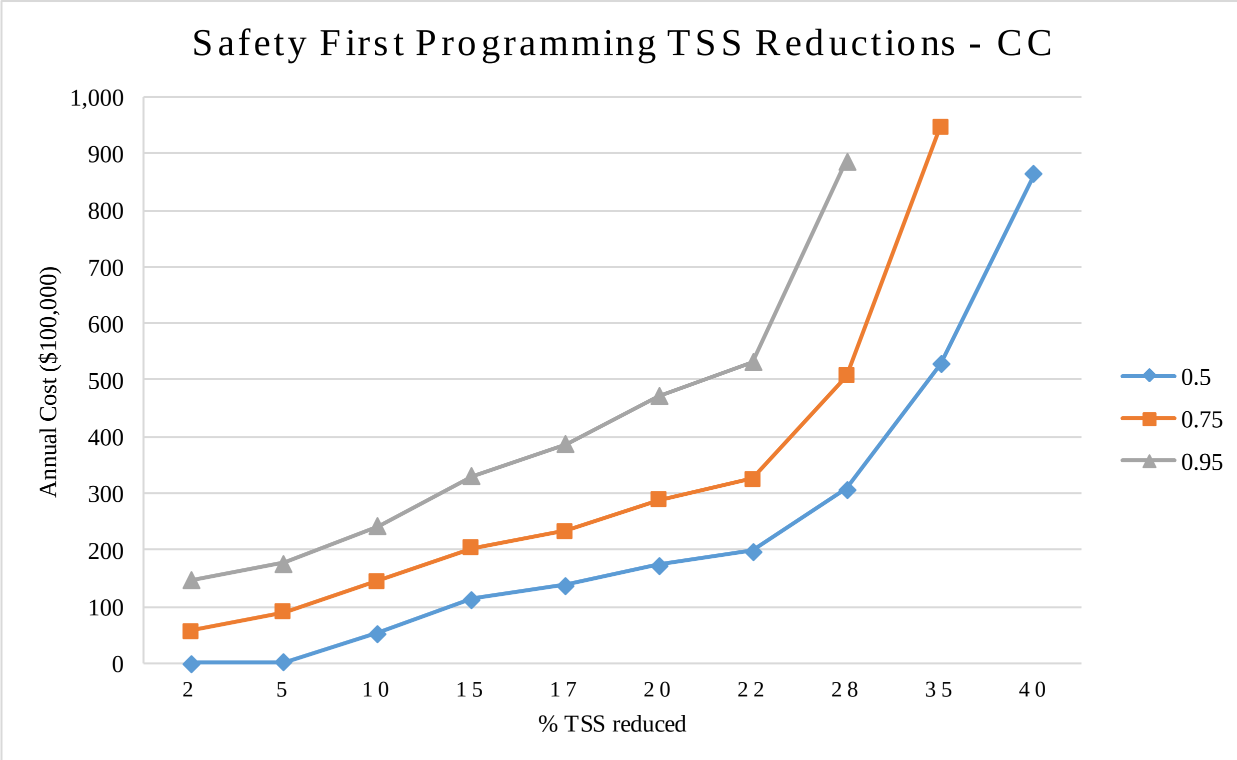


Table 18. Area Treated by BMPs Employed for TSS Variable Loadings Abatement under Climate Change

Prob. B	%	CAAB	CACD	PP1AB	PP1CD	MI1	BRE1AB	DS1	WS1AB	WS1CD	WP1	MSS	USR	Untreated
0.5	5												28	37853
	10								44		2421		29	35388
	15								44		5192		29	32616
	20								44		7964		29	29845
	28	219	1652				595	2831	44	345	5884		29	26282
	35	219	2166			5999	639	2624		345	92	42	29	25726
	40	219	2166	824	1034	8623	639			345	92	42	29	23868
0.75	5								44		4105		29	33703
	10								44		6682		29	31126
	15						171		44	345	8715		29	28577
	20	219	977				595	2831	44	345	5884		29	26957
	28	219	2166			5357	595	2831	44	345	527	42	29	25726
	35	219	2166	824	1597	8623	639			345	92	42	29	23305
0.95	5								44		8155		29	29653
	10						595	1978	44	345	6737		29	28153
	15	219	2166			207	595	2831	44	345	5677	42	29	25726
	20	219	2166			4321	595	2831	44	345	1563	42	29	25726
	28	219	2166	824	1191	8623	639			345	92	42	29	23711

See footnote for BMP definitions[20]

4.2.3 Safety First Programming Cost Comparison

Large divergences in cost schedules under varying probabilities of success for TN loadings abatement relative to TP and TSS loadings abatement indicate there is inherently more variation in TN loadings amongst weather years than TP and TSS loadings. TP and TSS loadings abatement followed similar cost schedules under all three varying levels of probabilities. This relationship is explained by the way through which TP loadings are exported from watersheds, by means of particulate TP being transported with TSS loadings. TN loadings remained the costliest to abate followed by TP and TSS loadings. This is due to BMPs being less effective for removing TN loads than TP or TSS loads. Urban stream restoration was relatively less effective for TN loadings abatement. In that urban stream restoration played a large role in the cost schedules of all three nutrient

[20] BMP units are in acres treated. USR units are in 100+ft stream segments restored. CAAB/CD = urban forest buffer under AB/CD soils, PP1AB/CD = permeable pavement under AB/CD soils, MI1 = infiltration practices, BRE1AB = bioretention under A/B soils, DS1 = bioswale, WS1AB/CD = vegetated open channels under AB/CD soils, WP1 = wet ponds and wetlands, MSS = mechanical street sweeping, UNM = urban nutrient management, USR = urban stream restoration, and Untreated = untreated acreage.

loadings, it can be deduced that by lowering the relative effectiveness of urban stream restoration's TN loading reductions effectiveness, the TN loadings abatement cost schedule will be the highest.

Despite there being less variation within nutrient loadings for altered climate conditions, controlling for nutrient loadings variability for altered climate conditions under CC was costlier than controlling for those for historical baseline climate conditions. The increases in the overall interannual means of nutrient loading for altered climate conditions were the predominant driver of the higher cost schedules. On average, the cost of controlling for TP loading variability increased 7.02 percent for altered climate conditions. The average percentage increases in the cost of controlling for TN and TSS loading variability for altered climate conditions were 2.13 percent and 5.79 percent, respectively[21]. For both climate scenarios analyzed, the cost schedules of TP and TSS loadings variability abatement rose in a similar fashion with TSS being the less costly of the two. The similarity in cost schedule increases for TP and TSS may be a product of the similar ways in which TP and TSS loadings are exported from urban watersheds. The larger respective increase in costs for TP and TSS indicated that they are more likely to be influenced by meteorological events within built environments than TN loadings.

4.3 Cost Minimization and Safety First Programming Cost Comparison

The costs of controlling for nutrient loading variability were substantially higher than controlling for mean nutrient loadings for both climate scenarios. The cost estimates produced using the Cost Minimization model drew their watershed goals from the average interannual nutrient loadings of the watershed, whereas the Safety First programming model emphasized the reductions of the deviations above this average. It can be inferred that when the Safety First programming model attempts to reduce nutrient loadings above the interannual average, costs schedules rise in an exponential fashion. We find that there are increases from Cost Minimization results even in cost schedules under the 0.5 probability of success. Reported in Tables 19 and 20 are costs from which

[21] The cost estimates from which we drew these comparisons can be found in Tables 19 and 20. As the historical climate rendered more watershed goals infeasible than the same goals under CC, we only could calculate the percent increase using cost estimates where the watershed goal was feasible in both time periods.

we calculated the average percent change in cost estimates between the two mathematical models (Tables 21 and 22). The average percent changes in cost estimates were calculated for the cost estimates produced by the Cost Minimization and Safety First programming models. We narrowed the cost estimates to the estimates displayed in Tables 19 and 20 because the Safety First programming model rendered more infeasible solutions for current climate conditions for a given percent loading reduction under a probability of success. Subsequently, the cost estimates from which we could compare estimates were narrowed. For example, TN variable loadings abatement for current climate conditions rendered no feasible solutions under the 0.95 probability of success. In that there was no baseline of comparison for this probability of success, we could only compare model estimates produced for the current climate to those for altered climate conditions from probabilities of success of 0.5 and 0.75.

For both climate scenarios, TP showed the largest cost differences between the Cost Minimization and Safety First programming models, which indicated that TP loadings have the largest levels of loadings variability among the three nutrients analyzed. In other words, the year-to-year differences in TP loadings are respectively more pronounced than TN or TSS loadings. TN loadings abatement had the least drastic average percent increase in cost estimates for both scenarios, although at the 0.95 probability of success the comparison could not be made due to the high levels of model infeasibility using Safety First programming.

