AN ANALYSIS OF ALTERNATIVE SOIL, NUTRIENT, AND WATER MANAGEMENT STRATEGIES

by

CRAIG MATTHEW SMITH

B.S., Kansas State University, KS, 2003
M.S., Kansas State University, KS, 2004

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
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Manhattan, Kansas

2011

Abstract

The two topics addressed in this dissertation are both related to surface water quality. Reservoir sedimentation and water quality trading are examined from economic and environmental perspectives. Each topic and the resulting policy implications are relevant to stakeholders at the local, state, and federal levels.

Reservoir Sedimentation

Reservoir sedimentation has been recognized as a major environmental, social, and economic issue in much of the Midwestern US. There is an effort to focus public and private funds to achieve the greatest return on the investment from soil erosion and sediment reduction strategies. How can physiographical and economic relationships within the watershed be quantified in such a way to provide insights into the selection of alternative management strategies? This study focuses on answering that question by integrating a physically-based watershed model with an economic analysis of alternative sedimentation reduction strategies for the case of Tuttle Creek Lake located in northeastern Kansas.

Several key finding of this study are that both physiographical and economic factors must be considered for cost-effective conservation to occur. Considering these factors and targeting BMP implementation from 8 to 23 times more cost-effective than random implementation. If targeting cannot be done effectively or if “intangible” costs of BMP implementation are too large, dredging is likely to be more cost-effective. While this research compares the cost-effectiveness of various BMP implementation approaches in Kansas with dredging, the benefits associated with each of these strategies is not addressed.

Water Quality Trading

While there is substantial evidence that nonpoint sources have lower nutrient reduction costs than point sources, experience with water quality trading (WQT) reveals a common theme: little or no trading activity. These outcomes suggest the presence of obstacles to trading that were not recognized in the design of existing programs.

To examine the ways that various market imperfections may impact the performance of a WQT market, an agent-based model is constructed, which simulates a hypothetical point-nonpoint market. This study first presents an overview of the concepts and simulation modeling technique used and then analyzes the effects of two prominent market impediments identified in the WQT literature: information levels and trading ratios.

The results imply that if market designers feel that only a limited number of trades will be consummated, creating an institution that provides accessible information about buyers’ prices is preferred to providing information about sellers’ prices. Overall, more information is always better, but it becomes less important with higher trading ratios.

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Finally, I want to express my gratitude, respect, reverence, and worship for my Savior, Jesus Christ. I hope to be a shining light for His glory and grace all of the days of my life.

Dedication

It's hard to believe that just 12 short years ago I was ready to drop out of college after just one-half of a semester at K-State. I was completely sick and tired of school and ready to go make some money and have something to show for my efforts. And to be honest, I occasionally felt a little that way through some of my PhD coursework. Without recounting all of the details of my journey, the take-home messages to me are that: 1) the Lord works in mysterious ways and 2) almost anything can be achieved by a person if they are motivated and driven. I wish to dedicate this dissertation, which represents the culmination of multiple years of effort and hard work, to my sons Jett and Colt. Whatever paths you end up taking in life, be motivated and drive hard while keeping your heart and eyes fixed upon your upward calling. The following verses from Philippians state this better and more completely.

12*Not that I have already obtained this or am already perfect, but I press on to make it my own, because Christ Jesus has made me his own.* ***13****Brothers, I do not consider that I have made it my own. But one thing I do: forgetting what lies behind and straining forward to what lies ahead,* ***14****I press on toward the goal for the prize of the upward call of God in Christ Jesus.* ***15****Let those of us who are mature think this way, and if in anything you think otherwise, God will reveal that also to you.* ***16****Only let us hold true to what we have attained.*

Philippians 3:12-16 (English Standard Version)

CHAPTER 1 - Overview

"...and when all the flocks were gathered there, the shepherds would roll the stone from the mouth of the well and water the sheep, and put the stone back in its place over the mouth of the well."

Genesis 29:3 (English Standard Version), approx. 1850 B.C.

"When the well is dry, we learn the worth of water."

Benjamin Franklin, 1746

"Gone are the days when water is taken for granted by city or rural residents, by recreational users, by agriculture or any other group who utilizes water."

Steve Irsik, Chair of Kansas Water Authority, 2004-present.

Water is the one of the primary foundations for life on Earth. Civilizations throughout history have risen and fallen, advanced and regressed, and prospered and suffered due to the availability of, or absence of, adequate quality water supplies. From Biblical times up through the present age, human civilizations have developed an appreciation, albeit of varying degrees, for the value of preserving and protecting our water resources.

Though the predominantly blue planet in which we live is three-fourths covered by oceans, rivers, and lakes, 98 percent of that water is too salty to drink. Of the 2 percent that is fresh, only half is found in rivers, lakes, or groundwater and readily available for human consumption.[1] Of this relatively tiny fraction of readily available fresh water, much is polluted to the point that it is unfit for drinking (Cech 2005). Though contaminated water and water shortages are often thought of as being "developing" country issues, even a casual follower of current events across the United States would recognize that we are continually confronted with these same types of issues here.

Increases in global demands for food, feed, and fuel over the past five years has given agricultural producers sufficient market signals (i.e., higher prices) to increase commodity production. Increased production requires additional land, nutrients, water, and other cropping inputs to be used to produce greater overall yields. If not done carefully, these changes in agricultural production can create the potential for greater sediment and nutrient runoff resulting in poorer surface water quality. Thus, the potential tradeoff between agricultural production and environmental quality has renewed urgency (Claassen 2009).

In an attempt to increase environmental quality, environmental regulations related to water quality in most areas across the country are trending toward more stringency. In addition, many of the new laws and regulations are pointing more fingers towards unregulated nonpoint sources of pollution, particularly agriculture. Many of these new regulations won't be passively accepted by all stakeholders involved. In the Chesapeake Bay, for example, the American Farm Bureau Federation and the Pennsylvania Farm Bureau have filed suit against the Environmental Protection Agency (EPA) for the issuance of a Chesapeake Bay total maximum daily load (TMDL). Nonpoint source pollution, and particularly agriculture, have been identified as major causes of TMDL non-compliance The farmer groups contend that the TMDL violates the Clean Water Act and the EPA's own regulations (US District Court 2011). There also may be the

[1] The majority is locked up in ice caps.

feeling among the farmer groups that if the TMDL is enforced in the Chesapeake Bay it may be just a matter of time before TMDLs are enforced nationwide.

At this same time, federal and many state and local budgets are not expanding, and in many cases, shrinking. It is fairly safe to say that public money spent on soil and water conservation will not be increasing in many areas around the country as we look towards the near future. Because of the tight budget situations, more effort (or at the very least, lip-service) is being exerted to ensure that dollars are spent in cost-effective ways in all areas of government. Thus, we need to get as much conservation as possible out of every dollar spent.

Cost-effective conservation is smart economics and is a way of getting the biggest "bang for the buck," but it may not be the most politically or socially palatable approach. Cost-effective conservation requires the frugal use of funding and does not pay individuals for practices they are already doing. Payments that do not leverage a change in conservation behavior deplete budget resources without improving environmental quality (Claassen 2009). Cost-effective conservation also targets funding to farmers who can generate the most environmental improvement at the lowest cost. This non-uniform approach may benefit some farmers, and consequently, has the potential to indirectly "harm" other neighboring farmers.[2] This unintended consequence has been recognized in previous policy programs (e.g., Conservation Security Program, CSP). So, there are obvious tradeoffs between cost-effectiveness and equity and an inverse relationship between the two appears to exist.

Competitive bidding is another approach for achieving cost-effective conservation. One strategy recently used in several watersheds across the country is known as a best management practice (BMP) auction. In a BMP auction, bids are submitted to the "agency" and then ranked

[2] Farmers who get conservation payments may be able to afford higher bids for cash renting cropland compared to neighboring farmers who did not receive the payments.

based upon the quantity of pollutant (e.g., soil, nutrients) reduction generated per dollar. Winning bids are awarded to producers that can provide the most pollution reduction for the least cost. The auction allows the buyer to identify and purchase the most cost-effective environmental improvements for a specified budget. The buyer could be a governmental entity, as is often the case, or a private firm seeking to achieve a reduction in emissions. The latter would be more akin to water quality trading. Auction research is ongoing and the potential of auctions to improve conservation program cost-effectiveness could be large (Claassen 2009). Attaining cost-effective conservation is not a simple or easy proposition. However, it will be necessary in order to achieve greater soil and water conservation in the years ahead.

The two topics addressed in this dissertation are both related to surface water quality. Reservoir sedimentation and water quality trading are examined from economic and environmental perspectives. Each topic and the resulting policy implications are relevant to stakeholders at the local, state, and federal levels. The remaining chapters are briefly described, in turn, below.

Chapter 2 focuses on reservoir sedimentation in the context of a Kansas reservoir. The research question being addressed is: How can physiographical and economic relationships within the watershed be quantified in such a way to provide insights into the selection of alternative management strategies? This chapter focuses on answering that question by integrating a physically-based watershed model with an economic analysis of alternative sedimentation reduction strategies. This will offer decision-makers better insight into the cost implications associated with achieving various water quality levels and sedimentation reduction goals within a large watershed.

Chapter 3 serves as a transition from Chapter 2 to Chapter 4. Chapter 4 brings point sources of pollution into the discussion and analysis. Other similarities and differences between the two analyses are discussed.

Chapter 4 also covers surface water, but incorporates point sources of pollution into the policy analysis through a market-based approach. Specifically, this chapter attempts to answer the following research question: How can water quality trading markets be designed in ways that take into account different levels of information among buyers and sellers and what are the implications for the determination of "optimal" trading ratios? To examine the ways that these market imperfections may interact to impact the performance of a WQT market, an agent-based model is constructed, which simulates a hypothetical point-nonpoint market.

Chapter 5 serves as a concluding "wrap-up" of this entire dissertation. The author's overall thoughts and lessons learned related to watershed management are presented. Additionally, reflections stemming from nearly 10 years of water resources research and related work are offered in this chapter.

CHAPTER 2 - From the Dust Bowl to the Mud Bowl: The Economics of Reservoir Sedimentation

Introduction

With the primary purposes of flood control, electricity generation, water supply, and the creation of jobs, many water reservoir impoundments were built in the US from 1930-1960. As most reservoirs were produced by the construction of dams on rivers and streams, there was the obvious and inevitable realization that sediment deposition and accumulation would occur behind dams. With this in mind, the majority of these structures were built to operate for a projected 50 to 200 years before various designated uses would be negatively impacted by excess sediment accumulation. For many of these reservoirs, the volume of water storage has been reduced by sedimentation. Sedimentation is the process by which sediment particles settle by gravity and deposit on the bottom of slow-moving waters. In some cases sediment accumulation has occurred slower than or on pace with projections, but in other cases sedimentation rates have greatly exceeded original estimates (Hargrove et al. 2010; Juracek 2007). Regardless of how closely actual rates match the original projections, the fact that 50 to 80 years have passed since dam closure on many US reservoirs indicates that reservoir sedimentation has and will become more of an environmental, social, and economic issue of concern going forward.

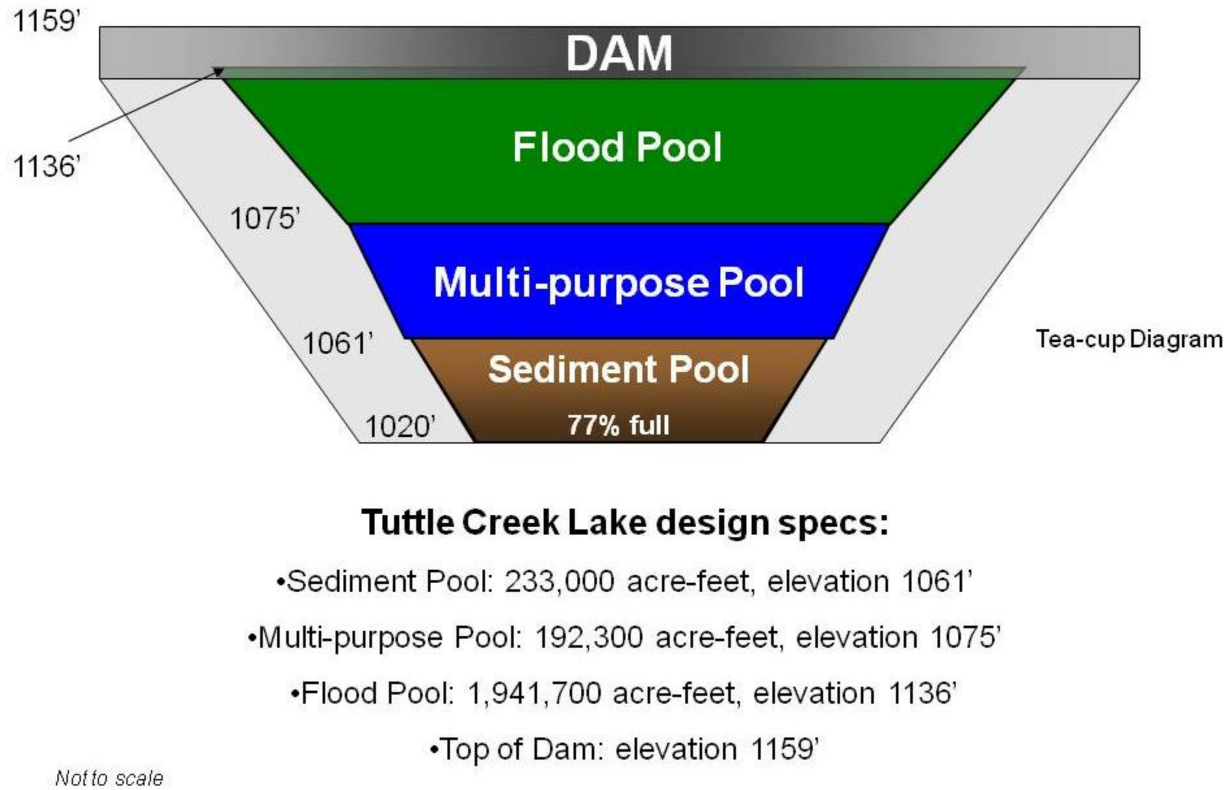
Erosion of cropland and streambanks have been identified as two culprits that not only cause significant damage to fields and lead to degraded aquatic ecosystems, but also result in sediment accumulations in downstream reservoirs. This poses environmental and economic concerns for stakeholders living in and around the watersheds and reservoirs affected by sedimentation. Sedimentation reduces reservoir storage capacity, negatively impacting public water supply, flood control capability, and water availability for downstream navigation. Both suspended and settled soil particles can affect the viability of aquatic life, reduce the recreational value of lakes and waterways, and increase operational costs to power plants, city water supplies, and navigation. Soil erosion also causes loss of cropland, particularly along stream and riverbanks, and lost soil productivity on crop and pasture land (Williams and Smith 2008).

Focus of this research

Reservoir sedimentation has been recognized as a major issue in much of the Midwestern US, including the state of Kansas. While there are many technical, environmental, and economic management problems associated with sediment sources and solutions to reservoir sedimentation, the state of Kansas has proactively recognized the need to protect, secure, and restore the life of its reservoirs (KWO 2010a). Because budgets are limited, every effort should be made to focus public and private funds to achieve the greatest return on the investment from soil erosion, sediment, and nutrient reduction strategies. This dissertation provides an evaluation of a large watershed and reservoir severely impacted by erosion and sedimentation. The results from this study will be useful to stakeholders and decision-makers at the field, watershed, state, and national level.

This study focuses on the Tuttle Creek Lake (TCL) watershed located in northeast Kansas. In the 47 years that have passed since dam closure, TCL has lost over 42 percent of its total (multi-purpose and sediment) storage capacity due to sediment accumulation (KWO 2010b). TCL exhibits, perhaps, one of the most critical cases of reservoir sedimentation in Kansas and throughout the Midwest. As of 2009, the Kansas Water Office estimated that the lake's sediment pool (Figure 2.1) had reached about 77 percent of design capacity (KWO 2010b).[3]

Figure 2.1 Reservoir design with Tuttle Creek Lake specifications



For several reasons, the loss of storage capacity and an overall degradation of reservoir quality are of importance to a variety of stakeholders. At the state level, the state of Kansas owns the rights to nearly 115,000 acre-feet (or nearly 60 percent of the multi-purpose pool) of water storage in TCL which it uses for augmenting flows in the Kansas River to ensure adequate supplies of surface water for downstream industries and municipalities (e.g., Topeka, Lawrence, and the greater Kansas City area). The US Army Corps of Engineers holds the rights to the remaining water in the multi-purpose pool, which it uses for water quality and navigational

[3] In construction, a sediment pool is some fraction of the total storage capacity reserved for sediment accumulation. Once the sediment pool is 100 percent full, the lake still exists but additional accumulation reduces the multi-purpose pool storage. It is at this point that owners of water storage are negatively impacted (although one could argue that they are impacted well before this point is reached as well).

purposes downstream, particularly in the Missouri River. The lake and surrounding parks also are important to the local economies. Smith and Leatherman (2008) estimated that TCL visitor expenditures generated $3.73 million (2007$) in direct economic activity (sales) within the regional (seven-county) economy, $1.74 million (2007$) in all types of income associated with the production of economic activities, and 82 area full- and part-time jobs. In another report, the US Army Corps of Engineers reported that the average annual economic benefits of TCL are $55 million (2000$) (USACE 2001). The breakdown given is $46.0 million in annual flood control benefits, $2.5 million in downstream navigation benefits, and $6.5 million in recreation and other benefits. In 1993 alone, the damages prevented from flooding equaled $1.25 billion. Clearly, this lake and the surrounding park areas provide many valuable benefits to stakeholders.