Table 19. Costs derived from Cost Minimization and Safety First Programming Models under Historical Climate[22]

Probability of Success	%	TN Annual Costs ($1000)		TP Annual Costs ($1000)		TSS Annual Costs ($1000)	
		CM	SFP	CM	SFP	CM	SFP
0.5	2	1,107	27,256	19	4,801	12	95
	5	6,390	33,823	48	8,598	30	113
	10	16,951	45,012	97	16,302	60	3,790
	15	29,428	80,206	3,294	24,260	89	9,740
	17	34,419	103,852	6,195	28,121	101	12,121
	20	41,906	142,152	10,837	34,578	119	15,691
	22			14,456	40,281	1,879	18,072
	28			25,579	62,639	11,268	28,075
	35					26,542	48,191
	40					37,706	74,046
0.75	2	1,107	40,688	19	15,908	12	3,092
	5	6,390	48,768	48	20,313	30	6,440
	10	16,951	87,798	97	28,496	60	12,019
	15			3,294	39,828	89	17,599
	17			6,195	45,132	101	19,978
	20			10,837	53,467	119	24,738
	22			14,456	64,783	1,879	28,403
	28					11,268	44,234
	35					26,542	77,204
0.95	2			19	52,566	12	22,564
	5			48	69,324	30	27,133
	10			97	161,753	60	36,895
	15					89	50,087
	17					101	57,090
	20					119	70,783
	22					1,879	84,875

[22] CM = Cost estimates calculated from the Cost Minimization model and SFP = cost estimates calculated from the Safety First programming model

Table 20. Costs derived from Cost Minimization and Safety First Programming Models under Climate Change[23]

Probability of Success	%	TN Annual Costs ($1000)		TP Annual Costs ($1000)		TSS Annual Costs ($1000)	
		CM	SFP	CM	SFP	CM	SFP
0.5	2	1,247	27,176	21	6,496	13	101
	5	6,473	33,752	53	10,509	32	121
	10	16,936	44,894	105	18,380	63	5,414
	15	29,281	79,895	4,809	26,750	95	11,370
	17	34,219	103,574	7,713	30,668	108	13,753
	20	41,626	141,679	12,737	38,251	662	17,327
	22			16,360	43,936	3,697	19,821
	28			27,963	83,786	13,368	30,805
	35					28,789	52,931
	40					39,805	86,448
0.75	2	1,247	42,480	21	18,642	13	5,712
	5	6,473	51,898	53	23,043	32	9,035
	10	16,936	96,696	105	31,788	63	14,573
	15			4,809	44,505	95	20,341
	17			7,713	49,768	108	23,423
	20			12,737	63,228	662	28,799
	22			16,360	99,700	3,697	32,560
	28					13,368	50,849
	35					28,789	94,732
0.95	2			21	31,649	13	14,643
	5			53	38,470	32	17,738
	10			105	50,678	63	24,301
	15					95	33,080
	17					108	38,757
	20					662	47,274
	22					3,697	53,263

[23] CM = Cost estimates calculated from the Cost Minimization model and SFP = cost estimates calculated from the Safety First programming model

Table 21. Average Percent Increase in Safety First Programming Cost Estimates from Cost Minimization Estimates - Historical Climate

Probability	*TN*	*TP*	*TSS*
0.5	595	7,579	4,417
0.75	1,552	22,248	14,360
0.95	Infeasible	193,825	74,016

Average percent changes between Cost Minimization and Safety First programming cost estimates decreased for altered climate conditions. The decrease is a product of nutrient loading variability, on average, decreasing slightly for altered climate conditions under CC. The average percent change in Cost Minimization and Safety First programming model cost estimates for TP did not back this claim, however. With the exception of the 0.95 probability of success, the average percent increase in cost estimates between Cost Minimization and Safety First programming were higher for altered climate conditions. The larger percent change for historical climate conditions for the 0.95 probability is likely due to the range of TP loadings being greater than those for altered climate conditions. The range of TP loadings for historical climate being higher than those for altered climate conditions is likely attributed to the identified positive linear trend in nutrient loadings for historical climate, as discussed in Chapter 3. Thus, it may be difficult to state whether nutrient loadings variability decreases or increases for altered climate conditions due to the positive linear trend in nutrient loadings for historical climate conditions.

Table 22. Average Percent Increase in Safety First Programming Cost Estimates from Cost Minimization Estimates – Climate Change

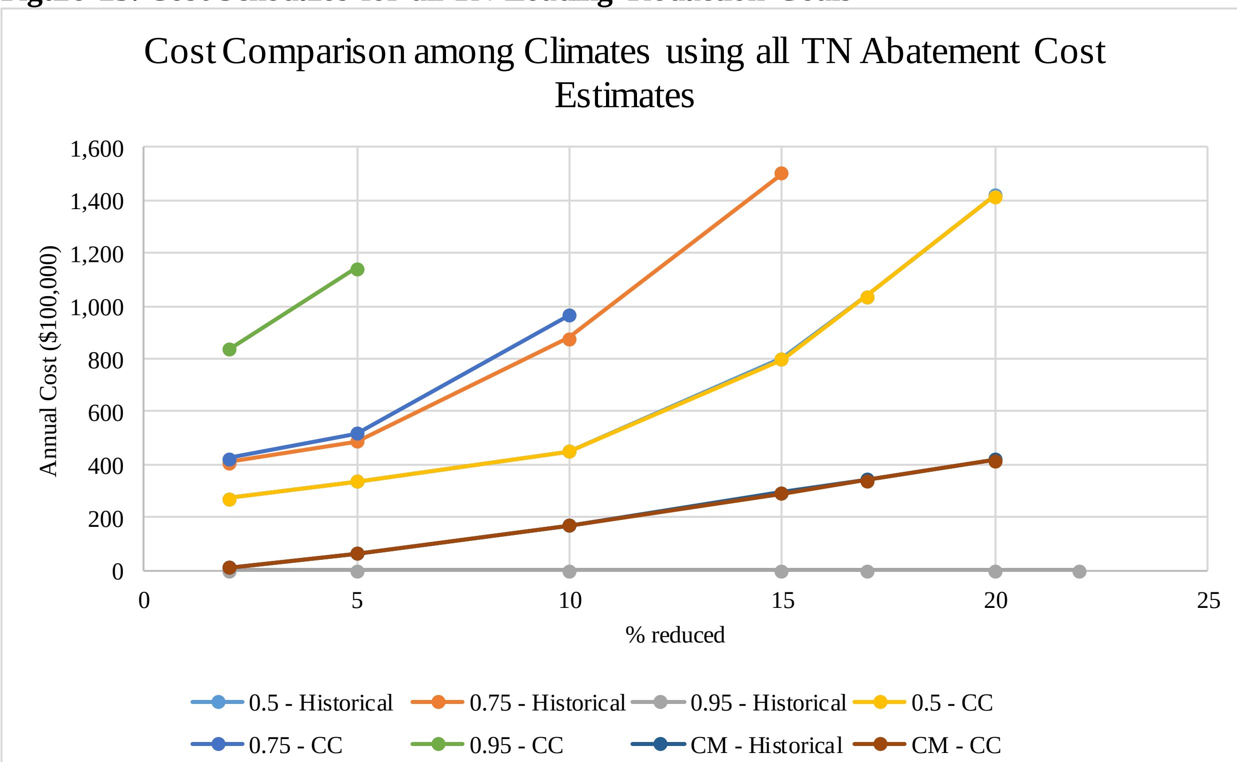
Probability	*TN*	*TP*	*TSS*
0.5	547	8,654	3,730
0.75	1,493	27,304	16,115
0.95	Infeasible	90,328	41,296

To compare the effects of CC on nutrient loading control costs, we selected TN loading reductions as an example for comparison. The costs for controlling for TN loading were more expensive for altered climate conditions than historical climate conditions[24]. When comparing the costs of abating mean interannual TN loadings, cost

[24] See Figure 23 and Tables 19 and 20 for further detail.

estimates for altered climate conditions were approximately one-half percent higher on average. The costs of abating interannual TN loadings variability for altered climate conditions resulted in an average increase of 2.13 percent. However, under the Safety First programming model, the cost comparison was more complex in that there were relatively large differences in costs under different probabilities of success for both time periods (Figure 23). We found that for altered climate conditions cost schedules under the 0.5 probability of success the costs were nearly identical, although at the 0.75 probability of success the cost estimates increased. Lastly, the costs of reducing TN loadings interannual variability were substantially higher than reducing the costs of reducing mean interannual TN loadings.

Figure 23. Cost Schedules for all TN Loading Reduction Goals



The following chapter will discuss the results of this study. We first present a synopsis of the study and discuss the implication of our results. As an applied analysis, we further give recommendations for policy makers. Lastly, we present some of the limitations and how future research may overcome these limitations.