Some of the above uses and activities will be negatively affected by poor water quality and/or sediment accumulation. In response to past and current water quality degradation, the lake has been listed on the state of Kansas's "303(d) list" for water quality impairment due to excessive levels of phosphorus, sulfate, pH, lead, biology, copper, and total suspended solids (EPA 2010).[4] Because of the importance of this resource, stakeholders from the national to the state to the local level have made the protection of TCL a priority.

To preserve and/or restore the reservoir and watershed, a reasonable approach may be to slow the trend of sediment accumulation and reduce nutrient depositions. In order to do that, corrective action is needed and this action would ideally be based on a better understanding of watershed and stream sediment loading characteristics as well as the costs of alternative reservoir/watershed management strategies. How can physiographical and economic relationships within the watershed be quantified to provide insights into the selection of cost-

[4] The term, "303(d) list," is short for the list of impaired waters that the Clean Water Act requires all states to submit for Environmental Protection Agency (EPA) approval every two years.

effective alternative management strategies? This study focuses on answering that question by integrating a geographic information system (GIS) based watershed model, reservoir rehabilitation management strategies, statistical analyses of historic watershed and water quality data, with an economic analysis of alternative sedimentation reduction strategies. This will offer decision-makers better insight into the cost implications associated with achieving various water quality criteria and sedimentation reduction goals within a large watershed.

Overview of Analysis Approach

This comprehensive study is unique because this is the first time that the information obtained regarding reservoir sediment inflows along with sediment removal strategies will be incorporated within an economic framework. Additional uniqueness is due to the large scale, of both the watershed and reservoir, on which this analysis focuses. An economic analysis used in combination with physically-based watershed modeling can provide valuable insights into the evaluation of alternative reservoir sedimentation management scenarios. The following is an outline of the general approach that is used to evaluate alternative strategies for sediment reduction and reservoir rehabilitation:

1. Data Collection
    a. Identify watershed characteristics.
    b. Identify the extent and types of best management practices (BMPs) and other management systems currently in place.[5]

[5] Best management practices (BMPs) are defined as practical, cost-effective actions that producers can take to conserve water, nutrients, and/or soil. Descriptions of specific BMPs will be discussed in detail later in this paper.

   c. Identify potential BMPs from TCL Watershed Restoration and Protection Strategy (WRAPS) group and expert opinion.

2. Decision Support System Development

   a. Identify critical source areas using a physically-based watershed model.

   b. Develop comprehensive cost-return analyses of BMPs to optimize economic returns (or minimize costs) to agricultural production and improve watershed scale water quality.

   c. Prescribe appropriate BMPs for each critical area (based on the corresponding diagnosis).

3. Economic Analysis

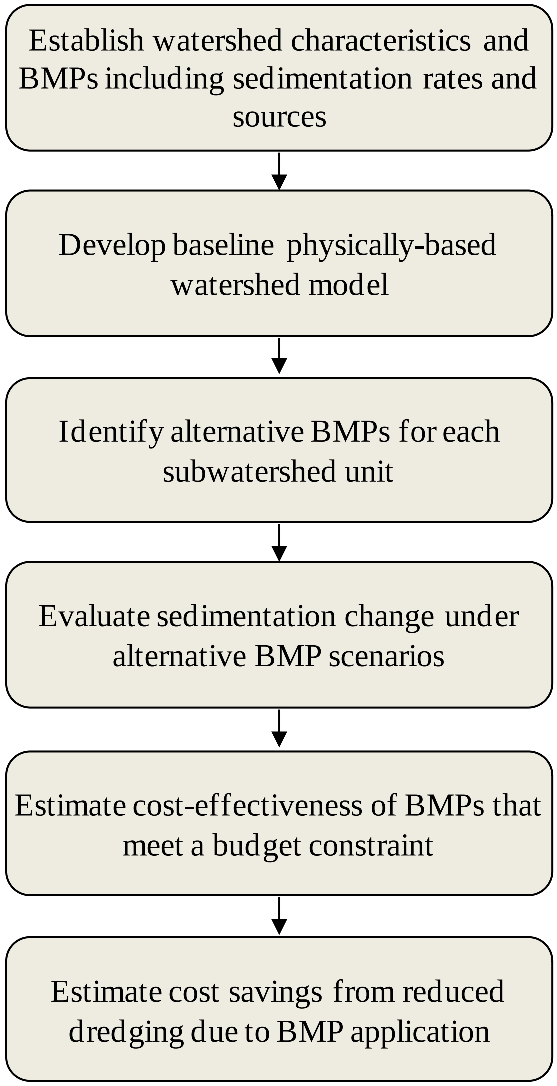
   a. Determine costs and returns of alternative BMPs modeled at field and watershed scale – including dredging of TCL.

   b. Evaluate sediment reduction cost-effectiveness using optimization and spatial targeting approaches.

   c. Estimate the amount of additional conservation funding that would be needed to achieve various levels of annual sedimentation reduction and compare the costs of watershed management scenarios to dredging (and various combinations of each) to a "do-nothing" scenario.

A visual depiction of the economic analysis used is displayed in Figure 2.2.

Figure 2.2 Approach used to analyze sedimentation reduction strategies for Tuttle Creek Lake



Relevant Literature

Identifying the land to target in a watershed is crucial for reducing the amount of sediment and nutrients entering a reservoir or exiting the watershed outlet. There have been several attempts to target and/or optimize BMP placement in agricultural watersheds (Yang et al. 2003; Yang et al. 2005; Khanna et al. 2003; Yuan et al. 2002; Rodriguez et al. 2011; Veith et al. 2004). While most of these analyses have occurred on much smaller watershed scales than the TCL watershed studied here, the methods and conclusions from these previous works are beneficial for the development of analysis techniques that will be used. Nevertheless, very little work has examined the economics of reservoir sedimentation in the context of dredging versus BMP implementation and that which had did not have a calibrated physically-based watershed model underlying the analysis. It is primarily these two elements (size/scale of the analyzed watershed and the inclusion of the economics of reservoir sedimentation) and the inclusion of multiple BMPs into the analysis that comprise the unique contributions to existing literature.

Yang et al. (2003)

Yang et al. (2003) developed an integrated framework of economic, environmental, and GIS modeling to examine alternative land retirement strategies in 12 contiguous agricultural watersheds in Illinois totaling 965 square miles. A main objective of this study was to analyze the cost effectiveness of the Conservation Reserve Enhancement Program (CREP), which has a key goal of reducing sediment loadings by 20 percent in the Illinois River.

In order to examine the cost effectiveness of CREP, the authors estimated sediment losses from land parcels, each 300ft x 300ft, using the Agricultural Nonpoint Source Pollution (AGNPS) model. A GIS interface was modified to prepare parcel-specific input data for the simulation model. Crop budgets were obtained and applied to each parcel of cropland and quasi-rents were estimated for each parcel. The quasi-rents were equal to total revenues minus total variable costs and represented a producer’s opportunity cost for taking the land out of production.

For the simulation model, the authors defined all land eligible for enrollment in CREP (required to be in the 100-year floodplain) to be equal to 900 feet along all streams and tributaries. The authors noted that for small streams the 900 ft buffer generally exceeded the 100-year floodplain boundaries, while for major tributaries and the Illinois River, this buffer could be narrower than the floodplain. For the most part, the 900 ft buffer included most of the land eligible for CREP enrollment, but it also included highly sloping land adjacent to streams that is typically outside of the 100-year floodplain.

The authors concluded that cropland selected for retirement in all watersheds was closer to water bodies, more sloping, more erosive, and more likely to receive larger volumes of upland sediment flows than cropland not selected for retirement. Many of the cropland parcels selected for retirement were located outside of the 100-year floodplain. Much of the floodplain cropland tended to be flatter and more productive than highly sloped land outside of the floodplain. Therefore, it would be much more cost effective to focus the CREP program on these highly sensitive lands to get the “biggest bang for the buck.” For example, the least cost-effective subwatershed yielded marginal sediment reduction costs of $256 per ton whereas the most cost-effective subwatershed had costs of just $42 per ton (2003$).

Yang et al. (2005)

Building upon previous work, Yang et al. (2005) first examined the cost-effectiveness of CRP and CREP in the Illinois River watershed. These two programs differed greatly in their eligibility requirements and selection mechanisms. In short, CRP eligibility included most cropland located in the watershed. Selection was based on the environmental benefits index (EBI) score and the producer’s bid price. CREP, on the other hand, had to be located in either the 100-year floodplains, on wetlands, or on sloping land adjacent to established riparian buffers. Note that the EBI was not used in selecting CREP enrollments, because it was assumed that any land parcel that met the restrictions of CREP automatically generated EBI scores above the typical cutoff level used in CRP.

Using a similar technique as described in Yang et al. (2003), Yang et al. (2005) found that in the absence of any land retirement in the watershed, 28,644 tons of sediment would enter streams in the watershed during a typical five-year storm event. Under CRP, 1,763 tons of sediment loss would be prevented at a cost of $109,767 per year for an average cost of abatement of $62 per ton. Under the status quo CREP, there were 5,889 cropland acres retired resulting in 6,485 tons of sediment abatement at a cost of $583,286 per year for an average cost-effectiveness of just under $90 per ton. Further analysis found that CREP parcels consisted of flatter, less erodible soils than the land enrolled in CRP. Through the use of Lorenz curves[6], it was found that environmental benefits (sediment loading reduction) were more variable across parcels than costs in both programs. These results suggested that there was considerable potential to improve on the performance of CREP.

The second objective of the Yang et al. (2005) study was to investigate if and how the cost-effectiveness of CREP could be improved upon. Three targeting strategies were tested. The first strategy was one in which all parcels (all of equal size) were ranked from low to high in terms of cost and the least expensive parcels were enrolled first until 5,889 acres of cropland were retired. The second approach involved ranking the parcels based on their potential environmental benefits and selecting the parcels, which offer the highest benefits until 5,889 acres of cropland were retired. The third targeting method took into account both benefits and costs and selected those parcels, which had the highest benefit to cost ratio until 5,889 acres of cropland were retired. It should be noted that when the opportunity cost of enrollment and the potential for sediment abatement benefits were compared across parcels in the CREP eligible

[6] A Lorenz curve shows the degree of inequality that exists in the distributions of two variables. Here, the curves depict the percentage of potential environmental benefits as a function of the percentage of acreage enrolled.

area, a negative correlation coefficient of -0.42 was calculated suggesting that all three targeting strategies should yield somewhat similar results.

The authors found that using the benefit or benefit/cost targeting schemes could have achieved abatement levels more than two times higher than the status quo CREP and at about 86 percent of the cost. Further, the benefit/cost targeting scenario could be just as cost-effective as CRP by reducing sediment loading at $84 per ton. It could possibly be more cost-effective if there weren't such stringent enrollment restrictions.

Yang et al. (2005) provided evidence that because sediment abatement benefits are more heterogeneous than costs across land parcels, the preferred selection criteria should at the very least be based on a measure of these benefits. A competitive selection process which takes into account benefits and costs can significantly improve the performance of CREP in Illinois relative to the status quo method of enrolling parcels on a first-come basis.

Khanna et al. (2003)

Working in the same geographic area as Yang et al. (2003), Khanna et al. (2003) developed a framework to determine cost-effectiveness of sediment reduction using land retirement within the CREP. A hydrologic model (AGNPS) with GIS data and an economic model were applied to a 61,717-acre Illinois watershed. Of this area, 8,172 acres were eligible for targeting, assuming that sloping cropland adjacent to a stream and riparian buffer within 900 feet of a stream were also considered eligible for land retirement using CREP. They found that to achieve a 20 percent sediment reduction for a 5-year storm, 11 percent of these acres would need to be in CREP with an average abatement cost of $31 per ton. With a 30 percent reduction goal the average cost was $47 per ton. Marginal costs rise from $29 per ton at a 10 percent reduction level to $117 per ton at the 30 percent reduction goal. Their results show that most of the land selected for enrollment is from highly sloping and highly erodible areas rather than flat floodplains that are not highly erodible.

Yuan et al. (2002)

Yuan et al. (2002) used a calibrated Annual AGNPS model to evaluate the effectiveness of BMPs for reducing sediment yield from a 30-acre subwatershed in the Mississippi Delta. The objectives of this study were to: 1) assess the impact of several BMPs on sediment yield from a typical Mississippi delta cropland watershed and 2) identify the most cost-effective BMPs for different tillage systems.

This simulation was accomplished by using 50 years of weather data to predict the potential impacts of three BMPs on three tillage systems (conventional-tillage, reduced-tillage, and no-till) for both cotton and soybean crops in the study subwatershed. The BMPs implemented in the simulations were: grade stabilization pipes, cover crops, and grass filter strips. The authors used two variants of cover crops: volunteer winter weeds and planted winter wheat cover crops.

BMP cost estimates were based upon 2001 data from the Mississippi Natural Resource Conservation Service (NRCS). Costs were divided into one-time initial fixed costs and annual variable costs. Finally, the annualized costs were divided by the subwatershed area (30 acres) to come up with “distributed costs” for each BMP.

The distributed annualized costs assuming a 5 percent interest (discount) rate and 25 year time horizon were $0 per ac for volunteer winter weeds cover crop, $16.20 per ac for winter wheat cover crop, $6.82 per ac for a vegetative filter strip, $3.05 per ac for a slotted inlet grade stabilization pipe, and $9.21 per ac for a 1.25 feet deep water impoundment, which was essentially a box inlet water control structure into which boards were stacked to impound water on the field year-round. The relative cost-effectiveness of each BMP was calculated by dividing the total annualized cost by the sediment yield reduction of each BMP within a tillage system. It should be noted that Yuan et al. (2002) assumed that the tillage system had an impact on predicted sediment yield, but not on profitability.

The authors found that the marginal sediment reduction costs for all BMPs were about $7.00 per ton for conventional and reduced tillage and $9.60 per ton with no-till. The greater cost with no-till occurred because no-till alone reduces sediment yield by 50 percent and further reductions tend to be more difficult and expensive.

This analysis did not find 33 feet (10m) wide filter strips to be a particularly cost-effective BMP for any of the tillage systems. This was because filter strips required more land to be taken out of production than with an impoundment, and the estimated sediment reduction benefit was less. Filter strips could be installed at a lower initial cost, but when one factored in the annual land rental costs the total distributed annualized costs were higher.

Not surprisingly, this study found that allowing volunteer winter annual weeds to grow following harvest was the most cost-effective BMP for all tillage systems as there was no cost associated with this BMP. Slotted inlet pipes and slotted board riser pipes were the next most cost-effective BMPs; however, these pipes did not achieve the 50 percent sediment reduction goal from conventional and reduced tillage systems unless combined with some type of cover crop. Vegetative filter strips (33 ft wide) were the least cost-effective of the BMPs considered. The authors suggested that narrower filter barriers (i.e., 3.3 ft wide) may be more cost-effective for sediment reduction.

Yuan et al. (2002) concluded by asserting that decisions on the adoption of BMPs should be made after jointly considering the environmental and economic impacts. The results reported in this study could be considered valid for other agricultural regions similar to the Mississippi delta with fields slopes of less than 1 percent and where sediment is the primary cause of water quality impairment.

Rodriguez et al. (2009)

Rodriguez et al. (2009) used a nondominated sorting genetic algorithm (NSGA-II) to evaluate the optimal fitness of 35 different BMPs (combinations of pasture management, buffer zones, and poultry litter application practices) on the basis of subfield (i.e., HRU) pollutant loads estimated with the Soil and Water Assessment Tool (SWAT). The uniqueness of this study was that the authors analyzed the combined effect that pastureland, buffer zone, and poultry litter management could have as a phosphorus or nitrogen reduction strategy. The studied region was the Lincoln Lake watershed, which is a subwatershed within the Illinois River watershed. It is a relatively small watershed (12.36 mi^2) located in northwest Arkansas. This watershed has been the focus of an interstate water quality dispute between Oklahoma and Arkansas regarding the role that animal agriculture, particularly poultry, contributes to excess phosphorus concentrations.

The final NSGA-II optimization model generated a number of near-optimal solutions by selecting from the 35 BMP combinations for placement on any of the 461 pasture HRUs. Thus, the search space consisted of 35^{461} (or 6.54×10^{711}) possible combinations. The authors claimed that the final optimization model ran for 10,000 generations and 800 populations and were completed in less than one hour using a supercomputer.

The optimization routines operated by placing BMP combinations to reduce nutrient loading (phosphorus or nitrogen or both) while simultaneously minimizing total cost (defined as the summation of standard production costs and the additional costs for each BMP combination).

They compared these results to the baseline or current pasture management situation. In compiling the results, the authors found the lowest-cost, the medium-cost, and the highest-cost solutions of the 800 available.

By implementing all the BMP combinations recommended in the lowest-cost solution, total phosphorus could be reduced by at least 76 percent while increasing cost by less than 2 percent in the entire watershed. This value represented an increase in cost of $2.22 per ac compared to the baseline. For the medium- and the highest-cost solutions, implementing all of the prescribed BMPs could decrease total phosphorus immensely but would increase the total cost by 7 and 25 percent, respectively.

When the optimization routine focused on nitrogen reduction for all cost implementation solutions, the total nitrogen loads were reduced by at least 98.9 percent. The authors did not reveal the percentage cost increases for these scenarios or the scenarios in which both phosphorus and nitrogen were the focus. They did, however, state that even though the majority of the BMPs were recommended to reduce both nutrients, their frequencies and placement distributions across the HRUs will determine their effectiveness. Thus, they recommend an optimization (targeting) strategy similar to theirs' be used to help guide BMP implementation in a watershed.

Veith et al. (2004)

Veith et al. (2004) sought to determine if selection of sediment reducing BMPs through genetic algorithm optimization, a performance-based method, could identify more cost-effective BMP scenarios than targeting, a plan-based method. The comparison between the two methods was conducted for a 2,506 ac predominantly agricultural-based watershed in Virginia.

The authors defined plan-based methods as those which draw from past field studies and scientific theory to assign pollutant reduction efficiencies to BMPs. Performance-based methods, on the other hand, use simulation models to assess changes in watershed response due to alternative BMP scenarios.

In this study, the baseline scenario was one with all cropland managed as conventionally tilled corn silage. The targeting scenario was defined as a plan-based method, which focused pollution control on areas within the watershed that have the greatest potential for sediment losses. Specifically, the targeting strategy used in this study involved converting all cropland with the majority of the field slope greater than 3 percent to minimum-tillage corn silage on the contour with a winter wheat cover crop.

Three optimization plans were evaluated. These included the full combination of BMPs used by the targeting strategy along with the option of applying BMPs individually across the watershed. Optimization plan 1 was most similar to the targeting strategy in that there were only two management variations of corn silage: conventional tillage or minimum-tillage on the contour with a winter wheat cover crop. Optimization plans 2 and 3 allowed for many more management variants and thus did not allow for a fair comparison to the targeting strategy. For that reason, this literature review will only compare the targeting strategy to optimization plan 1.

The optimization procedure was comprised of three components all operating within a Genetic Algorithm framework: optimization, NPS prediction, and economic analysis. The NPS component utilized the Universal Soil Loss Equation and a sediment routing routine developed by Veith (2002). The economic analysis component utilized enterprise budgeting from the Virginia Farm Management Crop and Livestock Enterprise Budgets.

The targeting strategy was first applied to the baseline scenario, and it was found that watershed sediment yield was reduced by 2,507 lb/ac. Because the optimization routines required a pollutant reduction goal, the goal was set to match the results from the targeted strategy - 2,507 lb/ac. Cost-effectiveness of each solution was calculated by dividing the amount of additional costs (from adopting the BMPs) by the amount of sediment decrease. Under the targeting strategy, the estimated cost-effectiveness of sediment reduction was $53.93 per lb/ac, whereas in the optimization plan 1, the cost-effectiveness was estimated to be about $47.19 per lb/ac. Optimization plans 2 and 3 resulted in even higher levels of cost-effectiveness than optimization plan 1.

The explanation offered for the increased cost-effectiveness of optimization plan 1 over targeting was that optimization plan 1 applied BMPs primarily on high-sloped fields that bordered streams whereas with the targeting strategy, any field with greater than 3 percent slope had the set of BMPs applied regardless of the proximity to the stream.

The authors concluded by stating that targeting strategies offer the benefit of lesser data requirements and less computing time. However, when a complete cost-benefit analysis was performed for this study, which included the costs associated with additional data requirements and computing time for optimization models, the optimization model (plan 1) still proved to be more cost-effective than the targeting strategy. The optimization techniques used in this study also offer some flexibility in BMP implementation by providing a number of near-optimal solutions in contrast to the targeted approach, which offers one and only one BMP implementation scenario.

Hansen and Hellerstein (2007)

Hansen and Hellerstein (2007), evaluated the impact of soil conservation on reservoir services. To do this, it was assumed that reservoir services (flood control, recreational opportunities, aesthetic beauty, power generation, etc.) are a function of the level of sediment in the reservoir. An implication of this approach is that sediment that settles in a reservoir the year before the reservoir is dredged will impose little environmental cost. The authors extended the use of replacement cost theory, which differed from past work, which focused on sediment's impact on future dredging costs; hence, sediment that settled in a reservoir the year before it was dredged would impose the greatest social cost.

This framework was used to value the effect that a marginal change in soil erosion had on current and future reservoir benefits. They analyzed impacts across more than 70,000 reservoirs across 2,111 Hydrologic Unit Code (HUC) areas of the 48 contiguous states. The results showed that marginal reductions in soil erosion provide benefits ranging from zero to $1.38 per ton. As expected, HUCs with no reservoirs offered no reservoir-related soil conservation benefits. And, those HUCs with relatively more reservoirs tended to have greater soil conservation benefits.

There were several assumption made in order to derive estimates of the parameters in the benefit function. One of the more notable assumptions in their analysis, which has some relevance to our analysis is that dredging was assumed to be optimal once a reservoir had lost 30 percent of its capacity. According to the authors, past studies have found that, across reservoirs, dredging occurs with 15-45 percent capacity loss. They tested the sensitivity of this assumption by re-estimating benefits based on a 20 and 40 percent loss in capacity and found that the median benefit estimates ranged from approximately 15 percent higher to 1 percent lower.

Williams and Smith (2008)

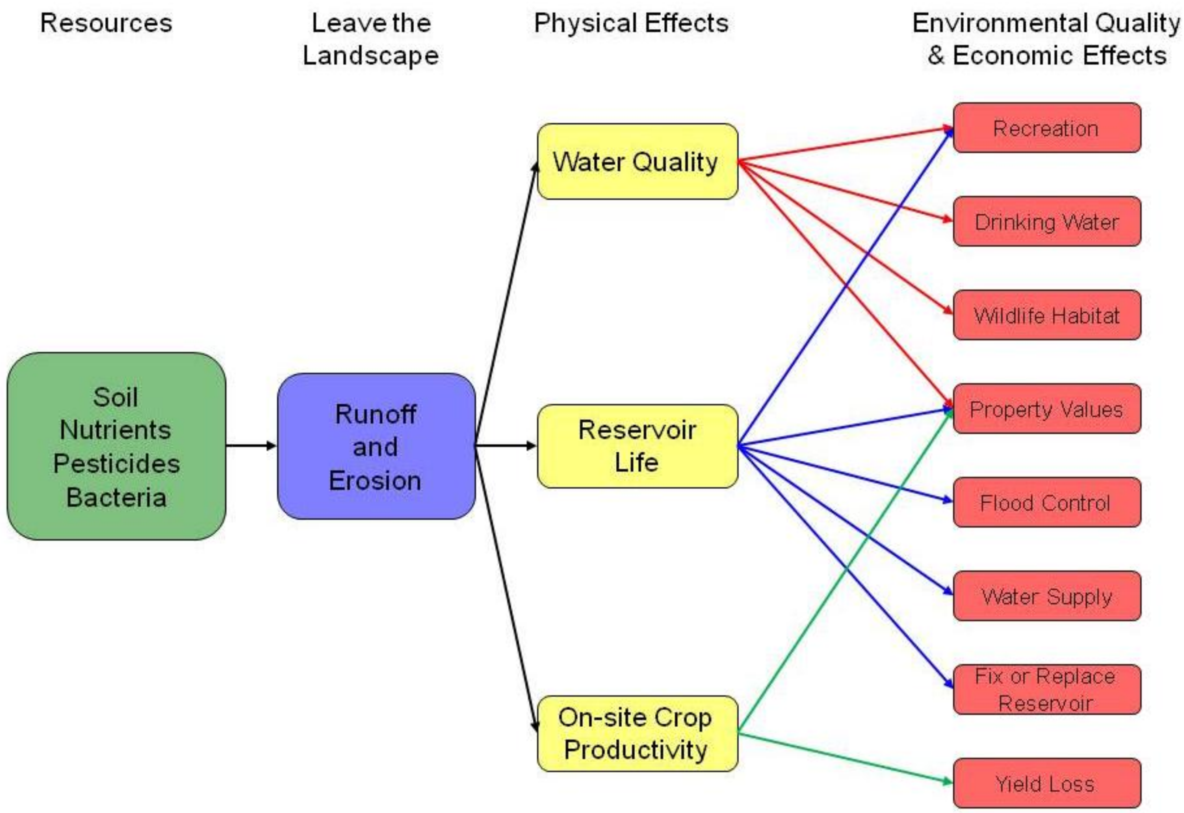
In 2008, Williams and Smith prepared a sedimentation white paper on the economics of watershed protection and reservoir rehabilitation. They noted that this was a broad topic and enormous task. This is partially due to there being very little literature on the economics of sediment control at the watershed scale and virtually no studies addressing whether dredging of sediment or prevention of sedimentation is more economical. The research began by giving an overview of the costs of soil erosion and sedimentation based on existing literature. The authors went on to analyze the potential savings from implementing some individual in-field erosion control methods in a watershed to reduce the future cost of dredging sediment from a reservoir. The estimates, they noted, were meant to provide some perspective on the savings that may be gained by using individual soil erosion management practices to reduce the need for dredging. They found that it may be more economical for the government to fund expenditures for management practices to reduce further erosion and sedimentation in a watershed than to rely on future use of dredging in situations where the amount of accumulated sediment has not reduced the usefulness of the reservoir. They qualify this by mentioning that their analysis is not complete due to the lack of critical data. Specifically, the study identified the following items as necessary information: the source of the sediment, how suitable the management practices will be for various locations in a watershed, and the number of acres that actually need application of these practices from a technical and economic perspective.

The research performed here provides and applies much needed data and builds upon the previous work of Williams and Smith (2008) as well as Yang et al. (2003) and Khanna et al. (2003). Again the uniqueness of this research includes the size/scale of the analyzed watershed along with considerations of the economics of reservoir sedimentation. Williams and Smith (2008) was a first attempt at this, but relied on many assumptions regarding watershed characteristics and BMP effectiveness. This research extends Williams and Smith (2008) by incorporating estimated data from a calibrated physically-based watershed model.

Conceptual Framework

Soil erosion and nutrient runoff from cropland results in decreased on-site productivity as well as numerous offsite consequences (Williams and Smith 2008). Offsite, surface water quality can become impaired and reservoir life shortened. These physical effects in turn have negative consequences on the environment and regional economy. Figure 2.3, which is adapted from Williams and Smith (2008), shows the flow of these effects. This analysis primarily focuses on soil erosion and nutrient runoff from cropland affecting water quality and the life of a reservoir. While this analysis indirectly and qualitatively considers recreation, flood control, and water supply effects, options for protecting and/or restoring (i.e., BMP implementation and/or dredging) the reservoir are quantitatively examined.

Figure 2.3 General effects of soil erosion and other pollutant runoff



The conceptual framework can be divided into two parts. First, there is an underlying conceptual model for the BMP implementation scenarios on cropland within the watershed. The second part involves the concepts of dredging alongside or in place of BMP implementation. This conceptual framework section will be split into two subsections, which cover the two previously mentioned parts.

STAGE I: "BMP implementation" conceptual model description

Environmental protection within production agriculture often relies on incentives to induce adoption and implementation of BMPs. The logic behind this is straightforward. Agricultural producers generally seek and adopt profit-enhancing practices and technologies on their own without compensation from outside sources. If a conservation BMP is profit-enhancing (benefits outweigh expected costs), producers will recognize this over time and choose to adopt the practice. One has to look no further than the increasing utilization of no-till over the past two decades. As for some other BMPs (e.g., filter strips), the producer may not receive any financial benefit from adoption. The benefits might go to stakeholders downstream and society in general. This is the definition of an externality. If a producer's goal is to maximize profit, there is often no incentive to adopt some BMPs.

Economic considerations are a key determinant in the adoption of BMPs. Although some producers have already adopted such practices, an expansion in adoption will occur only if the practices become profitable (in the absence of regulatory mandates). Simultaneously, it is important to recognize that producers across a watershed face different cost and production conditions. Although specific production practices may be profitable for some producers in some locations, they are not likely to be profitable for all producers in all locations. Further, the benefits of some BMPs accrue mostly to society at large and farmers are not compensated for these external benefits. Federal, state, local agencies, and private organizations seek to provide incentives for environmental protection where markets have failed to do so (Claassen 2009). This analysis considers the financial costs that would have to be expended (e.g., from a governing authority) in order to entice producers to adopt a given set of BMPs across the watershed.

The underlying conceptual model may be best represented in flow-chart organizational form based on (but modified to fit this analysis) work by Vellidis et al. (2009). The conceptual model is shown in Figure 2.4. It shows the linkages among socioeconomic factors and producers' BMPs while explicitly integrating cause and effect among socioeconomic factors, producers' decision making, and physically-based outcomes. The entire model is constrained by a federal, state, and/or regional conservation program. That is, it is assumed that all profit-enhancing BMPs have been adopted at an earlier time and any additional BMP implementation will occur if and only if a conservation program (Box A) provides sufficient financial support. Within this program, there is a suite of BMPs that can be adopted by producers. Physically-based and agronomic factors (Box B) as well as economic and social factors (Box C) determine whether or not BMPs will be adopted. Maintenance constraints (Box D) as well as physically-based and agronomic constraints (Box E) determine the effectiveness of the BMPs post-implementation. Further economic and social factors (Box F) can help to ensure that the BMPs remain in place throughout the life of the contract. A detailed description of the 6 levels of the constraints is below.

A. Conservation program constraints - The program constraints are based on funding availability, geographical eligibility, and resource focus.

B. Physically-based and agronomic constraints I- The first level of physically-based and agronomic constraints refer to the suitability of BMPs to different soil types, climatic conditions and cropping patterns. For example, no-till may not be suitable for heavy clay soils or a continuous corn rotation. Because of such constraints, more funding may have to be offered to different regions. This essentially accounts for any non-economic factor that affects BMP implementation.

C. Economic and social constraints I - The first level of economic and social constraints refer to acceptability of BMPs to producers. This may be due to social or economic reasons which may be related to the physically-based and agronomic constraints in part (B). The economic factors also may include available cost-share (i.e., one-time payments made to partially or fully offset initial installation costs) for given BMPs.

D. Maintenance constraints - Once BMPs are implemented periodic maintenance is required to maintain effectiveness. This also has an economic component.

E. Physically-based and agronomic constraints II - The second level of physically-based and agronomic constraints occur at both the farm- and watershed-level. These constraints help determine the effectiveness of the BMPs. Watershed models can be used to predict the amount of pollution reduction achieved at the farm- or field-level all the way up to the watershed-level.

F. Economic and social constraints - The second level of economic and social constraints include the adequacy of program payments. These include annual incentive and maintenance payments. The annual incentive payments must compensate the producer for the annual loss of production as well as any maintenance (e.g., mowing of a filter strip) that may be necessary to ensure longer-term BMP effectiveness.

Figure 2.4 Conceptual model linkages and data flow within the integrated economic model

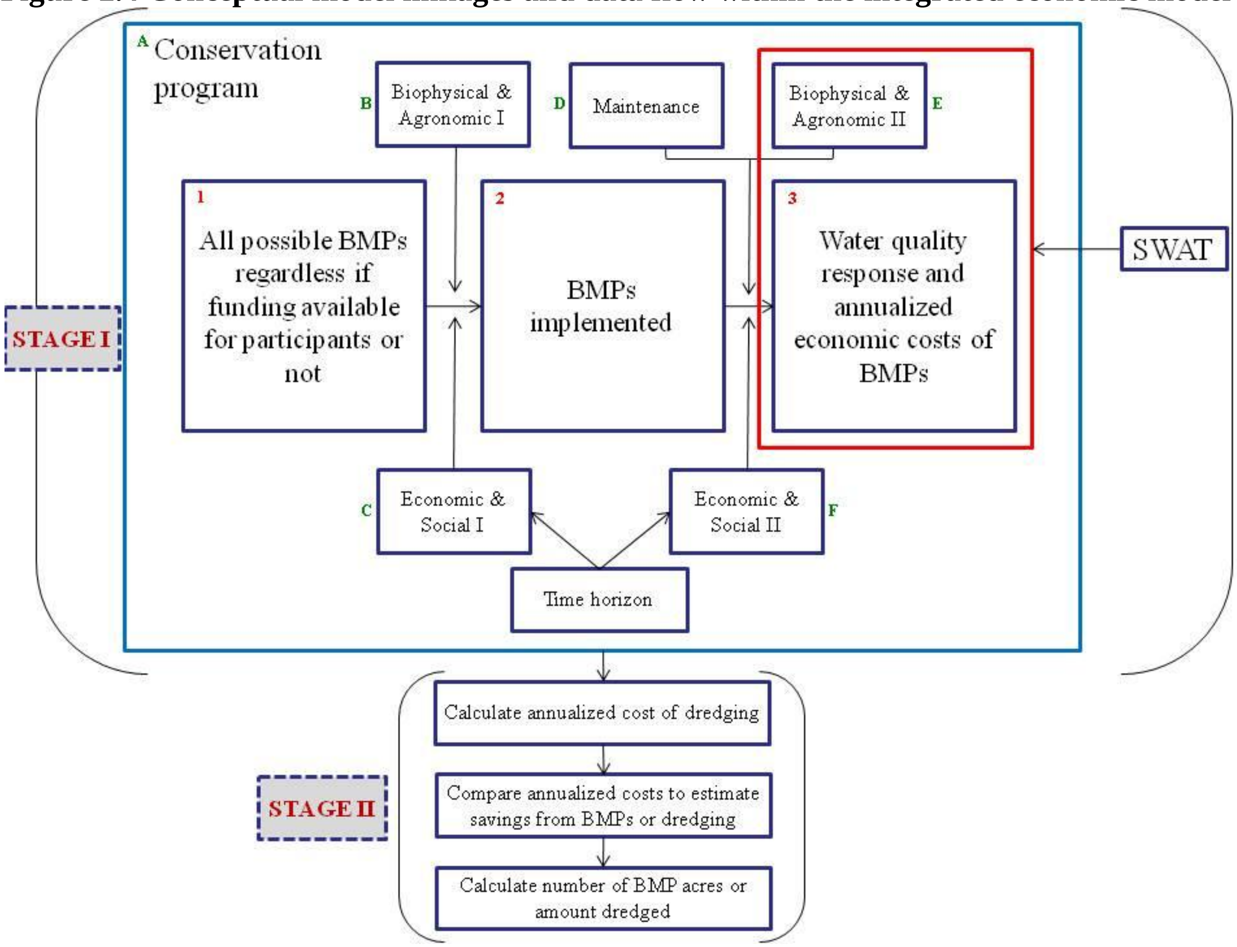


Figure 2.4 illustrates how the conceptual model is implemented. The SWAT physically-based watershed model is used to evaluate the watershed's water quality response to the different BMP implementation scenarios. The amount of annual conservation payments needed to induce implementation of BMPs to different amounts of acreage is estimated based on partial budgeting as well as historical rental rates. This is described in detail in the "Data" section. The final results or output from this part of the analysis include amounts of pollutant reduction along with the annual total and marginal costs of BMP implementation. A more detailed description of these concepts follows.