CHAPTER 5: CONCLUSIONS

5.1 Summary

Urban environments have been identified as a key non-point source contributor of nutrient loadings into surrounding watersheds. Surges of interannual nutrient loadings into local water systems are more damaging than mean interannual nutrient loadings alone. In accordance with the Chesapeake Bay TMDL, Virginia outlined in its Watershed Implementation Plan (WIP) the need to reduce urban nutrient loadings.

Designing water quality policy that incorporates structural and land use change should no longer be based on historic climate conditions alone. Interannual mean nutrient loadings and nutrient loadings variability are expected to increase for altered climate conditions brought about by CC. While there are many studies that outline cost-effective ways in which nutrient loading may be abated from urban environments (Altieri & Gedan, 2014), there are comparatively fewer studies that develop predictive frameworks for abating nutrient loadings for altered climate conditions under CC. Thus, there is a lack of information regarding water quality policy and how cost-effective it will be in controlling urban nutrient loading for altered climate conditions. The public desires to improve water quality, yet resources to achieve goals are limited. Therefore, it is important that policy models incorporate the effects of CC, so water quality programs can be efficiently adapted to match these changing conditions.

In order to analyze how CC may affect water quality policy in urban environments, we selected the Difficult Run watershed located in Fairfax County, Virginia for a site of study. As often prescribed by the Chesapeake Bay Commission, EPA, Chesapeake Bay Program, and Virginia's WIP, we utilized BMPs as a control mechanism for the reduction of nutrient loadings stemming from the watershed. Our first objective was to compare the costs of reducing mean interannual nutrient loadings in the watershed based on historical climate conditions to those predicted for altered climate conditions under CC. The second objective was to compare the costs of reducing interannual nutrient loadings variability in the watershed to the interannual nutrient loadings variability predicted for altered climate conditions under CC. The last objective was to compare the costs of reducing the average interannual nutrient loadings to the costs of reducing interannual nutrient loadings variability. Using mathematical programming, we calculated how the costs of the two different water quality policies differed for differing climates and then drew comparisons.

The costs of reducing nutrient export via BMP implementation in the Difficult Run watershed for altered climate conditions were higher than those calculated for the historical baseline climate conditions. We found that costs for altered climate conditions rose substantially for TP and TSS when controlling for mean interannual nutrient loadings over the 2040-2068 simulated time period. We also found that the costs of controlling for interannual nutrient loadings variability over the same 28-year time period increased for altered climate conditions, albeit not as drastically as the costs rose for controlling for mean interannual loadings for altered climate conditions. Controlling for interannual nutrient loading variability using Safety-First constraints resulted in substantially higher cost estimates than controlling for mean interannual nutrient loadings for both climate scenarios. Clear BMP selection patterns arose for all three nutrients across both time periods.

The cost increases for abating mean interannual nutrient loading for altered climate conditions varied among the three nutrients analyzed. Costs increased for abating the average TP and TSS loadings for altered climate conditions by nearly 32 and 31 percent, respectively, whereas the average percent rise in costs for TN loading reductions was 0.56 percent. Despite the costs of mean interannual TN loading abatement for altered climate conditions rising at a slower rate than the other two nutrients, mean interannual TN loadings remained the costliest to abate. TN loading abatement costs did not change as much as TP or TSS loading abatement costs change due to the moderate increases in simulated TN loadings for altered climate conditions in addition to the already high costs of TN loading abatement calculated for the baseline climate.

When comparing the costs of reducing interannual nutrient loading variability for altered climate conditions to those calculated for the historical baseline climate conditions, we saw less drastic increases in costs than those seen when comparing the costs of controlling for mean interannual nutrient loadings among historical climate conditions and for altered climate conditions. Nonetheless, the costs of reducing nutrient loadings variability increased for altered climate conditions. TP loading reduction costs increased the most by roughly seven percent, TSS by six percent, and TN by two percent. Raising the probability of success for meeting nutrient loading reductions drastically increased the cost estimates for both climate scenarios.

Across all three nutrients and two climate scenarios analyzed, there were clear preferences with respect to BMP selection. Urban stream restoration was much more cost effective than any other BMP, and in return it was selected first. Low Impact Development (LID) practices such as bioretention, bioswale, wet ponds and wetlands, and vegetated open channels (wet swale) were selected after the constraint on urban stream restoration sites was met. Although LID is not as effective as urban stream restoration, it is more cost effective than traditional urban BMPs, such as dry-extended detention ponds, street sweeping, and urban nutrient management. Traditionally used BMPs were selected, but only after high respective loading reductions were defined and the model had no other alternate BMPs from which to choose.

5.2 Recommendations for Policy Makers

Drawing from cost estimates produced by both methodologies for both climate scenarios, we found that reducing TSS export from the Difficult Run watershed was less expensive than reducing TP and TN export. The costs of TP loading reductions were also far less than TN loading reductions. Urban environments contribute more TSS loadings into the Chesapeake Bay than TN or TP loadings. According to BayFAST's nutrient loading reduction goals (Ganeshmal, 2014), the Potomac River Basin has committed to reduce a larger amount of TSS loadings than TN loadings by 2025 with 2009 nutrient loadings constituting the baseline. If policy makers are indifferent as to which nutrient of interest they wish to abate, the lower relative costs of TSS abatement and high respective loadings suggest that stakeholders within the Difficult Run watershed should pursue policies abating TSS loadings. Urban stream restoration is extraordinarily effective at reducing nutrient loads, especially those of TSS. Thus, if policy makers seek to minimize the cost of meeting nutrient loading reduction goals for current and potential future climates, urban stream restoration's cost effectiveness supports efforts to pursue stream identification and restoration throughout the Difficult Run watershed.

Due to the lifespan of structural BMPs and high transactions costs of policy implementation, it is advisable to incorporate future changes in climate into current urban water quality policy. The BMP cost estimates for which King & Hagan (2011) calculated assume all project life spans are 20 years with proper maintenance. However, some BMPs have been estimated to last much longer with proper maintenance. BayFAST (2014) estimates the project lifespans of urban tree planting and constructed wetlands and wetponds are up to 75 years, for example. Further, the creation and implementation of water quality policies consume time and resources from policy makers and their advisors, often referred to as a form of transactions costs. If a watershed pollution reduction goal is to be met today and throughout a policy's total lifespan, policy makers should front-load BMP implementation in the current time period in order to offset the meteorological changes as predicted for the future. By compensating for these changes today, policy makers and their advisors may avoid having to revisit and redesign policies that have failed to reach long-term water quality goals.

5.3 Limitations and Future Study

The results of this study allow policy makers to compare the costs of reducing nutrient export from the Difficult Run watershed to those for altered climate conditions holding all else equal. Like many other research studies, the results of this study prompted several questions regarding model specifics, sensitivity analysis, and results accuracy. This study did not address variability outside of nutrient loading. BMPs' effectiveness values are mean estimates set by a regulatory authority for ease of use by stormwater permittees in the Commonwealth of Virginia. These effectiveness estimates, however, are known to fluctuate due to a variety of environmental variables, such as rainfall intensity and temperature.

Enhanced spatial specificity for BMP implementation could have been derived by allowing for the disaggregation of subcatchments within the Difficult Run watershed. By allowing for enhanced spatial specificity, one can generate more realistic cost estimates. Lastly, only one regional climate model under the A2 CC scenario was analyzed leaving to question how other CC projections may affect the cost of reducing nutrient export from the Difficult Run watershed. By addressing these issues, one may generate more robust cost estimates and give policy makers and their advisors better information for crafting long-term, sustainable water quality policy for the Difficult Run watershed.

BMP effectiveness values were standardized by VA for ease of use regarding permit allocations, although these standardized values are not very useful when calculating the actual watershed end of stream nutrient loads after BMP implementation. For altered climate conditions under CC, BMP effectiveness values are expected to become even more variable. As BMPs often have a minimum, mean, and maximum associated effective value, additional methods may incorporate uncertainty regarding BMP effectiveness into mathematical programming models. Using the effectiveness range for the BMP, one may perform a Monte Carlo simulation creating a triangular distribution from which he or she may randomly draw effectiveness values for use in the mathematical programming model.

Another method for introducing uncertainty regarding the BMP's effectiveness value is by constructing inexact left-hand side chance constraints, as outlined by Xie et al. (2015). By building a margin of error into the BMP's effectiveness value, this method simulates a safety-first style protection into the value so that a watershed pollution constraint may be satisfied with an accompanying user-defined probability of achievement.

Lastly, specific field level simulations could be run in SWMM to derive a more precise BMP effectiveness value. However, these simulations would require extensive time and funding, and may not be feasible if answers in real time are desired.