Here, we consider the problem of a watershed manager who seeks to achieve maximum pollution (i.e., sediment, nitrogen, and/or phosphorus) reduction subject to an annual budget constraint. The individual costs of implementing a given BMP on a given cropland parcel are equal to the sum of the lost revenues and the additional costs incurred (both one-time and annual over a 15-year time horizon) for a given farm. Nonpecuniary benefits (e.g., wildlife enhancement) from BMP adoption may also be a consideration for some producers/landowners, but these are obviously difficult to quantify and are ignored in this analysis. The annual aggregate cost of pollution reduction is represented by the sum of the annualized individual BMP implementation costs incurred.

To model the pollutant loading from each land parcel, a watershed model is developed. The model estimates edge-of-field loading and also factors in a delivery ratio to predict the average annual amount of pollutants entering the reservoir based on the application of BMPs. Cost and load reduction factors are used for each BMP-farm combination to estimate individual cost-effectiveness values (e.g., dollars per ton of sediment reduction).

Two types of management strategies are modeled: targeted and random BMP implementation. The targeted approach implements BMPs on cropland that have the most attractive cost-effectiveness values (e.g., the lowest dollars per ton of sediment reduction). Implementation continues until the budget constraint is reached. The random approach models the case in which BMPs are implemented in a random fashion, which spreads the BMPs randomly across the watershed. This approach is possibly more akin to the status quo conservation programs in use currently across the country (although some targeting approaches are used in some programs) (Nelson et al. forthcoming).

Finally, total and marginal cost curves can be derived for pollutant reduction for each management strategy modeled. These costs can be compared to the marginal costs of dredging.

From this, the "optimal" amount of sediment reduction achieved via BMP implementation and via dredging can be derived given the assumptions and constraints of the model.

STAGE II: "Dredging versus BMP implementation" conceptual model description

Along with BMP implementation, dredging is another method for reducing the amount of sediment in TCL. While dredging may also reduce the amount of nitrogen and phosphorus in the reservoir, analyzing these nutrient reductions with any precision requires knowledge of concentration levels in the dredged material. This is beyond the scope of this research and, thus, only sediment is considered in the "dredging versus BMP implementation" analysis.

Because sediment accumulation in TCL (and any reservoir for that matter) is inevitable, dredging is likely to be needed at some point in the future to preserve TCL. As will be discussed later in this study, dredging can be a relatively expensive option. However, at some point it may become feasible if the costs of dredging are less than additional BMP implementation on a per unit basis of sediment reduction. The question is: at what point does this occur? The answer can be found by comparing the marginal costs of BMP implementation with the costs of dredging.

As Williams and Smith (2008) point out, the decision on whether or not to dredge will depend on sediment source, sedimentation rate with and without management practices, effectiveness and cost of management practices, dredging cost inflation, the planning horizon, and the discount rate used to calculate present values. If accumulated sediment has not negatively impacted current reservoir services (e.g., recreation, flood control), then it might be reasonable to forego dredging in favor of investing in additional in-field and in-stream conservation practices to reduce the need for future dredging.

Following Williams and Smith (2008), this analysis also examines how many acres a BMP can be applied to if savings generated from reduced dredging finance the implementation of the BMP. Estimated future savings from dredging costs avoided because of implementing sediment reduction BMPs are a key component of this analysis. To determine these values, the reservoir sedimentation rates are estimated with and without BMP implementation over a 15-year planning period. A 15-year period is chosen because this is approximately equal to the number of years until the sediment pool is 100 percent full given average annual sediment loading rates. The costs of dredging 15 years in the future also are estimated based on the current rate of sedimentation versus a reduced rate of sedimentation that will result from implementing BMPs. This analysis is limited to costs; therefore, any benefits resulting from reduced erosion, sedimentation, and/or any nutrient reduction that may occur are not considered here. The method used for comparing dredging with BMPs also is shown in Figure 2.4.

Data

The data requirements for this study include both economic and physically-based data. This section begins by describing the types of BMPs considered and the economic costs (in 2009$) of each. The physically-based data for the simulations are generated from a calibrated watershed model. The second part of this section focuses on the model development and the physiographical results that are to be incorporated into the alternative watershed management simulations.

Best Management Practices

There are two main types of strategies for reducing the amount of sediment and nutrients that enter a reservoir: in-field and in-stream strategies. According to Devlin and Barnes (2008), in the Kansas River basin (which the Tuttle Creek watershed is a part of) unprotected croplands contributed the majority of sediment loads. While streambank erosion may contribute a significant amount of sediment to TCL, the watershed model developed here only considers the control of in-field sediment and nutrient sources.[7] The three in-field strategies analyzed are filter strips, no-till, and permanent vegetation.

The simulation program developed here requires the calculations of BMP costs. Existing research in this area shows that the costs and returns to BMPs are highly variable. According to a comprehensive BMP cost study performed by Williams and Smith (2008), the costs for implementing no-till, for example, may range from -$37.00 to more than $37.00 per acre. In other words, some producers may see significant economic returns (due to lower crop input costs and/or higher yields) from adopting no-till while others may see increased costs and/or lower yields. In general, however, Williams and Smith (2008) indicated that most sediment reducing BMPs exhibit positive costs. A relevant study by Valentin et al. (2004) utilized actual farm-level economic and BMP adoption data to rigorously analyze the relationship between BMP use and farm income. They showed that while the adoption of nutrient BMPs had a significant positive effect on net farm income for wheat and corn in Kansas nearly all of the soil conservation BMPs had no statistically significant impact on farm income.

In general, it is likely that cropland BMPs have already been adopted by producers, who stand to reap significantly increased net returns from doing so. While there may be other producers who have the potential to benefit economically from adopting a given BMP, for whatever the reason, they may resist implementing that BMP. Additionally, there are likely many producers who would see decreased income by the adoption of certain BMPs. An assumption made for this study is that in order to induce any further BMP adoption within the Tuttle Creek watershed, cost-share and/or incentive payments would have to be made to producers. The next

[7] The Soil and Water Assessment Tool (SWAT) watershed model does not have the ability to analyze sediment and nutrient loading due to streambank erosion unless site specific data can be provided.

step is determining the level of costs (incentives) for inducing more BMP adoption for purposes of the simulation routines.

Filter strips (also known as vegetative buffers) are land areas maintained in permanent vegetation that reduce nutrient and sediment losses from agricultural fields, improve runoff water quality, and provide wildlife habitat (Williams and Smith 2008). Generally, filter strips are placed at the edge of the field near or around bodies of surface water. There are several federal and state programs to encourage producers to adopt and maintain filter strips. In order to calculate the annualized costs of a filter strip, the KSU Vegetative Buffer Decision-Making Tool (Smith and Williams 2010) is used.

There are several cost-related assumptions that have to be made and entered into the tool. It is assumed that 2009 cash rents by county would be used as the lost opportunity cost of converting cropland to a grass filter strip or permanent vegetation (Dhuyvetter and Kastens 2009; USDA-NASS 2009). These are slightly higher than current CRP rental rates and are representative of rates typically paid for acres enrolled through the Continuous CRP enrollment. The higher rates are used because it is assumed that land converted to filter strips would be high quality land requiring more of a rental payment than typical CRP land.

Another assumption is that the procedure used for installing a filter strip involves the use of a cover crop before planting. This is based on discussion with NRCS personnel in the region. In addition, it is assumed that there would be $50 (5 hrs x $10 per hr) per acre one-time producer labor costs associated with the establishment of a filter strip and the design life (or time horizon) for the filter strip would be fifteen years. In line with Smith (2004) and Williams and Smith (2008), it is assumed that each acre of filter strip affects or treats runoff from 25 acres of cropland. The calculated annualized costs for an acre cropland treated by a filter strip by county can be seen in Table 2.1. A comprehensive filter strip budget example can be found in Table 2.2. Note, that a 15-year time horizon is used for reasons stated earlier and a discount rate of 4.625 percent is used, which is based on the year 2009 "Plan Formulation Rate for Federal Water Projects" (NRCS 2009).

Table 2.1 "Original" BMP Annualized costs over a 15-year time horizon

County, State	Annualized Cost ($/acre) for Filter Strips per cropland acre treated[1]	Annualized Cost ($/acre) for No-till	Annualized Cost ($/acre) for Permanent Vegetation
Clay, KS	$3.83	$13.00	$81.05
Gage, NE	$5.67	$20.00	$108.15
Jefferson, NE	$5.67	$20.00	$101.93
Marshall, KS	$4.71	$13.00	$89.23
Nemaha, KS	$4.79	$13.00	$92.46
Pawnee, NE	$5.47	$20.00	$105.52
Pottawatomie, KS	$4.31	$13.00	$86.58
Republic, KS	$3.88	$13.00	$76.63
Riley, KS	$4.55	$13.00	$81.87
Washington, KS	$4.56	$13.00	$83.07

[1] Annualized cost of filter strip divided by 25 cropland acres (treated)

Table 2.2 Filter strip budget for Marshall Co., KS

General Data For Filter Strip in Marshall Co., KS

Discount Rate	**4.63%**	
Cropland Rental Rate - not CCRP rental rate	**$76.19**	per acre / year
Annual Cropland Rental Growth Rate	**3.07%**	
Total Annual Costs	**$6.67**	per acre / year
Inflation Rate of Annual Costs	**4.00%**	

Project Length (feet)	**660**
Project Width (feet)	**66**
Acres (length x width/43,560)	**1.00**
Length of analysis (years)	**15**
Cropland Property Tax ($/acre)	**$5.00**
Tame Grass Property Tax ($/acre)	**$5.00**

COSTS		PAYMENTS RECEIVED	
Total one-time	**$175.44**	Total one-time	**$0.00**
Total annual	**$6.67**	Total annual	**$0.00**

Net Present Value Table: Filter Strip (per acre)

Year	One Time Costs	Annual Costs	One Time Payments	Annual Payments	Net Property Tax Impact
0	$175.44	$0.00	$0.00	$0.00	$0.00
1	$0.00	$6.67	$0.00	$0.00	$0.00
2	$0.00	$6.94	$0.00	$0.00	$0.00
3	$0.00	$7.21	$0.00	$0.00	$0.00
4	$0.00	$7.50	$0.00	$0.00	$0.00
5	$0.00	$7.80	$0.00	$0.00	$0.00
6	$0.00	$8.12	$0.00	$0.00	$0.00
7	$0.00	$8.44	$0.00	$0.00	$0.00
8	$0.00	$8.78	$0.00	$0.00	$0.00
9	$0.00	$9.13	$0.00	$0.00	$0.00
10	$0.00	$9.49	$0.00	$0.00	$0.00
11	$0.00	$9.87	$0.00	$0.00	$0.00
12	$0.00	$10.27	$0.00	$0.00	$0.00
13	$0.00	$10.68	$0.00	$0.00	$0.00
14	$0.00	$11.11	$0.00	$0.00	$0.00
15	$0.00	$11.55	$0.00	$0.00	$0.00
Sum totals	$175.44	$133.56	$0.00	$0.00	$0.00
Present Value	$175.44	$91.73	$0.00	$0.00	$0.00
Net Present Value	**($267.17)**				
Annualized Value	**($25.09)**				

NPV Table: Cropland Rent (per acre)

Year	Rent
0	$0.00
1	$76.19
2	$78.53
3	$80.94
4	$83.42
5	$85.99
6	$88.63
7	$91.35
8	$94.15
9	$97.04
10	$100.02
11	$103.09
12	$106.26
13	$109.52
14	$112.88
15	$116.35
Sum totals	$1,424.34
Present Value	$985.69
Net Present Value	**$985.69**
Annualized Value	**$92.57**

Total economic cost equals annualized cost of filter strip plus annualized cropland rents forgone = $117.66

No-till is a form of conservation tillage in which herbicides are used in place of tillage for weed control and seedbed preparation (Williams and Smith 2008). No-till has seen increased adoption rates through much of the past two decades. According to Smith et al. (2007), nearly 30 percent of producers in the central Great Plains are currently utilizing 100 percent no-till management strategies. According to Dhuyvetter and Kastens (2005), no-till is generally adopted in central and eastern Kansas due to decreased costs, but higher yields and associated revenue provide incentives for no-till adoption in western Kansas. As previously stated, the costs and returns associated with no-till adoption are highly variable and are farm specific (see Williams and Smith 2008).

Currently, the EQIP program will pay a Kansas producer $13.00 per acre per year for up to 3 years for converting to a no-till management system (NRCS 2010). In Nebraska, a producer can be paid $20.00 per acre per year for 3 years for converting to no-till (Torpin 2010). Based on these data, it is assumed that the annualized cost for inducing producers to convert to no-till would be $13.00 per acre per year in Kansas and $20.00 per acre per year for those farms in Nebraska all over a 15-year time horizon (Table 2.1).

Land retirement, which includes the establishment of permanent vegetation, has the potential to significantly reduce soil erosion. The CRP program currently provides incentives to make up for the value of lost production. The KSU Vegetative Buffer Decision-Making Tool (Smith and Williams 2010) is used to calculate the annualized costs of converting cropland field to permanent native grass vegetation over a 15-year time horizon. The values used represent the lost value of production and are set equal to the average CRP rental rates for each county in 2009. Table 2.1 displays the annualized costs per county for land retirement. A detailed budget for permanent vegetation (land retirement) can be found in Table 2.3.

Table 2.3 Permanent vegetation budget for Marshall Co., KS

General Data For Permanent Vegetation in Marshall Co., KS

Discount Rate	**4.63%**	
Cropland Rental Rate - not CCRP rental rate	**$58.51**	per acre / year
Annual Cropland Rental Growth Rate	**3.07%**	
Total Annual Costs	**$6.67**	per acre / year
Inflation Rate of Annual Costs	**4.00%**	

Project Length (feet)	**660**
Project Width (feet)	**66**
Acres (length x width/43,560)	**1.00**
Length of analysis (years)	**15**
Cropland Property Tax ($/acre)	**$5.00**
Tame Grass Property Tax ($/acre)	**$5.00**

COSTS		PAYMENTS RECEIVED	
Total one-time	**$101.42**	Total one-time	**$0.00**
Total annual	**$6.67**	Total annual	**$0.00**

Net Present Value Table: Permanent Vegetation (per acre)

Year	One Time Costs	Annual Costs	One Time Payments	Annual Payments	Net Property Tax Impact
0	$101.42	$0.00	$0.00	$0.00	$0.00
1	$0.00	$6.67	$0.00	$0.00	$0.00
2	$0.00	$6.94	$0.00	$0.00	$0.00
3	$0.00	$7.21	$0.00	$0.00	$0.00
4	$0.00	$7.50	$0.00	$0.00	$0.00
5	$0.00	$7.80	$0.00	$0.00	$0.00
6	$0.00	$8.12	$0.00	$0.00	$0.00
7	$0.00	$8.44	$0.00	$0.00	$0.00
8	$0.00	$8.78	$0.00	$0.00	$0.00
9	$0.00	$9.13	$0.00	$0.00	$0.00
10	$0.00	$9.49	$0.00	$0.00	$0.00
11	$0.00	$9.87	$0.00	$0.00	$0.00
12	$0.00	$10.27	$0.00	$0.00	$0.00
13	$0.00	$10.68	$0.00	$0.00	$0.00
14	$0.00	$11.11	$0.00	$0.00	$0.00
15	$0.00	$11.55	$0.00	$0.00	$0.00
Sum totals	$101.42	$133.56	$0.00	$0.00	$0.00
Present Value	$101.42	$91.73	$0.00	$0.00	$0.00
Net Present Value	**($193.15)**				
Annualized Value	**($18.14)**				

NPV Table: Cropland Rent (per acre)

Year	Rent
0	$0.00
1	$58.51
2	$60.31
3	$62.16
4	$64.07
5	$66.03
6	$68.06
7	$70.15
8	$72.30
9	$74.52
10	$76.81
11	$79.17
12	$81.60
13	$84.10
14	$86.69
15	$89.35
Sum totals	$1,093.82
Present Value	$756.96
Net Present Value	**$756.96**
Annualized Value	**$71.09**

Total economic cost equals annualized cost of permanent vegetation plus annualized cropland rents forgone = $89.23

Physically-based Model and Results

This subsection presents the physically-based model that quantifies the environmental impacts of practices adopted by farmers. In particular, the Soil and Water Assessment Tool (SWAT) model is applied to the Tuttle Creek watershed located in Kansas and Nebraska to predict the changes in sediment, nitrogen, and phosphorus loading at the watershed outlet (entering TCL), in response to the adoption of the three cropland in-field BMPs.[8] The first part briefly describes the study region and the input data for the SWAT model. The next part presents the modeling scenarios, which correspond to the three BMPs of interest plus a baseline (no BMPs) situation. Each scenario requires detailed inputs about tillage and other agronomic practices. The third part then presents the modeling results from the various scenarios and explains how the data needed for the simulations are assembled. The fourth and final part briefly summarizes the model and results.