Enhanced spatial specificity with respect to nutrient loading simulation and BMP implementation is required in order to produce more accurate cost estimates. When imposing constraints on urban stream restoration, we erred on side of less available restorable stream segments for urban stream restoration than more. Therefore, a greater number of urban stream restoration projects could possibly be identified within Fairfax County, which would reduce our cost estimates significantly. It is important to note, however, that we did not have adequate information to separate potential urban stream restoration sites by land owner. By not having adequate property rights information, we cannot say with certainty that all of the urban stream restoration sites chosen can be restored due to property ownership issues.

When watersheds are disaggregated into small subcatchments, or sub-watersheds, specific locations within the watershed containing hydrogeomorphic information and nutrient loading may be pinpointed and remediated. Disaggregated watersheds containing more than one subcatchment can be modeled in mathematical programming models where the programming model optimizes across all subcatchments such that the least cost of meeting a pollution goal is met, much like the models used in this study. However, as the subcatchments are not independent of one another, dynamic programming is required to account for the interactions amongst subcatchments. The use of dynamic programming would allow greater traceability of BMP implementation. Some subcatchments, for example, may contain greater levels of nutrient loading relative to neighboring subcatchments, thus the dynamic programming model would opt to concentrate BMP implementation in the subcatchment generating more nutrient loadings. On the contrary, if the exemplified subcatchment flows into a subcatchment that already has multiple BMPs established, the dynamic programming model would recognize this interaction and choose to place BMPs elsewhere to meet the user-defined pollution reduction goal. The drawback of dynamic programming is that it requires significantly more time to construct than the models used in this study.

We simulated nutrient loadings using SWMM for the Difficult Run watershed for two climates, the historical baseline climate and a future climate drawing from one modified regional climate model (RCM) of the ten RCMs produced by the North American Climate Change Assessment Program (NARCCAP). NARCCAP closely follows the Intergovernmental Panel on Climate Change's (IPCC) A2 scenario. The A2 scenario is based on several "business as usual" assumptions, such as delayed developments in renewable energy, continued divergences between developed and developing nations, and slow convergences in regional fertility patterns. Although there are multiple climate models that comprise the A2 family, there are three other climate model families from which to choose, each of which being comprised of many models. These three climate model families each follow different scenarios built upon different assumptions for the Earth's development. Within the realm of most research studies and policy relevant analyses, evaluating a single watershed under all four climate scenarios is impractical. However, as there are 10 RCMs under the A2 scenario produced by NARCCAP, it might be feasible to evaluate the watershed using two or three RCMs where the other RCMs describe alternate realities in which future development varies and follows scenarios more closely aligned with other climate model families as described by the IPCC. By incorporating these different climate scenarios, one may produce a larger set of cost schedules for reducing nutrient loadings in the Difficult Run watershed for altered climate conditions under CC. Drawing from these cost schedules, a range of cost estimates may then be presented to decision makers, so that they may have more information regarding the future costs of water quality policies.

In conclusion, the methods employed in this research paper were sufficiently robust to complete this analysis of the Difficult Run watershed, although there is work to be done. As always within the realm of research, a question may lead to an answer, but the answer leads to two more questions. CC in and of itself is a dynamic problem where the actions we make today affect all of the potential decisions we may make in the future. Therefore, by forecasting cost schedules via simulations and optimizations – like that of this analysis – we can learn how our decisions today may affect the issues of tomorrow and respond accordingly. Policy makers and their advisors can use this information so that they may design well-informed policies that can stand the test of time.

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APPENDICIES

Appendix A: Best Management Practices

Table A.1. Best Management Practice Definitions

BMP	**Code**	**Description**
Sheet Flow Conservation Area (Urban Forest Buffer) – A/B Soils	CAAB	An area of trees at least 35 ft wide on one side of a stream, usually accompanied by trees, shrubs and other vegetation that is adjacent to a body of water. The riparian area is managed to maintain the integrity of stream channels and shorelines, to reduce the impacts of upland sources of pollution by trapping, filtering, and converting sediments, nutrients, and other chemicals. Used for A/B soils.
Sheet Flow Conservation Area (Urban Forest Buffer) – C/D Soils	CACD	An area of trees at least 35 ft wide on one side of a stream, usually accompanied by trees, shrubs and other vegetation that is adjacent to a body of water. The riparian area is managed to maintain the integrity of stream channels and shorelines, to reduce the impacts of upland sources of pollution by trapping, filtering, and converting sediments, nutrients, and other chemicals. Used for C/D soils.
Permeable Pavement, level one – A/B Soils	PP1AB	Pavement or pavers that reduce runoff volume and treat water quality through both infiltration and filtration mechanisms. Water filters through open voids in the pavement surface to a washed gravel subsurface storage reservoir, where it is then slowly infiltrated into the underlying soils or exits via an underdrain. When sand and vegetation are present, high reduction efficiencies can be achieved. Used for A/B Soils
Permeable Pavement, level one – C/D Soils	PP1CD	Pavement or pavers that reduce runoff volume and treat water quality through both infiltration and filtration mechanisms. Water filters through open voids in the pavement surface to a washed gravel subsurface storage reservoir, where it is then slowly infiltrated into the underlying soils or exits via an underdrain. When sand and vegetation are present, high reduction efficiencies can be achieved. Used for C/D Soils
Infiltration Practices, level one	MI1	A depression to form an infiltration basin where sediment is trapped and water infiltrates the soil. No underdrains are associated with infiltration basins and trenches, because by definition these systems provide complete infiltration.

Bioretention Basin, level one – A/B Soils	BRE1AB	An excavated pit backfilled with engineered media, topsoil, mulch, and vegetation. These are planting areas installed in shallow basins in which the storm water runoff is temporarily ponded and then treated by filtering through the bed components, and through biological and biochemical reactions within the soil matrix and around the root zones of the plants. Used for A/B soils.
Bioretention Basin, level one – C/D Soils	BRE1CD	An excavated pit backfilled with engineered media, topsoil, mulch, and vegetation. These are planting areas installed in shallow basins in which the storm water runoff is temporarily ponded and then treated by filtering through the bed components, and through biological and biochemical reactions within the soil matrix and around the root zones of the plants. Used for C/D soils.
Dry Swale (Bioswale), level one – AB/CD Soils	DS1	With a bioswale, the load is reduced because, unlike other open channel designs, there is now treatment through the soil. A bioswale is designed to function as a bioretention area. No specific soil type required.
Wet Swale (Vegetated Open Channels, no underdrain), level one – A/B Soils	WS1AB	Vegetated open channels that are designed to capture and treat or convey the design storm volume (Stormwater Retention Volume (SWRv)). Open channel systems shall not be designed to provide stormwater detention except under extremely unusual conditions. Open channel systems must generally be combined with a separate facility to meet these requirements. Used for A/B soils.
Wet Swale (Vegetated Open Channels, no underdrain), level one – C/D Soils	WS1CD	Vegetated open channels that are designed to capture and treat or convey the design storm volume (Stormwater Retention Volume (SWRv)). Open channel systems shall not be designed to provide stormwater detention except under extremely unusual conditions. Open channel systems must generally be combined with a separate facility to meet these requirements. Used for C/D soils.
Filter, level one (Filtering Practices) – AB/CD Soils	F1	Practices that capture and temporarily store runoff and pass it through a filter bed of either sand or an organic media. There are various sand filter designs, such as above ground, below ground, perimeter, etc. An organic media filter uses another medium besides sand to enhance pollutant removal for many compounds due to the increased cation exchange capacity achieved by increasing the organic matter. No specific soil type required.

Constructed Wetland, level one (Wet Ponds and Wetlands) – C/D Soils	CW1	Developing a wetland that did not previously exist on an upland or deep water site. Results in a gain in wetland acres. Nutrients and suspended particles are removed via settling. Nitrogen is further removed primarily via plant and microbial uptake and nitrification-denitrification reactions, while phosphorus is further removed by soil absorption.
Wet Pond, level one – C/D Soils	WP1	A water impoundment structure that intercepts stormwater runoff then releases it to an open water system at a specified flow rate. These structures retain a permanent pool and usually have retention times sufficient to allow settlement of some portion of the intercepted sediments and attached nutrients/toxics. Until recently, these practices were designed specifically to meet water quantity, not water quality objectives. There is little or no vegetation living within the pooled area nor are outfalls directed through vegetated areas prior to open water release. Used for C/D soils.
Dry Extended Detention Pond, level one – A/B Soils	EDP1AB	Dry extended detention (ED) basins are depressions created by excavation or berm construction that temporarily store runoff and release it slowly via surface flow or groundwater infiltration following storms. Dry ED basins are designed to dry out between storm events, in contrast with wet ponds, which contain standing water permanently. As such, they are similar in construction and function to dry detention basins, except that the duration of detention of stormwater is designed to be longer, theoretically improving treatment effectiveness. Use for A/B soils.
Dry Extended Detention Pond, level one – C/D Soils	EDP1CD	Dry extended detention (ED) basins are depressions created by excavation or berm construction that temporarily store runoff and release it slowly via surface flow or groundwater infiltration following storms. Dry ED basins are designed to dry out between storm events, in contrast with wet ponds, which contain standing water permanently. As such, they are similar in construction and function to dry detention basins, except that the duration of detention of stormwater is designed to be longer, theoretically improving treatment effectiveness. Use for C/D soils.