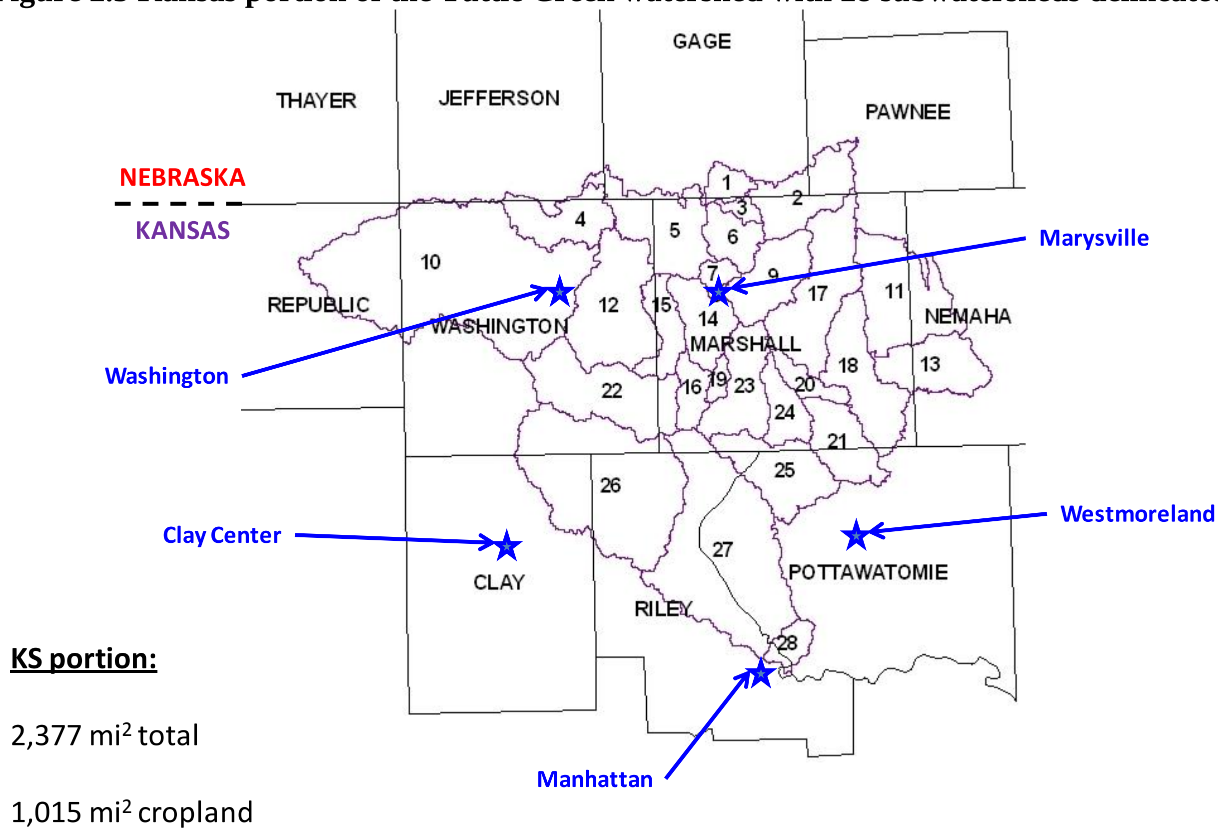
Model Inputs

A necessary component of an effective BMP implementation plan is a way to estimate the amount of pollution reduction achieved from the adoption of certain BMPs. In order to analyze the potential of various BMP management scenarios in the Tuttle Creek watershed, a SWAT watershed model was developed for the portion of the Tuttle Creek watershed located almost completely in Kansas (Figure 2.5). It should be noted that the sediment and nutrient contributions from the greater Nebraska portion of the watershed were included in the analysis, but treated as exogenous in the models. In other words, no BMP applications occurred in the greater Nebraska portion of the TCL watershed. The average annual amounts of pollutants

[8] As described later, BMP implementation only occurs in the “Kansas” portion of the watershed. The word “Kansas” is in quotes because very small portions of the analyzed subwatersheds actually lie in Jefferson, Gage, and Pawnee counties located in Nebraska.

coming from Nebraska streams and rivers into the Kansas portion of the TCL watershed are 817,394 tons of sediment, 39,817,689 pounds of total nitrogen, and 9,354,214 pounds of total phosphorus. In terms of total pollutant loading into TCL, Nebraska contributes 30.5, 75.7, and 75.2 percent of the annual sediment, nitrogen, and phosphorus, respectively. Stated differently, Kansas is responsible for 1,861,031 tons of sediment, 12,765,177 pounds of total nitrogen, and 3,084,057 pounds of total phosphorus loading into TCL each year.

Figure 2.5 Kansas portion of the Tuttle Creek watershed with 28 subwatersheds delineated



The SWAT (2009) model was developed and is maintained by the USDA Agricultural Research Service (ARS) (Arnold et al. 1998; Neitsch et al. 2005; Gassman et al. 2007; Douglas-Mankin et al. 2010). SWAT is a watershed-scale model widely used for quantifying the impact of land management practices (Nejadhashemi et al. 2011; Rodriguez et al. 2011). Briefly, the

SWAT model was developed to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large complex watersheds with varying soils, land-use, and management conditions over long periods of time. Major model components include weather, hydrology, soil temperature, plant growth, nutrients, pesticide, and land management (Gassman et al. 2007). Each watershed is divided into subwatersheds and then into hydrologic response units (HRUs) based on land-use, slope, and soil distributions.

A preliminary step in the watershed model development process was to access reliable landuse data. The most recent comprehensive land use data set available was the National Land Cover Data (NLCD) created and compiled by the United States Geological Survey in 2001.

In addition to the 2001 NLCD landuse data, other physically-based data were acquired for use in the SWAT model. State Soil Geographic Database (STATSGO) soils data was incorporated into the model along with 31 years of relevant National Climatic Data Center (NCDC) weather data (i.e., daily temperatures and precipitation). A summary of the land use, slope, and hydrologic soil groups (see note at bottom of Table 2.4) located in each of the 28 subwatersheds are displayed in Table 2.4.

Table 2.4 Summary of land use, slope, and soil group by subwatershed

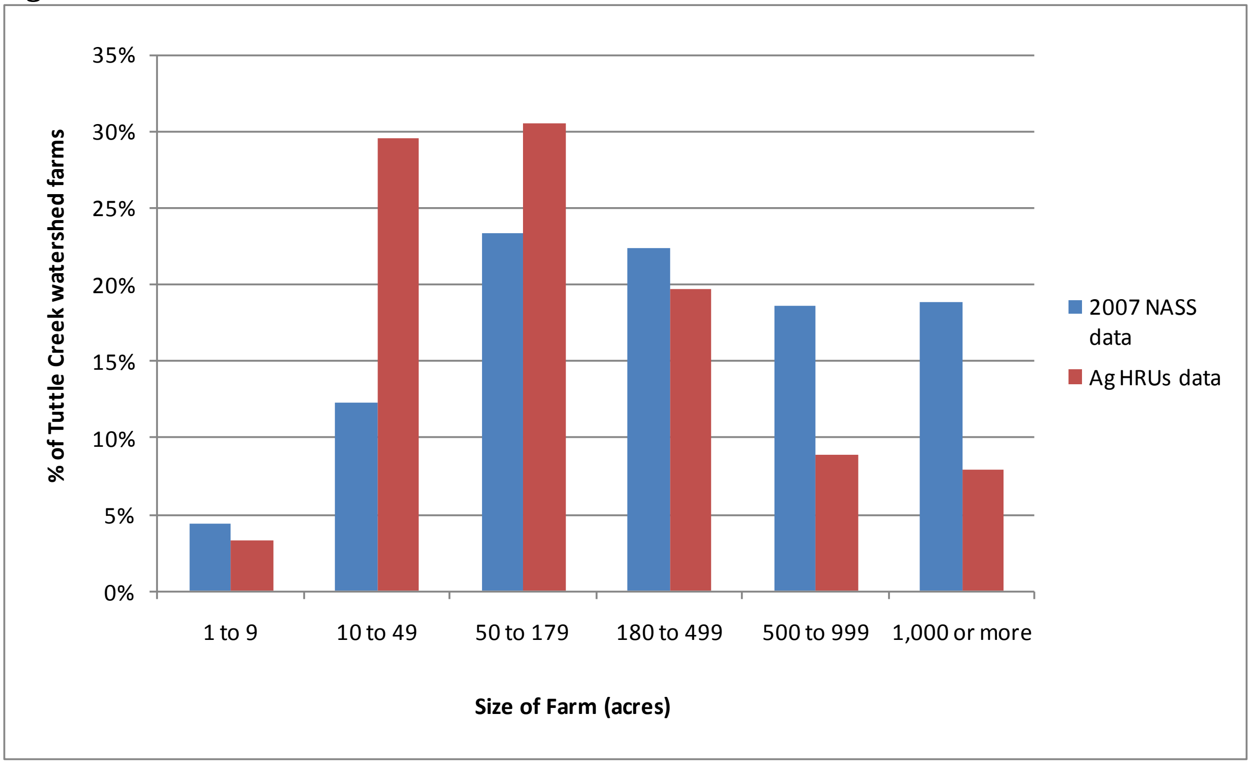
		Land Use (%)						Slope (%)					Hydrologic Soil Group (%)[9]			
Sub-watershed	Area (ac)	Crop	Urban	Forest	Range	Wet-land	Water	0-2	2-4	4-6	6-8	8+	A	B	C	D
1	12,393	44.5	4.6	8.4	41.1	0.0	1.4	76.1	18.6	4.3	1.0	0.0	0.0	16.2	83.8	0.0
2	48,527	63.5	3.8	4.9	27.2	0.0	0.6	79.5	17.6	2.9	0.0	0.0	0.0	1.5	0.0	98.5
3	6,267	57.1	4.7	12.3	22.9	0.0	3.0	76.5	19.5	4.0	0.0	0.0	0.0	20.5	33.9	45.6
4	39,374	36.4	2.9	7.5	51.4	0.4	1.3	62.9	25.3	9.3	2.2	0.3	0.0	41.2	55.2	3.6
5	60,724	58.8	4.4	6.6	29.6	0.3	0.4	75.4	19.4	4.6	0.6	0.0	0.0	4.3	95.7	0.0
6	23,890	67.0	4.4	6.2	20.0	0.7	1.7	73.6	24.1	2.3	0.0	0.0	0.0	16.2	40.4	43.4
7	7,734	50.8	11.4	6.5	26.2	2.3	2.8	78.2	20.5	1.4	0.0	0.0	0.0	26.5	40.6	32.9
8	1,450	39.1	12.6	0.0	39.4	0.0	8.9	100.0	0.0	0.0	0.0	0.0	0.0	49.7	0.0	50.3
9	42,852	68.6	5.8	5.2	19.5	0.4	0.6	78.0	17.7	3.6	0.7	0.0	0.0	1.0	0.0	99.0
10	259,609	43.1	4.4	6.0	45.8	0.1	0.5	67.3	21.4	8.4	2.7	0.3	0.0	34.8	63.2	1.8
11	75,604	72.2	4.4	3.9	19.0	0.0	0.6	66.4	24.8	7.7	1.1	0.0	0.0	3.3	0.0	96.7
12	81,114	41.1	4.1	5.8	46.3	1.1	1.7	63.2	23.2	10.7	2.7	0.2	0.0	19.5	60.6	19.9
13	45,102	50.7	4.7	6.9	35.9	0.0	1.9	61.5	23.7	12.3	2.5	0.0	0.0	6.5	0.0	93.5
14	34,557	42.2	4.7	8.9	40.2	2.1	1.9	57.7	22.5	12.6	5.0	2.1	0.0	14.1	46.2	39.7
15	26,028	52.6	4.2	7.6	34.0	0.7	0.9	60.4	27.7	9.9	2.1	0.0	0.0	6.8	78.5	14.7
16	17,768	40.8	6.7	8.2	41.5	1.0	1.8	63.7	22.5	10.2	3.0	0.6	0.0	17.3	41.9	40.8
17	75,559	58.3	4.6	7.2	28.8	0.5	0.6	62.9	25.9	9.4	1.8	0.0	0.0	7.7	0.0	92.3
18	59,506	40.3	4.4	10.1	43.5	0.7	1.0	56.5	26.5	13.7	3.1	0.2	0.0	7.1	0.0	92.9
19	6,183	16.8	11.3	7.4	57.9	3.5	3.1	58.6	16.7	12.7	7.1	5.0	0.0	26.0	24.4	49.6
20	14,667	40.3	3.8	10.3	44.0	1.5	0.0	63.3	25.2	10.3	1.2	0.0	0.0	12.7	0.0	87.3
21	38,499	20.2	4.0	9.7	65.5	0.3	0.3	54.0	26.5	14.1	4.9	0.5	0.0	0.3	42.1	57.6
22	76,565	44.6	4.0	6.1	44.8	0.2	0.3	67.9	22.1	7.8	2.1	0.1	0.0	4.8	63.1	32.1
23	45,733	38.0	3.6	8.7	47.0	1.4	1.3	56.7	23.3	14.5	4.9	0.6	0.0	15.3	18.9	65.8
24	23,823	24.7	2.9	10.5	59.3	1.0	1.5	57.8	20.9	14.1	5.9	1.4	0.0	18.6	33.4	48.0
25	53,826	8.5	2.5	12.0	74.2	1.8	1.1	49.1	19.5	17.2	9.7	4.6	0.0	7.2	62.2	30.6
26	160,864	33.6	3.7	5.8	56.3	0.2	0.3	59.4	26.0	10.5	3.1	1.0	0.0	14.2	47.8	38.0
27	169,764	8.7	4.3	16.6	59.4	1.2	9.7	44.4	18.6	16.7	11.2	9.1	0.0	12.0	69.4	18.7

[9] Group A soils have the lowest runoff potential as they typically have predominantly gravel or sand textures. Group B soils have moderately low runoff potential when thoroughly wet. Group C soils have moderately high runoff potential and Group D soils are comprised of significant amounts of clay and exhibit the highest erosive potential

The entire Tuttle Creek watershed area is 6,144,000 acres, with 25 percent of the entire watershed area residing in Kansas. According to data compiled from the 2007 National Agricultural Statistics Service (NASS) reports, the average farm size in the watershed was 482 acres with a size distribution depicted in Figure 2.6. The median sized farm in the watershed was calculated from the NASS data to be approximately 243 acres. In order to delineate a watershed to fit the NASS results while maintaining reasonable shape and size for hydrology, the Kansas portion of the Tuttle Creek watershed was divided into 27 subwatersheds.[10] Subwatersheds were further divided into 2,752 HRUs, which are unique combinations of land use and soil that occur within an individual subwatershed. Within these 2,752 HRUs, only 1,858 were categorized as cropland. According to the data in Table 2.4, approximately 41 percent of the total land area in the analyzed watershed is classified as cropland, 4 percent urban, 8 percent forest, 45 percent range/pastureland, 1 percent wetland, and 2 percent is categorized as surface water.

[10] Actually, the TCL watershed was divided into 28 subwatersheds (Figure 2.5) which was necessary to calculate loading into TCL. However, subwatershed 28 is located on the backside of the dam and does not contribute any loading to the reservoir. For this reason, the results only include loading from subwatersheds 1 through 27.

Figure 2.6 Size distribution of farms in the Tuttle Creek watershed



Focusing on the 1,858 agricultural HRUs, the average size was 350 acres with the smallest being 5 acres and the largest being approximately 8,175 acres in size. The median size for the HRUs was 107 acres. About 60 percent of the HRUs were between 10 and 179 acres while nearly 80 percent were sized between 10 and 499 acres. The size distribution of the agricultural HRUs followed somewhat closely to the NASS derived distribution of farms as shown in Figure 2.6. The HRU data consisted of many farms in the 10 to 179 acre range, which resulted in a slightly smaller average farm size than the NASS data. The median values of 107 acres and 243 acres for the HRUs and the NASS data, respectively, again supported the fact of there being many “smaller” sized farms.

Modeling Scenarios

Based on previous research and reports (Williams et al. 2009; Langemeier and Nelson 2006; O’Brien and Duncan 2008a-d), data for cropping rotations and the associated field operations were developed for the Kansas and Nebraska portions of the Tuttle Creek watershed. For the Kansas side, there were four major crops planted and harvested under six different cropping rotations. For the Nebraska side, there were four major crops occurring under three different cropping rotations. Having knowledge of predominant crop rotations and knowing the reported crop acreage from the NASS, the proportions of each cropping rotation were estimated for each state-side of the TCL watershed. The crop acreage was very near the reported crop acreage reported by the NASS. Table 2.5 shows the crop and rotation breakdown for each state side of the watershed. It was assumed that these crop rotations existed in the TCL over the 31 year SWAT modeling simulation period.