Street Sweeping	MSS	Street sweeping and storm drain cleanout practices rank among the oldest practices used by communities for a variety of purposes to provide a clean and healthy environment, and more recently to comply with their National Pollutant Discharge Elimination System stormwater permits. The ability of these practices to achieve pollutant reductions is uncertain given current research findings. Only a few street sweeping studies provide sufficient data to statistically determine the impact of street sweeping and storm drain cleanouts on water quality and to quantify their improvements. The ability to quantify pollutant loading reductions from street sweeping is challenging given the range and variability of factors that impact its performance, such as the street sweeping technology, frequency and conditions of operation in addition to catchment characteristics. Fewer studies are available to evaluate the pollutant reduction capabilities due to storm drain inlet or catch basin cleanouts.
Urban Nutrient Management, blended	UNM	Urban nutrient management involves the reduction of fertilizer to grass lawns and other urban areas. The implementation of urban nutrient management is based on public education and awareness, targeting suburban residences and businesses, with emphasis on reducing excessive fertilizer use.
Urban Stream Restoration	USR	Stream restoration in urban areas is used to restore the urban stream ecosystem by restoring the natural hydrology and landscape of a stream and to improve habitat and water quality conditions.

*Definitions adapted and taken from King and Hagan (2011)

Appendix B: BMPs employed in Mathematical Modeling Solutions

Table B.1. Area Treated by BMPs Employed for TN Cost Minimization Model under Historical Conditions

%	CAAB	CACD	PP1AB	PP1CD	MI1	BRE1AB	DS1	WS1AB	WP1	MSS	UNM	USR
1												20
2							275	44				29
3							817	44				29
4							1358	44				29
5							1899	44				29
6							2440	44				29
7						131	2831	44				29
8						618	2831	21				29
9					437	639	2831					29
10					883	639	2831					29
11					1328	639	2831					29
12					1774	639	2831					29
13					2220	639	2831					29
14					2665	639	2831					29
15					3111	639	2831					29
16					3557	639	2831					29
17					4002	639	2831					29
18					4448	639	2831					29
19					4894	639	2831					29
20					5339	639	2831					29
21					5785	639	2831					29
22	219	1198			5792	639	2831		92			29
23	219	2511			6129	639	2494		92			29
24	219	2511			8623	639			92	42	34	29
25	219	2511			8623	639			92	42	4243	29
26	219	2511			8623	639			92	42	8452	29
27	219	2511			8623	639			92	42	12661	29
28	219	2511			8623	639			92	42	16867	29
29	219	2511			8623	639			92	42	21079	29
30	219	2511	524		8623	639			92	42	24124	29
31	219	2511	824	1594	8623	639			92	42	24124	29

Table B.2. Area Treated by BMPs Employed for TP Cost Minimization Model under Historical Conditions

%	CAAB	CACD	PP1AB	MI1	BRE1AB	DS1	WS1AB	WP1	MSS	UNM	USR
1											2
2											5
3											7
4											9
5											11
6											14
7											16
8											18
9											20
10											23
11											25
12											27
13						83					29
14						529					29
15						974					29
16						1420					29
17						1866					29
18						2311					29
19						2757					29
20						2831	44	656			29
21						2831	44	1500			29
22						2831	44	2342			29
23						2831	44	3183			29
24						2831	44	4025			29
25						2831	44	4867			29
26						2831	44	5709			29
27					353	2831	44	5884			29
28	311				639	2831		5884			29
29	1068				639	2831		5884			29
30	1826				639	2831		5884			29
31	2140	444			639	2831		5884			29
32	2140	590		764	639	2831		5120			29
33	2140	590		1711	639	2831		4173			29
34	2140	590		2658	639	2831		3226			29
35	2140	590		3605	639	2831		2279			29
36	2140	590		4552	639	2831		1332			29
37	2140	590		5499	639	2831		385			29
38	2140	590	327	5792	639	2831		92			29
39	2140	590	801	5792	639	2831		92			29
40	1921	590	1043	5792	639	2831		92	42	6505	29

41	1921	590	1043	5792	639	2831		92	42	14923	29
42	1921	590	1043	5792	639	2831		92	42	23341	29

Table B.3. Area Treated by BMPs Employed for TSS Cost Minimization Model under Historical Conditions

%	CAAB	CACD	PP1AB	PP1CD	MI1	BRE1AB	DS1	WS1AB	WS1CD	WP1	MSS	USR
1												1
2												3
3												4
4												6
5												7
6												8
7												10
8												11
9												13
10												14
11												15
12												17
13												18
14												20
15												21
16												22
17												24
18												25
19												27
20												28
21								44	70			29
22							302	44	345			29
23							775	44	345			29
24							1249	44	345			29
25							1723	44	345			29
26							2196	44	345			29
27							2670	44	345			29
28						277	2831	44	345			29
29					98	595	2831	44	345			29
30					497	595	2831	44	345			29
31					895	595	2831	44	345			29
32					1294	595	2831	44	345			29
33					1693	595	2831	44	345			29
34					2092	595	2831	44	345			29
35					2490	595	2831	44	345			29
36					2889	595	2831	44	345			29
37					3288	595	2831	44	345			29
38					3687	595	2831	44	345			29
39					4085	595	2831	44	345			29
40					4484	595	2831	44	345			29

41					4883	595	2831	44	345			29
42					5282	595	2831	44	345			29
43					5680	595	2831	44	345			29
44	219	326			5792	595	2831	44	345			29
45	219	1084			5792	595	2831	44	345			29
46	219	1842			5792	595	2831	44	345			29
47	219	2166			7027	639	1597		345	92	42	29
48	219	2166	164		8623	639			345	92	42	29
49	219	2166	610		8623	639			345	92	42	29
50	219	2166	824	357	8623	639			345	92	42	29

Table B.4. Area Treated by BMPs Employed for TN Abatement under Climate Change

%	CAAB	CACD	PP1CD	MI	BRE1AB	DS1	WS1AB	WP1	MSS	UNM	USR
1											21
2						318	44				29
3						854	44				29
4						1389	44				29
5						1924	44				29
6						2460	44				29
7					144	2831	44				29
8					634	2831	44				29
9					639	2831					29
10					639	2831					29
11					639	2831					29
12					639	2831					29
13					639	2831					29
14					639	2831					29
15					639	2831					29
16					639	2831					29
17					639	2831					29
18					639	2831					29
19					639	2831					29
20					639	2831					29
21					639	2831					29
22	219	996			639	2831		92			29
23	219	1921			639	2831		92			29
24	219	1921		2471	639	360		92			29
25	219	1921		2831	639			92	42	3547	29
26	219	1921		2831	639			92	42	7711	29
27	219	1921		2831	639			92	42	11875	29
28	219	1921		2831	639			92	42	16039	29
29	219	1921		2831	639			92	42	20203	29
30	219	1921	110	2831	639			92	42	24124	29
31	219	1921	1984	2831	639			92	42	24124	29

Table B.5. Area Treated by BMPs Employed for TP Cost Minimization Model under Climate Change

%	CAAB	CACD	PP1AB	PP1CD	BRE1AB	DS1	WS1AB	WP1	MSS	UNM	USR
1											3
2											5
3											7
4											10
5											12
6											15
7											17
8											20
9											22
10											25
11											27
12						101					29
13						548					29
14						994					29
15						1440					29
16						1886					29
17						2332					29
18						2778					29
19						2831	44	92			29
20						2831	44	92			29
21						2831	44	92			29
22						2831	44	92			29
23						2831	44	92			29
24						2831	44	92			29
25						2831	44	92			29
26					378	2831	44	92			29
27	219	136			639	2831		92			29
28	219	894			639	2831		92			29
29	219	1652			639	2831		92			29
30	219	2411			639	2831		92			29
31	219	2411			639	2831		92			29
32	219	2411			639	2831		92			29
33	219	2411			639	2831		92			29
34	219	2411			639	2831		92			29
35	219	2411			639	2831		92			29
36	219	2411			639	2831		92			29
37	219	2411	360		639	2831		92			29
38	199	2411	844		639	2831		92	42		29
39		2411	1043		639	2831		92	42	7101	29
40		2411	1043		639	2831		92	42	15528	29

41	2411	1043	639	2831	92	42	23955	29

Table B.6. Area Treated by BMPs Employed for TSS Cost Minimization Model under Climate Change

%	CAAB	CACD	PP1AB	PP1CD	MI1	BRE1AB	DS1	WS1AB	WS1CD	WP1	MSS	USR
1												2
2												3
3												4
4												6
5												7
6												9
7												10
8												12
9												13
10												15
11												16
12												18
13												19
14												21
15												22
16												24
17												25
18												27
19												28
20								44	227			29
21							394	44	345			29
22							861	44	345			29
23							1329	44	345			29
24							1795.	44	345			29
25							2262	44	345			29
26							2729	44	345			29
27						325	2831	44	345			29
28					138	595	2831	44	345			29
29					531	595	2831	44	345			29
30					925	595	2831	44	345			29
31					1318	595	2831	44	345			29
32					1711	595	2831	44	345			29
33					2105	595	2831	44	345			29
34					2498	595	2831	44	345			29
35					2892	595	2831	44	345			29
36					3285	595	2831	44	345			29
37					3679	595	2831	44	345			29
38					4072	595	2831	44	345			29
39					4465	595	2831	44	345			29
40					4859	595	2831	44	345			29

41					5252	595	2831	44	345			29
42					5646	595	2831	44	345			29
43	219	251			5792	595	2831	44	345			29
44	219	998			5792	595	2831	44	345			29
45	219	1746			5792	595	2831	44	345			29
46	219	2166			6673	639	1950		345	92	42.	29
47	219	2166	96		8623	639			345	92	42	29
48	219	2166	535		8623	639			345	92	42	29
49	219	2166	824	233	8623	639			345	92	42	29
50	219	2166	824	913	8623	639			345	92	42	29

Table B.7. Area Treated by BMPs Employed under Historical TP Abatement Safety First Programming

Prob. B	%	CAAB	CACD	PP1AB	PP1CD	MI1	BRE1AB	DS1	WS1AB	WP1	MSS	UNM	USR	Untreated
0.5	2							1437					29	36415
	5							2604					29	35248
	10							2831	44	3200			29	31777
	15						524	2831	44	5884			29	28569
	17	219	947				639	2831		5884			29	27332
	20	219	2511			524	639	2831		5356			29	25768
	22	219	2511			2177	639	2831		3707			29	25768
	28	219	2511	671		5792	639	2831		92			29	25097
0.75	2							2831	44	2969			29	31960
	5							2831	44	5019			29	29910
	10	219	1073				639	2831		5792			29	27206
	15	219	2511			2046	639	2831		3746			29	25768
	17	219	2511			3583	639	2831		2209			29	25768
	20	219	2511	48		5792	639	2831		92			29	25720
	22	219	2511	817		5792	639	2831		92			29	24951
0.95	2	219	2511			5737	595	2831		147			29	25768
	5		2511	1043		5792	639	2831		92	42	572	29	24330
	10		2511	1043	1261	5792	639	2831		92	42	23641	29	

Table B.8. Area Treated by BMPs Employed under Historical TSS Abatement Safety First Programming

Prob. B	%	CAAB	CACD	PP1AB	PP1CD	MI1	BRE1AB	DS1	WS1AB	WS1CD	WP1	MSS	USR	Untreated
0.5	2												22	37859
	5												26	37855
	10								44		1665		29	36143
	15								44		4434		29	33374
	17								44		5541		29	32267
	20								44		7203		29	30606
	22								44		8310		29	29498
	28	219	734				595	2831	44	345	5884		29	27200
	35	219	2166			4587	595	2831	44	345	1297	42	29	25726
	40	219	2166	824	192	8623	639			345	92	42	29	24710
0.75	2								44		1340		29	36468
	5								44		2898		29	34910
	10								44		5494		29	32314
	15								44		8090		29	29718
	17						84		44	345	8715		29	28664
	20						595	2373	44	345	6342		29	28153
	22	219	844				595	2831	44	345	5884		29	27090
	28	219	2166			3440	595	2831	44	345	2444	42	29	25726
	35	219	2166	824	407	8623	639			345	92	42	29	24495
0.95	2						595	406	44	345	8309		29	28153
	5	219	417				595	2831	44	345	5884		29	27517
	10	219	1007			1313	595	2831	44	345	4571	42	29	25726
	15	219	1007			5136	595	2831	44	345	748	42	29	25726
	17	219	1007			7772	639	851		345	92	42	29	25726
	20	219	1007	794		8623	639			345	92	42	29	24932
	22	219	1007	824	928	8623	639			345	92	42	29	23974

Table B. 9. Area Treated by BMPs Employed under CC TP Abatement Safety First Programming

Prob. B	%	CAAB	CACD	PP1AB	MI1	BRE1AB	DS1	WS1AB	WP1	MSS	UNM	USR	Untreated
0.5	2						1958					29	35894
	5						2831	44	505			29	34472
	10						2831	44	4167			29	30810
	15	219	486			639	2831		5884			29	27793
	17	219	1804			639	2831		5884			29	26475
	20	219	2511		1589	639	2831		4296			29	25768
	22	219	2511		3236	639	2831		2648			29	25768
	28		2511	1043	5792	639	2831		92	42	5089	29	19813
0.75	2						2831	44	4289			29	30688
	5					233	2831	44	5884			29	28860
	10	219	2181			639	2831		5884			29	26098
	15	219	2511		3401	639	2831		2483			29	25768
	17	219	2511		4926	639	2831		958			29	25768
	20	219	2511	711	5792	639	2831		92			29	25057
	22		2511	1043	5792	639	2831		92	42	10058	29	14844
0.95	2	219	2134			639	2831		5884			29	26145
	5	219	2511		1652	639	2831		4232			29	25768
	10	219	2511		5190	639	2831		694			29	25768
	15		2511	1043	5792	639	2831		92	42	9962	29	14940
	17		2511	1043	5792	639	2831		92	42	22542	29	2360

Table B.10. Area Treated by BMPs Employed under CC TSS Abatement Safety First Programming

Prob. B	%	CAAB	CACD	PP1AB	PP1CD	MI1	BRE1AB	DS1	WS1AB	WS1CD	WP1	MSS	USR	Untreated
0.5	2												24	37857
	5												28	37853
	10								44		2421		29	35388
	15								44		5192		29	32616
	17								44		6301		29	31507
	20								44		7964		29	29845
	22						46		44	345	8715		29	28702
	28	219	1652				595	2831	44	345	5884		29	26282
	35	219	2166			5999	639	2624		345	92	42	29	25726
	40	219	2166	824	1034	8623	639			345	92	42	29	23867
0.75	2								44		2559		29	35249
	5								44		4105		29	33703
	10								44		6682		29	31126
	15						171		44	345	8715		29	28577
	17						595	1183	44	345	7532		29	28153
	20	219	977				595	2831	44	345	5884		29	26957
	22	219	2166			56	595	2831	44	345	5828	42	29	25726
	28	219	2166			5357	595	2831	44	345	527	42	29	25726
	35	219	2166	824	1597	8623	639			345	92	42	29	23305
0.95	2								44		6716		29	31093
	5								44		8155		29	29653
	10						595	1978	44	345	6737		29	28153
	15	219	2166			207	595	2831	44	345	5677	42	29	25726
	17	219	2166			1853	595	2831	44	345	4031	42	29	25726
	20	219	2166			4321	595	2831	44	345	1563	42	29	25726
	22	219	2166			6140	639	2483		345	92	42	29	25726
	28	219	2166	824	1191	8623	639			345	92	42	29	23711

Appendix C: Land Type Shadow Prices

Table C.1. Shadow Prices for Historical TN Abatement Cost Minimization

%	Land Type											
	AB2	AB5	AB6	CD2	CD5	CD6	AD4	AD15	AD25	MSS	UNM	USR
2	-107											-83093
3	-107											-83093
4	-107											-83093
5	-107											-83093
6	-107											-83093
7	-368						-406					-94000
8	-841	-841					-1142					-113760
9	-1087	-1087					-1357					-119540
10	-1087	-1087					-1357					-119540
11	-1087	-1087					-1357					-119540
12	-1087	-1087					-1357					-119540
13	-1087	-1087					-1357					-119540
14	-1087	-1087					-1357					-119540
15	-1087	-1087					-1357					-119540
16	-1087	-1087					-1357					-119540
17	-1087	-1087					-1357					-119540
18	-1087	-1087					-1357					-119540
19	-1087	-1087					-1357					-119540
20	-1087	-1087					-1357					-119540
21	-1087	-1087					-1357					-119540
22	-5328	-5328					-5069	-4506	-229			-219184
23	-8327	-8327	-937	-937	-937	-937	-7692	-7692	-978			-289626
24	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-664415
25	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-664415
26	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-664415
27	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-664415
28	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-664415
29	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-664415
30	-54711	-54711	-15432	-15432	-15432	-15432	-56975	-56975	-12574	-2161	-3424	-1379371
31	-54711	-54711	-15432	-15432	-15432	-15432	-56975	-56975	-12574	-2161	-3424	-1379371