Table 2.5 Percentage of crops and rotations in the TCL watershed

Kansas side of TCL watershed		**Nebraska side of TCL watershed**	
Crop	**Percentage of Cropland**	**Crop**	**Percentage of Cropland**
Corn (C)	37%	Corn (C)	63%
Grain Sorghum (G)	29%	Grain Sorghum (G)	3%
Soybeans (S)	28%	Soybeans (S)	31%
Wheat (W)	7%	Wheat (W)	3%
Cropping Rotation		**Cropping Rotation**	
C-S	25%	C-S	55%
Continuous S	5%	Continuous C	35%
Continuous C	15%	G-S-W	10%
S-W	25%		
Continuous W	10%		
G-S-W	20%		

In addition to the cropping rotations, the associated field operations and enterprise budgets also were developed. Examples of the field operations used for a continuous corn cropping rotation are shown in Table 2.6. These operations were utilized by the SWAT model.

The remaining field operations by cropping rotation and enterprise budgets can be found in Appendix A.[11]

Table 2.6 Continuous corn rotation under conventional tillage

Date	Practice	SWAT Practice	Amount
3/27	Tandem disk	Tandem disk plow	
4/5	Chisel	Chisel plow	
4/5	Knife anhydrous ammonia	Anhydrous ammonia	116 lbs/ac
4/15	Field cultivate	Field cultivator	
4/15	Herbicide application	Atrazine	1.9 lbs/ac
4/15	Herbicide application	Metolachlor	1.5 lbs/ac
4/16	Plant corn	Plant/Begin growing season	
4/16	Nitrogen application	Elemental nitrogen	14 lbs/ac
4/16	Phosphorus application	Elemental phosphorus	47 lbs/ac
5/20	Herbicide application	Dicamba	0.3 lbs/ac
10/1	Harvest corn	Harvest and kill	
11/5	Chisel	Coulter Chisel plow	

Under the baseline scenario, the crops (and thus, cropping rotations) were randomly applied throughout the watershed consistent with the data displayed in Table 2.5. The cropland was rotated in a manner consistent with the data in Table 2.5 throughout the course of the 31 years of weather simulation in the SWAT model. In the baseline case, it was assumed that there were no filter strips in place and all cropland was farmed using conventional tillage as shown in Table 2.7.

Table 2.7 Description of scenarios

	Baseline	Scenario #1	Scenario #2	Scenario #3
Tillage System	Conventional	Conventional	No-till	N/A
Filter Strip?	NO	YES	NO	N/A
Types of crops	Cropping	Cropping	Cropping	Native grass

[11] The field operations data were used in the SWAT watershed model. The enterprise budget data were not directly utilized to calculate BMP costs, but have been included in Appendix A for additional information.

In scenario 1, the cropland also was under conventional tillage. However, this scenario included a 33 ft wide grass filter strip at the edge of each cropland HRU. It is assumed that each acre of filter strip treats runoff from 25 acres of cropland. Note, that the edge of each HRU does not necessarily border a body of surface water, hence each filter strip does not necessarily border a body of surface water. The cropping rotations were the same as in the baseline scenario (Table 2.7).

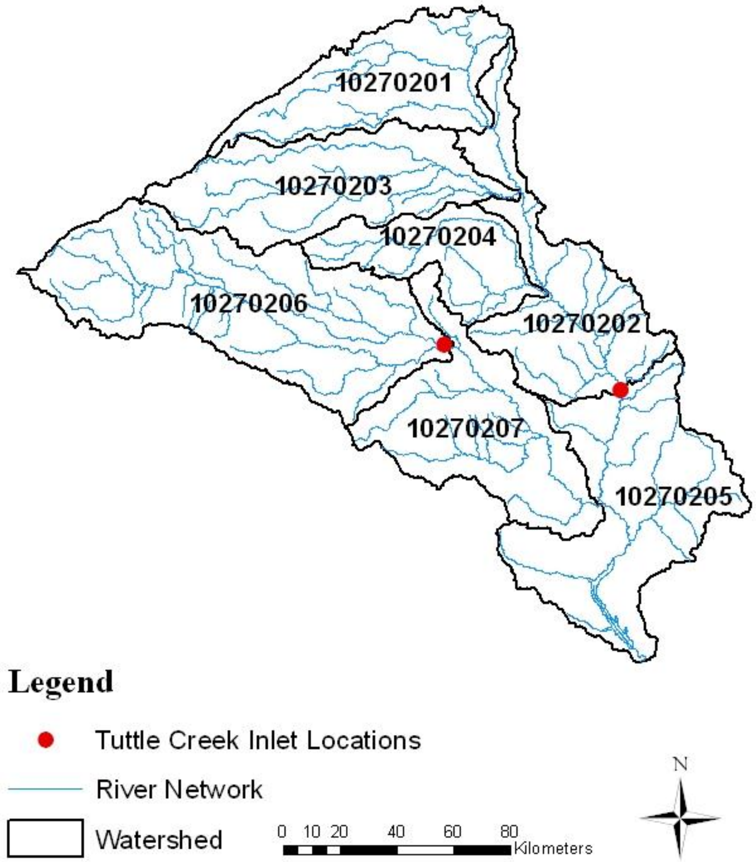
Scenario 2 employed 100 percent no-till management on all cropland. The only operations that break the surface of the ground are planting and drilling in a 100 percent no-till system. Chemicals are used for weed control. There were no filter strips in place and the cropping rotations were the same as in the baseline scenario (Table 2.7).

Scenario 3 involved converting all cropland into native grass (Table 2.7). The native grass permanent vegetation (land retirement) was a mixture of bluestem grasses, switchgrass, and Indiangrass. Once established, there was no cultivation involved with the permanent vegetation, and it was assumed that there would be no fertilization.

Model Calibration and Validation

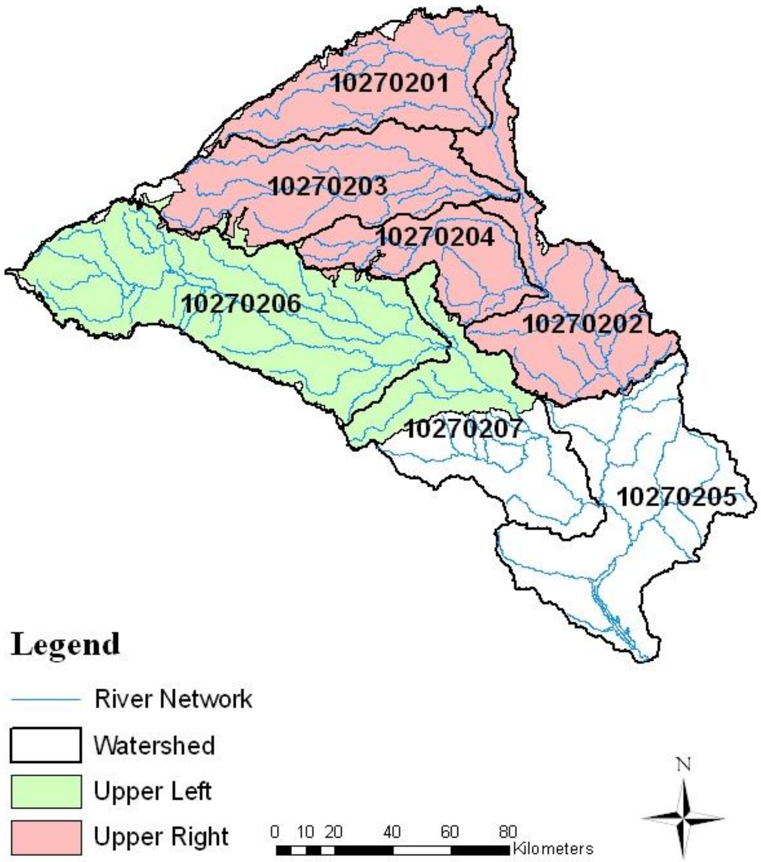
The goal of this stage of the study was to calibrate the SWAT model for the TCL watershed. Two major rivers (Big Blue River and Little Blue River) discharge water and sediment to TCL. Therefore, there was a need to estimate and incorporate flow and sediment inputs from these rivers (inlets). The locations of the inlets are identified in Figure 2.7.

Figure 2.7 TCL watershed inlets



In order to estimate sediment input to the TCL watershed, we set up and calibrated two watersheds for flow and sediment. We called the first watershed Upper Left (HUC 10270207), which contains the Little Blue River. The second watershed was named the Upper Right (HUC-10270201, HUC-10270202, HUC-10270203, and HUC-10270204), which contains the Big Blue River. The two watersheds are identified in Figure 2.8. The results from the calibrated models above were used as inputs to the TCL watershed. The final stage involved calibration of the TCL watershed for flow and sediment.

Figure 2.8 Upper left and right watersheds

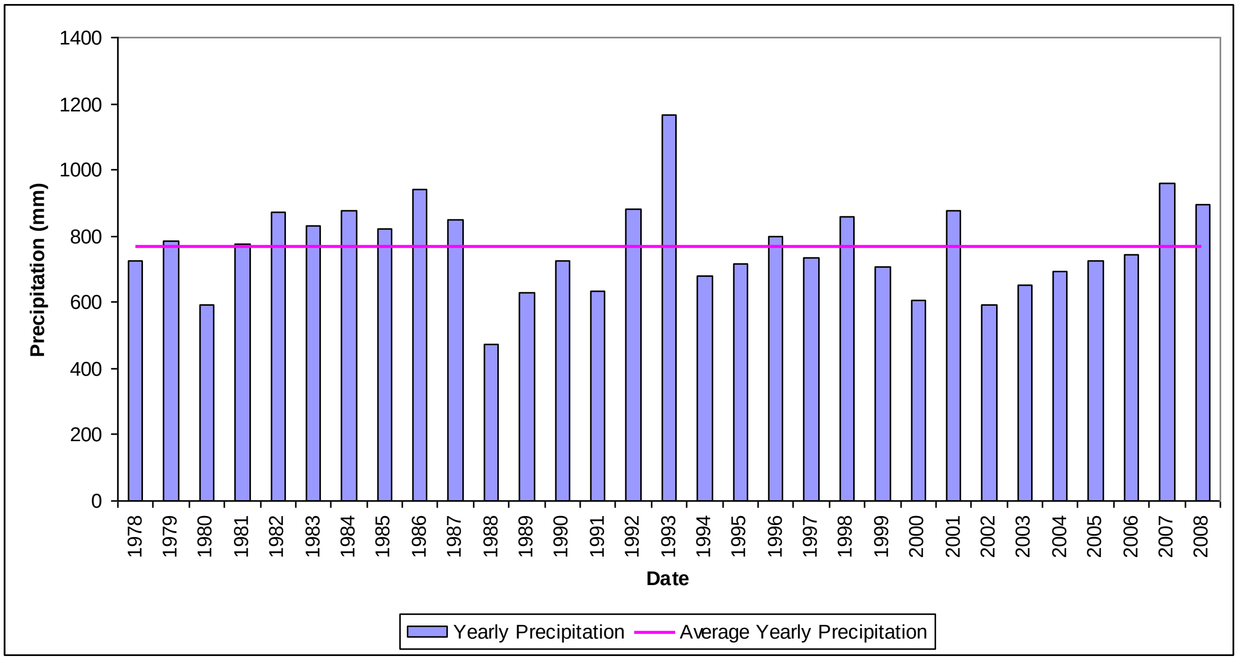


The following datasets were required to set up the watershed models in SWAT:

- Land use: National Land Cover Database 2001 (NLCD 2001)
- Soils: State Soil Geographic Database (STATSGO)
- Topography: USGS 90-meter Digital Elevation Model (DEM)
- River Network: Environmental Protection Agency (EPA) Reach File Version 1.0
- Weather: National Climatic Data Center (NCDC) weather stations

There is need to identify at least one dry climatological period and one wet climatological period for the model setup and calibration. Precipitation from 24 weather stations over 31 years were used to estimate average annual precipitation shown in Figure 2.9. The period of 1998-2002 was selected for model calibration and validation; data from 1997 was used for model warm-up.

Figure 2.9 Annual precipitation for the TCL watershed



The model was set up based on 31 years (1978-2008) of climatological data from 9 stations in this watershed (Figure 2.10). Observed streamflow discharge was obtained from the US Army Corps of Engineering station (upstream of TCL), while total suspended solids (TSS) concentration was obtained from Kansas Department of Health and Environment sampling point 000240 shown in Figure 2.11. Calibration for TCL was completed using SWAT2009. The results of observed versus uncalibrated and calibrated model output as well as statistical analyses and model performance before and after calibration can be found in Nejadhashemi et al. (2011).

Although no BMPs were applied in the base case within the SWAT model, it is important to note that the SWAT model was calibrated to actual flow and sediment inputs. This means that the calibrated loading values incorporate the fact that there are BMPs in place in the TCL watershed. Because there are BMPs in place throughout the TCL watershed and because the location of these BMPs is not known, assumptions are made in determining where BMPs are already in place. This process used for accomplishing this will be covered in greater detail later in the "Economic Simulation Model" section.

Figure 2.10 TCL watershed weather stations

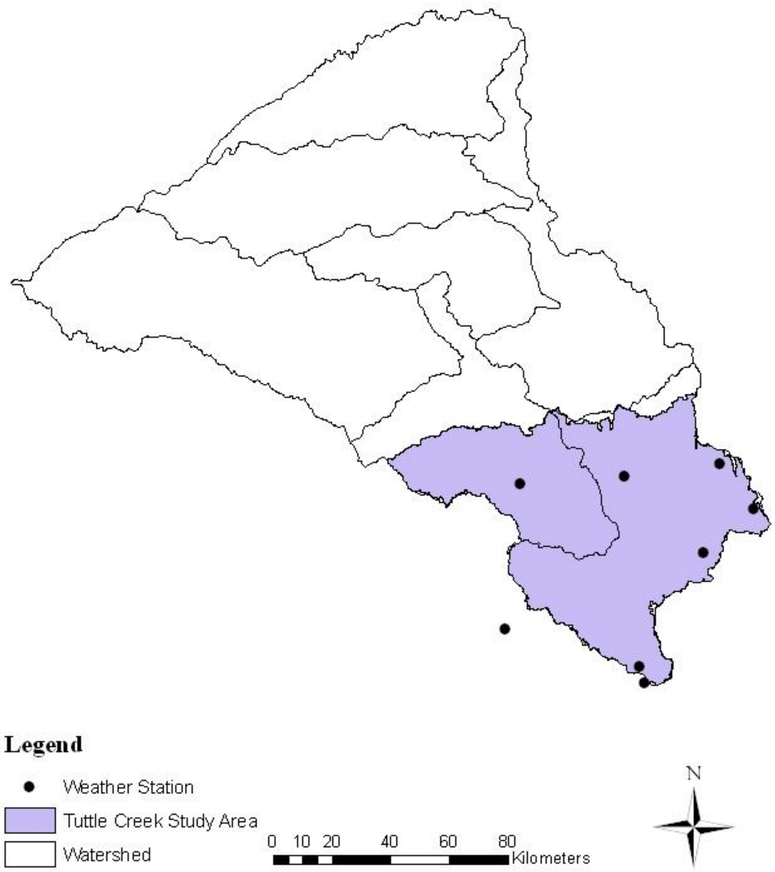
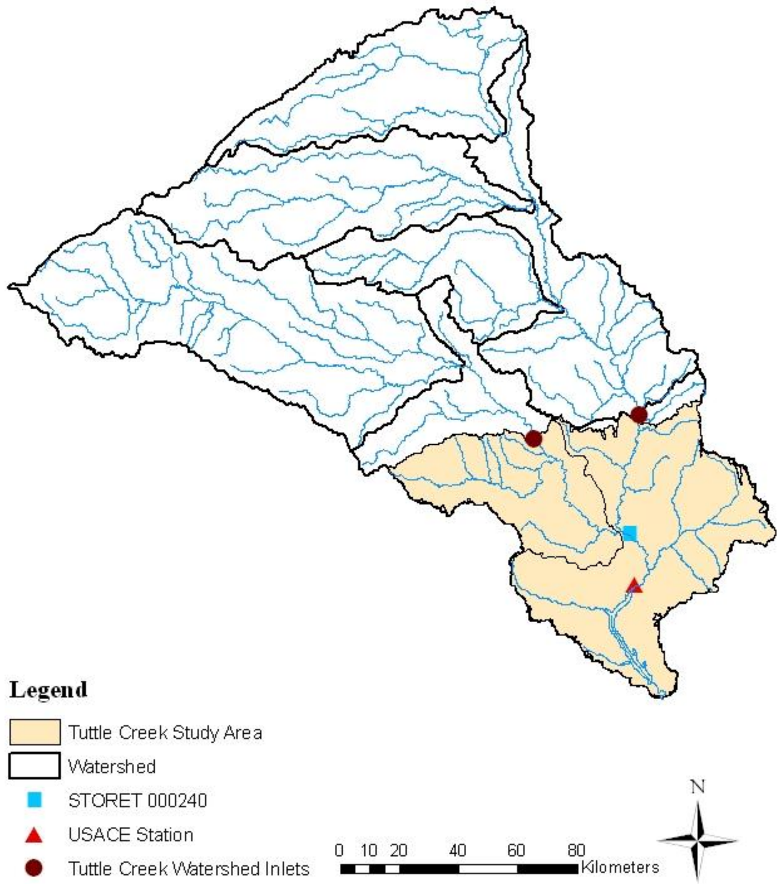


Figure 2.11 TCL watershed monitoring stations



Modeling Results and Findings

As described previously, scenarios 1, 2, and 3 assume BMP application across all cropland HRUs in the Kansas portion of the TCL watershed. While it is not realistic to assume that all cropland in the watershed will be treated by a BMP simultaneously, we move forward with the assumption that the estimated HRU pollutant loading values maintain their relative rankings and any inaccuracies in loading predictions are negligible. This assumption allows us to utilize the SWAT analysis output (ex-post) as input into the economic models.