Table C.2. Shadow Prices for Historical TP Abatement Cost Minimization

%	Land Type											
	AB2	AB5	AB6	AB15	CD2	CD5	CD6	AD4	AD15	AD25	MSS	USR
13												-636488
14												-636488
15												-636488
16												-636488
17												-636488
18												-636488
19												-636488
20	-164							-806				-795139
21	-164							-806				-795139
22	-164							-806				-795139
23	-164							-806				-795139
24	-164							-806				-795139
25	-164							-806				-795139
26	-164							-806				-795139
27	-230							-929	-65	-65		-819447
28	-870	-870						-1799	-526	-526		-990740
29	-870	-870						-1799	-526	-526		-990740
30	-870	-870						-1799	-526	-526		-990740
31	-870	-870						-1799	-526	-526		-990740
32	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1439512
33	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1439512
34	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1439512
35	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1439512
36	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1439512
37	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1439512
38	-11461	-11461	-6230		-6230	-6230	-6230	-12390	-10044	-6133		-3076233
39	-11461	-11461	-6230		-6230	-6230	-6230	-12390	-10044	-6133		-3076233
40	-56300	-56300	-42201	-42201	-32606	-32606	-32606	-57229	-54883	-29871	-2063	-10949960
41	-56300	-56300	-42201	-42201	-32606	-32606	-32606	-57229	-54883	-29871	-2063	-10949960
42	-56300	-56300	-42201	-42201	-32606	-32606	-32606	-57229	-54883	-29871	-2063	-10949960

Table C.3. Shadow Prices for Historical TSS Abatement Cost Minimization

%	Land Type											
	AB2	AB5	AB6	AB15	CD2	CD5	CD6	AD4	AD15	AD25	MSS	USR
21	-794											-1075714
22	-862				-49							-1102221
23	-862				-49							-1102221
24	-862				-49							-1102221
25	-862				-49							-1102221
26	-862				-49							-1102221
27	-862				-49							-1102221
28	-1269				-339			-464				-1260113
29	-2141	-1122			-962			-1461				-1599174
30	-2141	-1122			-962			-1461				-1599174
31	-2141	-1122			-962			-1461				-1599174
32	-2141	-1122			-962			-1461				-1599174
33	-2141	-1122			-962			-1461				-1599174
34	-2141	-1122			-962			-1461				-1599174
35	-2141	-1122			-962			-1461				-1599174
36	-2141	-1122			-962			-1461				-1599174
37	-2141	-1122			-962			-1461				-1599174
38	-2141	-1122			-962			-1461				-1599174
39	-2141	-1122			-962			-1461				-1599174
40	-2141	-1122			-962			-1461				-1599174
41	-2141	-1122			-962			-1461				-1599174
42	-2141	-1122			-962			-1461				-1599174
43	-2141	-1122			-962			-1461				-1599174
44	-2176	-1167			-987			-1502	-48			-1612883
45	-2176	-1167			-987			-1502	-48			-1612883
46	-2176	-1167			-987			-1502	-48			-1612883
47	-9890	-9890	-4846		-5834	-4846	-4846	-9256	-9256	-978	-780	-4249592
48	-11406	-11406	-5689		-6676	-5689	-5689	-10856	-10856	-1315	-949	-4707842
49	-11406	-11406	-5689		-6676	-5689	-5689	-10856	-10856	-1315	-949	-4707842
50	-19910	-19910	-10413	-8031	-11400	-10413	-10413	-19832	-19832	-3205	-1893	-7278090

Table C.4. Shadow Prices for CC TN Abatement Cost Minimization

%	Land Types											
	AB2	AB5	AB6	CD2	CD5	CD6	AD4	AD15	AD25	MSS	UNM	USR
2	-107											-77002
3	-107											-77002
4	-107											-77002
5	-107											-77002
6	-107											-77002
7	-368						-406					-87149
8	-841	-841					-1142					-105532
9	-1087	-1087					-1357					-110908
10	-1087	-1087					-1357					-110908
11	-1087	-1087					-1357					-110908
12	-1087	-1087					-1357					-110908
13	-1087	-1087					-1357					-110908
14	-1087	-1087					-1357					-110908
15	-1087	-1087					-1357					-110908
16	-1087	-1087					-1357					-110908
17	-1087	-1087					-1357					-110908
18	-1087	-1087					-1357					-110908
19	-1087	-1087					-1357					-110908
20	-1087	-1087					-1357					-110908
21	-1087	-1087					-1357					-110908
22	-5328	-5328					-5069	-4506	-229			-203606
23	-5328	-5328					-5069	-4506	-229			-203606
24	-8327	-8327	-937	-937	-937	-937	-7692	-7692	-978			-269137
25	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-617800
26	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-617800
27	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-617800
28	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-617800
29	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-617800
30	-54711	-54711	-15432	-15432	-15432	-15432	-56975	-56975	-12574	-2161	-3424	-1282915
31	-54711	-54711	-15432	-15432	-15432	-15432	-56975	-56975	-12574	-2161	-3424	-1282915

Table C.5. Shadow Prices for CC TP Abatement Cost Minimization

%	Land Type											
	AB2	AB5	AB6	AB15	CD2	CD5	CD6	AD4	AD15	AD25	MSS	USR
12												-585065
13												-585065
14												-585065
15												-585065
16												-585065
17												-585065
18												-585065
19	-164							-806				-730984
20	-164							-806				-730984
21	-164							-806				-730984
22	-164							-806				-730984
23	-164							-806				-730984
24	-164							-806				-730984
25	-164							-806				-730984
26	-230							-929	-65	-65		-753341
27	-870	-870						-1799	-526	-526		-910887
28	-870	-870						-1799	-526	-526		-910887
29	-870	-870						-1799	-526	-526		-910887
30	-870	-870						-1799	-526	-526		-910887
31	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1323644
32	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1323644
33	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1323644
34	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1323644
35	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1323644
36	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1323644
37	-11461	-11461	-6230		-6230	-6230	-6230	-12390	-10044	-6133		-2829014
38	-29112	-29112	-16613	-16613	-16613	-16613	-16613	-30041	-27695	-15478	-783	-6025893
39	-56300	-56300	-42201	-42201	-32606	-32606	-32606	-57229	-54883	-29871	-2063	-10949960
40	-56300	-56300	-42201	-42201	-32606	-32606	-32606	-57229	-54883	-29871	-2063	-10949960
41	-56300	-56300	-42201	-42201	-32606	-32606	-32606	-57229	-54883	-29871	-2063	-10949960

Table C.6. Shadow Prices for CC TSS Abatement Cost Minimization

%	Land Type											
	AB2	AB5	AB6	AB15	CD2	CD5	CD6	AD4	AD15	AD25	MSS	USR
20	-794											-999305
21	-862				-49							-1023937
22	-862				-49							-1023937
23	-862				-49							-1023937
24	-862				-49							-1023937
25	-862				-49							-1023937
26	-862				-49							-1023937
27	-1269				-339			-464				-1170658
28	-2141	-1122			-962			-1461				-1485731
29	-2141	-1122			-962			-1461				-1485731
30	-2141	-1122			-962			-1461				-1485731
31	-2141	-1122			-962			-1461				-1485731
32	-2141	-1122			-962			-1461				-1485731
33	-2141	-1122			-962			-1461				-1485731
34	-2141	-1122			-962			-1461				-1485731
35	-2141	-1122			-962			-1461				-1485731
36	-2141	-1122			-962			-1461				-1485731
37	-2141	-1122			-962			-1461				-1485731
38	-2141	-1122			-962			-1461				-1485731
39	-2141	-1122			-962			-1461				-1485731
40	-2141	-1122			-962			-1461				-1485731
41	-2141	-1122			-962			-1461				-1485731
42	-2141	-1122			-962			-1461				-1485731
43	-2176	-1167			-987			-1502	-48			-1498470
44	-2176	-1167			-987			-1502	-48			-1498470
45	-2176	-1167			-987			-1502	-48			-1498470
46	-9890	-9890	-4846		-5834	-4846	-4846	-9256	-9256	-978	-780	-3948634
47	-11406	-11406	-5689		-6676	-5689	-5689	-10856	-10856	-1315	-949	-4374464
48	-11406	-11406	-5689		-6676	-5689	-5689	-10856	-10856	-1315	-949	-4374464
49	-19910	-19910	-10413	-8031	-11400	-10413	-10413	-19832	-19832	-3205	-1893	-6762868
50	-19910	-19910	-10413	-8031	-11400	-10413	-10413	-19832	-19832	-3205	-1893	-6762868