The average sediment and nutrient loading estimates across all cropland HRUs are displayed by Table 2.8 along with percentage reductions in pollutant loading from the baseline for all three BMP scenarios.

Table 2.8 Acre-weighted average pollutant loading at edge of HRU across all agricultural HRUs (tons or lbs/ac/yr)

Pollutant	Baseline	Filter Strips	100% No-till	Permanent Veg.
	Average loading at edge of HRU (tons or lbs/acre/year)			
Sediment (tons/ac/yr)	2.87	0.78	2.21	0.15
Nitrogen (lbs/ac/yr)	19.65	5.61	16.19	2.67
Phosphorus (lbs/ac/yr)	4.75	1.30	4.89	0.36
	Percentage loading reduction from baseline (%)			
Sediment (tons/ac/yr)	-	72.6%	23.0%	94.6%
Nitrogen (lbs/ac/yr)	-	71.4%	17.6%	86.4%
Phosphorus (lbs/ac/yr)	-	72.6%	-3.0%	92.5%

Focusing on the loading at the edge of the agricultural HRUs, the average sediment loading under the baseline condition was estimated to be just below 2.9 tons/ac/yr. When 33 feet wide native grass filter strips were applied to all agricultural HRUs, the watershed-wide average sediment loading was reduced by 72.6 percent (Table 2.8) to 0.78 tons/ac/yr. Similar percentage reductions were achieved for nitrogen and phosphorus as well with 71.4 and 72.6 percent reductions for each of these nutrients, respectively.

The use of 100 percent no-till management applied to all cropland fields resulted in lesser sediment reduction than filter strips by reducing loadings by 23 percent across the watershed. When all of the cropland in the watershed was converted to a permanent stand of native grass, substantial reductions in sediment (and nutrient) loading resulted. Sediment loading was reduced by approximately 95 percent while nitrogen and phosphorus loadings were reduced by 86.4 and 92.5 percent, respectively.

To account for sediment and nutrient transport in the watershed, delivery ratios are typically derived for each subwatershed and for each HRU. The delivery ratio of pollutant loading is a function of the stream transport effects. The stream transporting effects are defined as the outflow pollutant load divided by the inflow load. The difference between inflow and outflow loads are due to pollutant deposition or other losses.

The methods used for determining the sediment delivery ratios for each subwatershed in the TCL watershed are briefly described next using subwatershed 1 as an example. First, we know the amount of sediment exiting subwatershed 1 (as well as from the other 26 subwatersheds) under baseline (and unaltered) conditions. We also know the amount of sediment entering TCL under baseline (and unaltered) conditions. In order to derive the sediment delivery ratio from subwatershed 1, the amount of sediment exiting subwatershed 1 is manually and artificially forced to zero within the SWAT model. Ceteris paribus conditions throughout the rest of the TCL watershed are employed in that the remaining 26 subwatersheds' data remain intact and unaffected. Next, the amount of sediment entering TCL is calculated under these altered conditions (i.e., with subwatershed one "zeroed" out). The difference in sediment loading at TCL from the unaltered and altered conditions is calculated. This difference is then divided by the amount of sediment exiting subwatershed 1 under unaltered conditions. This results in a sediment delivery ratio value for subwatershed 1. This same technique is used for calculating the remaining 26 delivery ratios for each subwatershed.

The sediment delivery ratios tend to be slightly variable across subwatersheds as displayed in Table 2.9. A delivery ratio of 0.56 in subwatershed 1 indicates that on average every one ton of sediment (leaving the edge of an HRU located in that subwatershed) results in 0.56 tons in TCL. The remaining 0.44 tons is assumed to be deposited within to the stream channel. In general, the subwatersheds located nearer TCL and/or a major tributary exhibit higher sediment delivery ratio values.

Table 2.9 Sediment delivery ratios by subwatershed

Subwatershed	Sediment Delivery Ratio
1	0.56
2	0.51
3	0.56
4	0.71
5	0.67
6	0.60
7	0.68
8	0.69
9	0.70
10	1.00
11	0.69
12	1.00
13	0.66
14	0.73
15	1.00
16	0.99
17	0.72
18	0.67
19	1.00
20	0.75
21	0.79
22	1.00
23	1.00
24	0.79
25	1.00
26	1.00
27	1.00

Here, there is an assumption that all nutrient loads reaching a major stream segment will be further transported to the watershed outlet (into TCL). Thus, the nutrient (both nitrogen and phosphorus) delivery ratios are assumed to be 100 percent for the entire portion of the Tuttle Creek watershed analyzed. The reasons for assuming 100 percent nutrient delivery ratios for subwatersheds 1 through 27 are two-fold. First, the SWAT model provides no standard way of calculating nutrient delivery ratios. Second, this assumption is reasonable when one considers the multi-year time horizon for which this analysis occurs and the relatively high nutrient delivery ratios (i.e., all over 95 percent) that were derived in previous northeast Kansas watershed research (Peterson et al. 2009).

Economic Simulation Model

The SWAT watershed model described in the previous section generated calibrated results of average annual pollutant loading by farm (HRU) for each of the scenarios presented in Table 2.7. Using this output from the SWAT watershed model as input, the economic analysis model simulates possible BMP implementation scenarios and estimates the resulting pollutant loading into a reservoir and the costs of implementing the BMPs. There are two versions of the economic analysis model. The first emulates an economically optimal BMP scenario where BMPs are placed in areas of the watershed where pollutant loading is reduced at the lowest cost. The other version emulates a random approach to BMP implementation in the watershed. This to some degree represents the status quo approach of uniform BMP implementation across a watershed and serves as a point of comparison for the economically optimal approach (Nelson et al. forthcoming). Both of these models operate under the criteria of meeting a specified pollutant reduction goal subject to a specified budget constraint. These models can focus on either sediment, nitrogen, or phosphorus reduction individually and can accommodate up to three different types of BMPs.

While it may appear that a genetic algorithm optimization model would be ideal for this analysis, the enormity of the TCL watershed makes this option infeasible.[12] The search space increases exponentially as the possible BMP implementation combinations is $3^{1,858}$ (which equals

[12] A genetic algorithm is a search heuristic that mimics the process of evolution by generating solutions to optimization problems using techniques inspired by evolution, such as inheritance, mutation, selection, and crossover.

3.10×10^{886}). In other words, too large of a search space given present-day computational and time constraints.

Considering the multitude of social, environmental, economic, and political factors present at any point in time in an agricultural watershed, attempting to effectively examine the cost-effectiveness of alternative watershed management schemes can be a difficult task. An increasingly popular method of analyzing complex systems is the utilization of agent-based simulation modeling. An agent-based model (ABM) is a class of computational models with agents representing autonomous decision-making units. This allows the analyst to assess the effects of agent decision-making on the system as a whole. Recently, ABM's have become a popular model choice for analyzing complex systems driven by micro-level decisions (Tesfatsion 2006). ABM's are particularly useful in emulating alternative market structures, specifically those where agents are heterogeneous and adapt their behavior to institutional rules.

ABM's are made up of two computational objects: the "agents" themselves and the "environment" in which they operate (Parker, Berger, and Manson 2002). In the Tuttle Creek watershed, the agents are the farm managers and the environment is the management mechanism that determines which BMPs are implemented and where. A goal of the simulations is to understand how changes in the environment (management mechanism) may induce different patterns and levels of BMP adoption among the agents.

Agents

The $i = 1{,}858$ farms (HRUs) are indexed by $i = 1, \dots, I$ and are considered potential BMP adopters and thus have the ability to reduce the amount of soil leaving their cropland fields. Here, it is assumed that a governing authority or watershed manager has set a goal of reducing the maximum amount of sediment, S units, (or nitrogen or phosphorus) entering TCL while operating under an annual fiscal budget of D dollars per year. Each farm can generate up to s_i units of sediment reduction at a total annualized cost of c_i. Using the cost of implementing each BMP data described previously, total costs, which include one-time and annual costs over a given time horizon for each BMP on each farm, are determined and assigned. Average per unit costs of pollutant reduction (dollars per pound of pollutant reduced) are calculated for each farm-BMP combination. Average per unit costs are assumed to vary across farms but are constant at the farm level. This cost property implies that the aggregate total and marginal cost curves will have "staircase" structures.

Each farm can potentially adopt one of B BMPs, $b = 1, \ldots, B$. Here $B = 3$, and the three BMPs are filter strips, no-till, and permanent vegetation. Let **A** denote the (I x B) "average per unit cost matrix" representing the per-unit costs for BMP implementation. If farm *i* is to adopt a given BMP, a_{ib} must be positive. That is, the BMP implemented must result in a positive amount of sediment reduction if sediment is the primary pollutant of concern. However, the associated nitrogen and phosphorus reductions may not be positive if sediment is the primary pollutant of concern. Before any BMP implementation occurred, the program eliminates any farm-BMP combination, which displays negative pollutant reduction[13] ($a_{ib} < 0$) because it is assumed that in all cases the watershed manager is knowledgeable of this and would not issue conservation funding to farms to adopt BMPs that actually increase the amount of pollutant runoff.

A deficiency of the data is that the physically-based information is at a subwatershed scale and the cost data is at the county level. This is because HRU's are not necessarily contiguous (Hernandez et al. 2003). Therefore, it is not possible to precisely determine the

[13] This is only for the objective pollutant (or pollutant of concern); not all three pollutants.

annualized costs of a given BMP for a HRU (farm). The following method is used to account for this issue.

First, the fraction of each subwatershed (numbered 1-27) in each county is determined. For example, subwatershed 26 covers four counties: Washington, Marshall, Clay, and Riley. Based on the data underlying Figure 2.5, subwatershed 26 is subdivided as 23 percent in Washington County, 2 percent in Marshall County, 25 percent in Clay County, and 50 percent in Riley County. Table 2.10 exhibits the county fractions for each subwatershed.

Table 2.10 Fraction of each county located in each subwatershed

Subwatershed \ County	Clay	Gage	Jefferson	Marshall	Nemaha	Pawnee	Pottawat-omie	Republic	Riley	Washing-ton	TOTAL
1	0.00	0.90	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	1.00
2	0.00	0.18	0.00	0.46	0.00	0.36	0.00	0.00	0.00	0.00	1.00
3	0.00	0.01	0.00	0.99	0.00	0.00	0.00	0.00	0.00	0.00	1.00
4	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.88	1.00
5	0.00	0.15	0.03	0.58	0.00	0.00	0.00	0.00	0.00	0.24	1.00
6	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
7	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
8	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
9	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.00	0.74	1.00
11	0.00	0.00	0.00	0.64	0.36	0.00	0.00	0.00	0.00	0.00	1.00
12	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.99	1.00
13	0.00	0.00	0.00	0.27	0.73	0.00	0.00	0.00	0.00	0.00	1.00
14	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
15	0.00	0.00	0.00	0.73	0.00	0.00	0.00	0.00	0.00	0.27	1.00
16	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
17	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
18	0.00	0.00	0.00	0.98	0.00	0.00	0.02	0.00	0.00	0.00	1.00
19	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
20	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
21	0.00	0.00	0.00	0.57	0.00	0.00	0.43	0.00	0.00	0.00	1.00
22	0.00	0.00	0.00	0.14	0.00	0.00	0.00	0.00	0.00	0.86	1.00
23	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
24	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
25	0.00	0.00	0.00	0.20	0.00	0.00	0.72	0.00	0.08	0.00	1.00
26	0.23	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.50	0.26	1.00
27	0.00	0.00	0.00	0.04	0.00	0.00	0.46	0.00	0.50	0.00	1.00

It is known that the farms within subwatershed 26 are located in one of four counties. The next step is to assign each farm to a single county. This was so that costs for BMP implementation could be assigned to each farm because costs varied by county. The percentages from Table 2.10 are used to determine this. For example, there are 36 farms in subwatershed 26. Based on the percentages in Table 2.10, it is determined that 8 of these farms are located in Washington County, 1 in Marshall County, 9 in Clay County, and 18 farms are located in Riley County.

The next step is determining which farms to place into each county. Because of a lack of accurate data, this determination is made through a stochastic process in Monte Carlo fashion. That is, for each iteration the 36 farms are assigned randomly to each of the four counties. But, the number of farms in each county do not vary from that discussed previously. The simulations are run 3,000 times and the results are averaged to ensure that the results are not just a "luck of the draw" occurrence.[14]

An assumption of the SWAT model is that there are no BMPs in place in the Base scenario. First-hand knowledge of the area as well as NRCS reports indicate that this is not the case. But, the challenge is to determine where BMPs have been put into place and where they exist today. Determining this with any precision and incorporating this into the SWAT model is a difficult and expensive task that is beyond the scope of this research. For that reason, the following method is used.

While personal knowledge and NRCS reports show that many soil saving BMPs have been implemented over the past three decades, other research has determined that some farmers

[14] To ensure that the final results were not sensitive to a particular set of random draws, all simulations were repeated 3,000 times in Monte Carlo fashion, with a "new" set of eligible farms picked each time. The authors tested this model and it was found that 3,000 iterations was sufficient to ensure that the mean performance measures computed across the 3,000 iterations was a stable statistic.

have extremely high willingness to accept (WTA) values and will most likely need very high payments for adoption and will not adopt certain BMPs under most realistic scenarios (Smith et al. 2007). Specifically, Smith et al. (2007) found that approximately 20 percent of Kansas farms have already adopted filter strips and 30 percent of farms have already adopted no-till. To account for these facts within this simulation model, it is assumed that 20 percent of the farms have already adopted BMPs and an additional 5 percent of farms have extremely high WTA values for BMP adoption. Thus, it is assumed that farms with these characteristics would not adopt new or additional BMPs in the model's time horizon and thereby are removed from the choice set.

At the beginning of each BMP implementation simulation, 25 percent of the farms are eliminated from the potential pool. Again, the problem is determining which 465 out of the 1,858 farms would be eliminated. To handle this, the 465 ineligible farms are picked in a random fashion each time and Monte Carlo techniques are used with 3,000 iterations.[15]

Once these initialization search and delete methods are completed, the simulation program proceeds to the selection process for BMP implementation (note, each of the 3,000 iterations consists of the initialization processes and BMP implementation routine).

Environment

The "environment" is the management mechanism that determines which BMPs are implemented on which farms in the watershed and the order in which these occur. The mechanism used is similar to a method used in the modeling of water quality trading markets. Specifically, the method modeled is a variant of the sequential, bilateral trading algorithm proposed by Atkinson and Tietenberg (1991).

[15] In later sections, this "random" method of removing 25 percent of the farms is replaced by an alternative method that removes 25 percent of the most erosive farms.

The BMP implementation process occurs by iterating over BMP implementation projects in the sequence they occur. With each implementation project, indexed by t, the algorithm begins by identifying the particular farm-BMP combination (*i*,*b*). Two different ways of doing this are modeled, one which simulates a highly targeted approach and the other which is random and more representative of a worst-case, potentially status-quo approach. These two implementation regimes are described below.

Once the farm-BMP combination is identified, a BMP is assumed to be implemented on that farm resulting in q_t units of sediment reduction. This quantity is recorded, along with the average annualized per unit cost (of sediment, nitrogen, or phosphorus), a_{ib} , total cost, $q_t a_{ib}$, and area treated by the BMP. Additionally, the average unit costs and reductions for each of the secondary pollutants (nitrogen and phosphorus in this example) are recorded. The **A** matrix is then updated by eliminating that farm (setting $a_{i:} = 0$) from further BMP implementation because of the restriction of one BMP implemented per farm. The model then iterates through additional BMP implementation projects using the same process until: 1) no positive values exist in the **A** matrix; 2) no other BMPs could be implemented without violating the budget constraint; or 3) the primary pollutant reduction goal has been met.

The two implementation regimes are:

1. Targeted BMP implementation: This scenario assumes full information by the watershed manager in that BMPs can be placed strategically in the watershed to deliver the greatest sediment reduction for least cost. In this optimal case, the algorithm determines the farm-BMP combination (a_{ib}), which has the lowest (and positive) average per unit cost of primary pollutant reduction. If this combination will not exceed either the pollutant reduction goal or the budget constraint, then the BMP will be implemented on this farm

and the resulting pollutant reduction and cost will be recorded in an output matrix as described above. This farm will then be removed from the possible choice set, which prevents it from being selected again.

2. Random BMP implementation: The random approach to BMP implementation assumes very low information by the watershed manager and occurs in much of the same fashion as the optimal approach with one very important distinction. That is, each farm-BMP combination (a_{ib}) is selected in a completely random manner in which no consideration is given to the average per unit costs of pollutant reduction assuming neither of the constraints will be violated.