Table C.7. Shadow Prices for Historical TN Abatement Safety First Programming

Prob. B	%	Land Type											
		AB2	AB5	AB6	CD2	CD5	CD6	AD4	AD15	AD25	MSS	UNM	USR
0.5	2	-1087	-1087					-1357					-110929
	5	-1087	-1087					-1357					-110929
	1	-5328	-5328					-5069	-4506	-229			-203644
	15	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-617913
	17	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-617913
	20	-54711	-54711	-15432	-15432	-15432	-15432	-56975	-56975	-12574	-2161	-3424	-1283148
0.75	2	-1087	-1087					-1357					-104227
	5	-5328	-5328					-5069	-4506	-229			-191548
	1	-24279	-24279	-5922	-5922	-5922	-5922	-24642	-24642	-4966	-640		-581716
	15	-54711	-54711	-15432	-15432	-15432	-15432	-56975	-56975	-12574	-2161	-3424	-1208251

Table C.8. Shadow Prices for Historical TP Abatement Safety First Programming

Prob. B	%	Land Type											
		AB2	AB5	AB6	AB15	CD2	CD5	CD6	AD4	AD15	AD25	MSS	USR
0.5	2												-558694
	5												-558694
	10	-164							-806				-698083
	15	-230							-929	-65	-65		-719441
	17	-870	-870						-1799	-526	-526		-869937
	20	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1264225
	22	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1264225
	28	-11461	-11461	-6230		-6230	-6230	-6230	-12390	-10044	-6133		-2702235
0.75	2	-164							-806				-649291
	5	-164							-806				-649291
	10	-870	-870						-1799	-526	-526		-809206
	15	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1176103
	17	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1176103
	20	-11461	-11461	-6230		-6230	-6230	-6230	-12390	-10044	-6133		-2514216
	22	-11461	-11461	-6230		-6230	-6230	-6230	-12390	-10044	-6133		-2514216
0.95	2	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-987848
	5	-56300	-56300	-42201	-42201	-32606	-32606	-32606	-57229	-54883	-29871	-2063	-8179928
	10	-58856	-58856	-44599	-44599	-34051	-34051	-34051	-59785	-57440	-31157	-2047	-8545084

Table C.9. Shadow Prices for Historical TSS Abatement Safety First Programming

Prob. B	%	Land Type											
		AB2	AB5	AB6	AB15	CD2	CD5	CD6	AD4	AD15	AD25	MSS	USR
	5												
	10	-522											-853988
	15	-522											-853988
	17	-522											-853988
0.5	20	-522											-853988
	22	-522											-853988
	28	-2176	-1167			-987			-1502	-1418	-1418		-1420077
	35	-4916	-4689	-1957		-2944	-1957	-1957	-4633	-3766	-3766	-202	-2357741
	40	-19910	-19910	-10413	-8031	-11400	-10413	-10413	-19832	-19832	-13913	-1893	-6409848
	2	-522											-800661
	5	-522											-800661
	10	-522											-800661
	15	-522											-800661
0.75	17	-1269				-339			-640	-640	-640		-1040170
	20	-1882	-788			-777			-1165	-1165	-1165		-1236994
	22	-2176	-1167			-987			-1502	-1418	-1418		-1331576
	28	-4916	-4689	-1957		-2944	-1957	-1957	-4633	-3766	-3766	-202	-2210979
	35	-19910	-19910	-10413	-8031	-11400	-10413	-10413	-19832	-19832	-13913	-1893	-6011311
	2	-1882	-788			-777			-1165	-1165	-1165		-1062935
	5	-2176	-1167			-987			-1502	-1418	-1418		-1144254
	10	-4916	-4689	-1957		-2944	-1957	-1957	-4633	-3766	-3766	-202	-1900342
0.95	15	-4916	-4689	-1957		-2944	-1957	-1957	-4633	-3766	-3766	-202	-1900342
	17	-9890	-9890	-4846		-5834	-4846	-4846	-9256	-9256	-7233	-780	-3016884
	20	-11406	-11406	-5689		-6676	-5689	-5689	-10856	-10856	-8244	-949	-3342341
	22	-19910	-19910	-10413	-8031	-11400	-10413	-10413	-19832	-19832	-13913	-1893	-5167769

Table C.10. Shadow Prices for CC TN Abatement Safety First Programming[25]

Prob. B	**%**	Land Types										
		AB2	AB6	AB15	CD2	CD15	AD4	AD15	AD25	MSS	UNM	USR
0.5	2	-1087					-1357					-103496
	5	-1087					-1357					-103496
	10	-5328					-5069	-4506	-229	-405		-190230
	15	-24279	-5922		-5922		-24642	-24642	-4966	-2774		-577771
	17	-24279	-5922		-5922		-24642	-24642	-4966	-2774		-577771
	20	-54711	-15432		-15432		-56975	-56975	-12574	-6578	-3424	-1200087
0.75	2	-1087					-1357					-96385
	5	-5328					-5069	-4506	-229	-405		-177396
	10	-24279	-5922		-5922		-24642	-24642	-4966	-2774		-539366
	15	-73385	-16988	-16988	-16988	-77206	-12574	-3466		-1606101		
0.95	2	-24279	-5922		-5922		-24642	-24642	-4966	-2774		-504567
	5	-24279	-5922		-5922		-24642	-24642	-4966	-2774		-504567

[25] Land type AB5 was not included in the table for ease of readership, although its shadow price yielded the exact same value as land type AB2 for each reduction under each probability of success. Land types CD5 and CD6 were treated the same where they each have the same shadow price as land type CD2 for each goal under each probability of success.

Table C.11. Shadow Prices for CC TP Abatement Safety First Programming

Prob. B	%	Land Types											
		AB2	AB5	AB6	AB15	CD2	CD5	CD6	AD4	AD15	AD25	MSS	USR
0.5	2												-512365
	5	-164							-806				-640283
	10	-164							-806				-640283
	15	-870	-870						-1799	-526	-526		-797994
	17	-870	-870						-1799	-526	-526		-797994
	20	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1159833
	22	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1159833
	28	-56300	-56300	-42201	-42201	-32606	-32606	-32606	-57229	-54883	-29871	-2063	-9598661
0.75	2	-164							-806				-592692
	5	-230							-929	-65	-65		-610844
	10	-870	-870						-1799	-526	-526		-738758
	15	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1073882
	17	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-1073882
	20	-11461	-11461	-6230		-6230	-6230	-6230	-12390	-10044	-6133		-2296114
	22	-56300	-56300	-42201	-42201	-32606	-32606	-32606	-57229	-54883	-29871	-2063	-8889631
0.95	2	-870	-870						-1799	-526	-526		-685560
	5	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-996689
	10	-3149	-3149	-1341		-1341	-1341	-1341	-4078	-1732	-1732		-996689
	15	-56300	-56300	-42201	-42201	-32606	-32606	-32606	-57229	-54883	-29871	-2063	-8252861
	17	-56300	-56300	-42201	-42201	-32606	-32606	-32606	-57229	-54883	-29871	-2063	-8252861

Table C.12. Shadow Prices for CC TSS Abatement Safety First Programming

Prob. B	%	Land Types											
		AB2	AB5	AB6	AB15	CD2	CD5	CD6	AD4	AD15	AD25	MSS	USR
0.5	2												
	5												
	10	-522											-794311
	15	-522											-794311
	17	-522											-794311
	20	-522											-794311
	22	-1269				-339			-640	-640	-640		-1031932
	28	-2176	-1167			-987			-1502	-1418	-1418		-1321039
	35	-9890	-9890	-4846		-5834	-4846	-4846	-9256	-9256	-7233	-780	-3481908
	40	-19910	-19910	-10413	-8031	-11400	-10413	-10413	-19832	-19832	-13913	-1893	-5963861
0.75	2	-522											-738418
	5	-522											-738418
	10	-522											-738418
	15	-1269				-339			-640	-640	-640		-959407
	17	-1882	-788			-777			-1165	-1165	-1165		-1141011
	20	-2176	-1167			-987			-1502	-1418	-1418		-1228279
	22	-4916	-4689	-1957		-2944	-1957	-1957	-4633	-3766	-3766	-202	-2039681
	28	-4916	-4689	-1957		-2944	-1957	-1957	-4633	-3766	-3766	-202	-2039681
	35	-19910	-19910	-10413	-8031	-11400	-10413	-10413	-19832	-19832	-13913	-1893	-5546148
0.95	2	-522											-687629
	5	-522											-687629
	10	-1882	-788			-777			-1165	-1165	-1165		-1062692
	15	-4916	-4689	-1957		-2944	-1957	-1957	-4633	-3766	-3766	-202	-1899907
	17	-4916	-4689	-1957		-2944	-1957	-1957	-4633	-3766	-3766	-202	-1899907
	20	-4916	-4689	-1957		-2944	-1957	-1957	-4633	-3766	-3766	-202	-1899907
	22	-9890	-9890	-4846		-5834	-4846	-4846	-9256	-9256	-7233	-780	-3016195
	28	-19910	-19910	-10413	-8031	-11400	-10413	-10413	-19832	-19832	-13913	-1893	-5166589