Scenarios Modeled

Each of the BMP implementation scenarios operate under varying budget constraints. The annual budget constraint varies from $50,000 to $450,000 per year in increments of $100,000. These values are in line with estimated minimum and maximum funding amounts that could be available from the state of Kansas (e.g., through WRAPS and Kansas Water Plan funding sources) for purposes of addressing sedimentation in the TCL watershed (KDHE 2009).

In addition to varying implementation regimes and budget constraints, the primary pollutant of concern also changes across scenarios. Specifically, simulations are first run which focus on reducing sediment accumulation in TCL. The resulting amounts of nitrogen and phosphorus reduction also are tabulated for these scenarios. In the same manner, scenarios, which focus on reducing nitrogen and phosphorus reduction, are run next. Table 2.11 lists the assumptions for each of the 30 original simulation scenarios modeled.

Table 2.11 Description of original scenarios

Scenario[1]	BMP Regime	Primary Pollutant	Annual Budget
Targ_S_50	Targeted	Sediment	$50,000
Targ_S_150	Targeted	Sediment	$150,000
Targ_S_250	Targeted	Sediment	$250,000
Targ_S_350	Targeted	Sediment	$350,000
Targ_S_450	Targeted	Sediment	$450,000
Rand_S_50	Random	Sediment	$50,000
Rand_S_150	Random	Sediment	$150,000
Rand_S_250	Random	Sediment	$250,000
Rand_S_350	Random	Sediment	$350,000
Rand_S_450	Random	Sediment	$450,000
Targ_N_50	Targeted	Nitrogen	$50,000
Targ_N_150	Targeted	Nitrogen	$150,000
Targ_N_250	Targeted	Nitrogen	$250,000
Targ_N_350	Targeted	Nitrogen	$350,000
Targ_N_450	Targeted	Nitrogen	$450,000
Rand_N_50	Random	Nitrogen	$50,000
Rand_N_150	Random	Nitrogen	$150,000
Rand_N_250	Random	Nitrogen	$250,000
Rand_N_350	Random	Nitrogen	$350,000
Rand_N_450	Random	Nitrogen	$450,000
Targ_P_50	Targeted	Phosphorus	$50,000
Targ_P_150	Targeted	Phosphorus	$150,000
Targ_P_250	Targeted	Phosphorus	$250,000
Targ_P_350	Targeted	Phosphorus	$350,000
Targ_P_450	Targeted	Phosphorus	$450,000
Rand_P_50	Random	Phosphorus	$50,000
Rand_P_150	Random	Phosphorus	$150,000
Rand_P_250	Random	Phosphorus	$250,000
Rand_P_350	Random	Phosphorus	$350,000
Rand_P_450	Random	Phosphorus	$450,000

[1] In later sections these original scenarios will include "_Orig." at the end to denote that these are the original scenarios modeled.

BMP Implementation Results

This section begins by summarizing the overall simulation results followed by more in depth analyses regarding the effects of targeting versus random BMP implementation strategies, budgetary constraint levels, primary pollutant of concern, and changing BMP costs.

Table 2.12 summarizes the results of the original 30 scenarios. The first column serves as a cross reference for the scenario assumptions listed in Table 2.11. The second through fourth columns report the average pollutant reduction costs per unit for sediment, nitrogen, and phosphorus, respectively. Note, these costs are not additive. Rather, they are simply the total cost divided by the amount of pollutant (sediment, nitrogen, or phosphorus) reduction.

The next five columns report information related to BMP projects implemented in terms of the description of the projects and the total amount of land treated by the BMPs.[16] Columns six through eight of this table provide more detail regarding the categories of the BMP projects in terms of the number of filter strips, no-till, and permanent vegetation projects, respectively. Column nine reports the total amount of land area treated by the BMP projects.

The final three columns of Table 2.12 report the total amount of pollutant reduction achieved for sediment, nitrogen, and phosphorus, respectively, by the implementation of the BMP projects.

Overall the lowest average annual cost of sediment reduction is achieved by the Targ_S_50 scenario which reduces sediment for $0.35 per ton. The highest cost per ton of sediment is with the Rand_S_450 scenario at $14.13 per ton. This is only slightly higher than the Rand_N_450 and Rand_P_450 scenarios which are $13.88 and $13.47 per ton, respectively.

[16] In the cases of no-till and permanent vegetation, one acre of BMP application "treats" one acre of cropland. However, in the case of filter strips, one acre of filter strip is assumed to "treat" runoff from 25 acres of cropland.

Table 2.12 Original simulation results

Scenario	Average sediment reduction cost for all land treated by BMPs (/ton)	Average nitrogen reduction cost for all land treated by BMPs (/lb)	Average phosphor-rous reduction cost for all land treated by BMPs (/lb)	Total # of BMP projects	# of Filter Strip Projects	# of No-till Projects	#of Permanent Vegetation Projects	Total area of land treated by BMPs (ac)	Total amount of sediment reduction (tons)	Total amount of nitrogen reduction (lbs)	Total amount of phosphorus reduction (lbs)
Targ_S_50	$0.35	$0.11	$0.43	84	84	0	0	10,578	139,488	427,374	114,162
Targ_S_150	$0.47	$0.12	$0.48	249	249	0	0	32,118	314,587	1,195,437	305,579
Targ_S_250	$0.55	$0.13	$0.52	327	327	0	0	53,640	447,431	1,835,904	473,438
Targ_S_350	$0.62	$0.14	$0.56	415	415	0	0	74,970	553,999	2,434,125	618,854
Targ_S_450	$0.69	$0.15	$0.59	502	502	0	0	96,494	640,157	3,019,082	752,754
Rand_S_50	$7.65	$1.25	$5.87	20	9	7	4	3,009	6,317	38,599	8,227
Rand_S_150	$10.95	$1.78	$8.34	33	14	11	8	6,604	13,169	80,838	17,288
Rand_S_250	$12.44	$2.03	$9.47	44	17	15	12	9,800	19,291	118,020	25,346
Rand_S_350	$13.45	$2.19	$10.12	53	20	18	15	12,630	24,838	152,538	33,035
Rand_S_450	$14.13	$2.29	$10.56	62	23	21	18	15,522	30,332	186,945	40,589
Targ_N_50	$0.50	$0.09	$0.45	122	122	0	0	10,721	97,558	524,256	108,760
Targ_N_150	$0.53	$0.11	$0.51	252	252	0	0	32,217	279,333	1,299,507	292,967
Targ_N_250	$0.60	$0.13	$0.53	373	373	0	0	53,593	414,752	1,955,732	464,351
Targ_N_350	$0.66	$0.14	$0.57	460	460	0	0	75,057	528,394	2,545,985	612,373
Targ_N_450	$0.71	$0.14	$0.59	530	530	0	0	96,068	624,512	3,074,626	747,955
Rand_N_50	$7.46	$1.20	$5.54	20	10	7	4	2,972	6,462	40,052	8,707
Rand_N_150	$10.68	$1.70	$7.76	33	14	11	8	6,487	13,464	84,412	18,524
Rand_N_250	$12.15	$1.94	$8.77	44	18	14	12	9,562	19,704	123,313	27,284
Rand_N_350	$13.20	$2.10	$9.42	53	21	17	15	12,283	25,257	158,814	35,386
Rand_N_450	$13.88	$2.20	$9.84	62	24	20	18	15,059	30,815	194,491	43,473
Targ_P_50	$0.41	$0.11	$0.39	94	94	0	0	10,676	120,530	460,259	125,746
Targ_P_150	$0.52	$0.13	$0.46	206	206	0	0	31,852	286,353	1,176,655	322,245
Targ_P_250	$0.59	$0.13	$0.50	317	317	0	0	53,326	417,752	1,840,376	491,548
Targ_P_350	$0.65	$0.14	$0.54	409	409	0	0	74,438	534,304	2,474,334	640,962
Targ_P_450	$0.71	$0.15	$0.58	540	540	0	0	95,902	630,748	3,033,672	769,160
Rand_P_50	$7.01	$1.12	$4.94	20	10	5	4	2,896	6,891	43,023	9,776
Rand_P_150	$10.16	$1.61	$6.98	33	15	9	9	6,210	14,197	89,725	20,676
Rand_P_250	$11.75	$1.86	$8.00	43	19	11	13	8,922	20,355	128,547	29,895
Rand_P_350	$12.80	$2.02	$8.63	52	23	13	16	11,443	26,119	165,374	38,758
Rand_P_450	$13.47	$2.12	$9.03	61	26	16	19	14,025	31,883	202,693	47,564

The cost of nitrogen reduction ranges from a low of $0.09 per pound in the Targ_N_50 scenario up to $2.29 per pound in the Rand_S_450 scenario. The lowest cost of reducing phosphorus is achieved with the Targ_P_50 scenario at an average cost of $0.39 per pound. The Rand_S_450 scenario has the highest phosphorus reduction costs of $10.56 per pound. This scenario results in the highest average costs across all of the pollutants.

The number of BMP projects range from a low of 20 in all of the random implementation scenarios operating under a $50,000 annual budget to a high of 540 BMPs in the Targ_P_450 scenario. Targeting nitrogen results in the highest number of BMP projects for each of the budget scenarios with the exception of $450,000.

The total area of land treated by BMPs ranges from 2,896 acres in the Rand_P_50 scenario up to 96,494 acres in the Targ_S_450 scenario. Across all of the pollutants and budget constraints, the targeted scenarios affect more land than the corresponding random scenarios. For example, there is 96,494 acres treated by BMPs in the Targ_S_450 scenario but only 15,522 acres are treated in the Rand_S_450 scenario.

The greatest amount of annual sediment reduction is achieved by the Targ_S_450 scenario at 640,157 tons. The most nitrogen reduction is 3,074,626 pounds (scenario Targ_N_450) while the greatest phosphorus reduction is 202,693 pounds per year (scenario Targ_P_450).

Targeting vs. Random BMP Implementation

Targeting should, by definition, result in more cost-effective primary pollutant reduction than random BMP implementation. In addition, to the extent that pollutants are positively correlated (e.g., installing a BMP to reduce sediment will also result in nitrogen and phosphorus reduction), targeting also could result in more cost-effective reduction across the secondary pollutants. This is found to be the case in the TCL watershed.

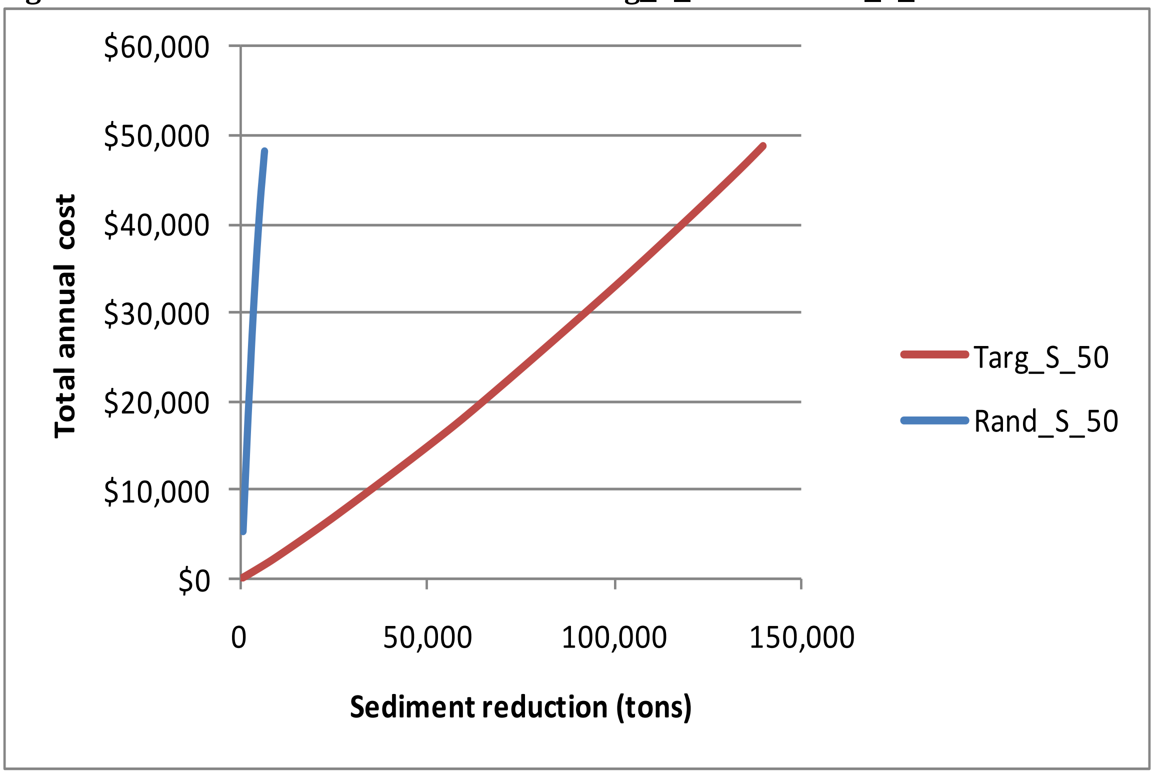
Focusing only on the "targeted" strategies, the first three columns of Table 2.12 demonstrate, as expected, that the average sediment reduction costs are lowest for the strategies, which target sediment reducing BMPs. The same holds true for the strategies which target the other pollutants (nitrogen and phosphorus). The average sediment reduction costs range from $0.35 to $0.69 per ton in the Targ_S strategies as the annual budget increases from $50,000 to $450,000 per year. Nitrogen reduction costs range from $0.09 to $0.14 per pound in the Targ_N scenarios across the low to high budget constraints. In likewise fashion, phosphorus reduction costs go from $0.39 to $0.58 per pound as the budget goes from $50,000 to $450,000 per year.

Targeted sediment strategies range from nearly 20.5 to over 23.2 times more cost-effective than random implementation strategies (in terms of sediment reduction). Targeted nitrogen strategies are about 14.8 to 20.4 times more cost-effective (in terms of nitrogen reduction) while targeted phosphorus reduction strategies are 17.1 to 19.9 times more cost-effective than random approaches (in terms of phosphorus reduction).

Targeted strategies result in a greater number of BMP projects and a larger number of acres treated by the projects relative to the random approaches. Not only does targeting require more effort up front in terms of watershed modeling, but it also requires more BMP contracts and/or meetings with producers.

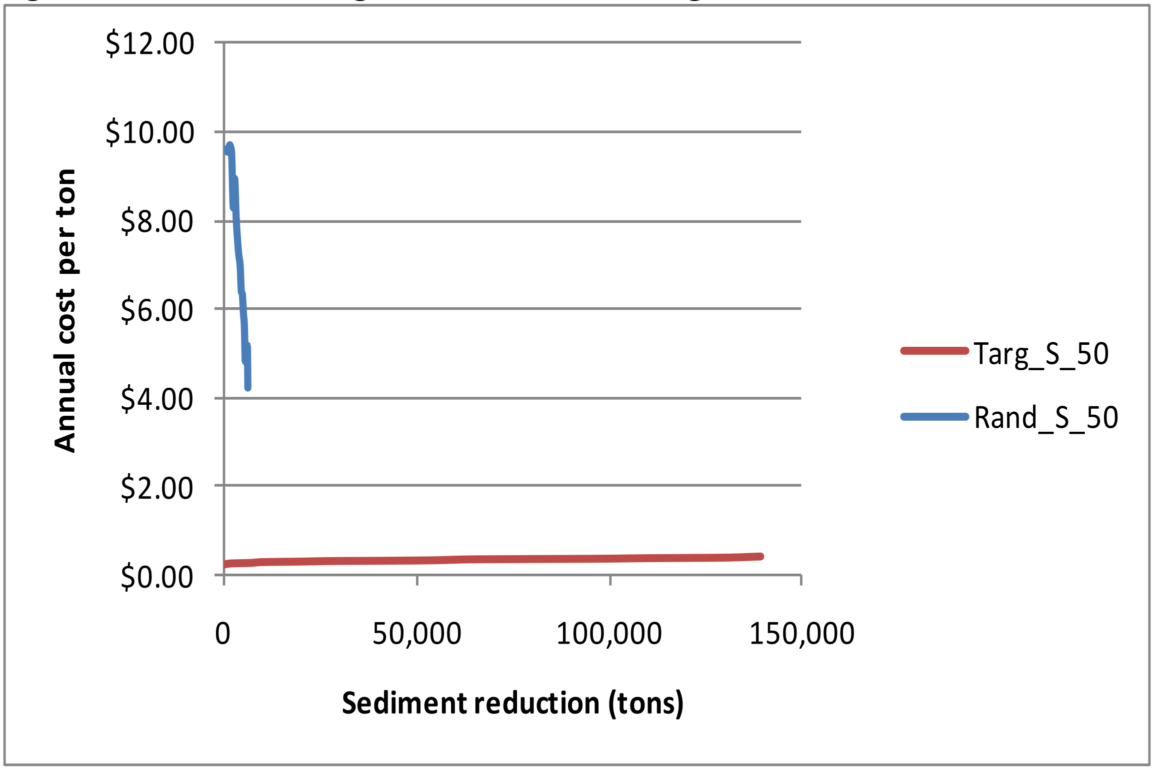
Figure 2.12 displays the total cost curves for the targeted versus random schemes focusing on sediment with a $50,000 annual budget. Across the entire range of values, the total cost curve for the targeted strategy is much flatter than the random case. The flatness of the total cost curve indicates that more sediment is being reduced at the same total cost. Given a $50,000 annual budget, the targeted strategy reduces over 22 times more sediment compared to the random case (139,488 tons compared to 6,317 tons of annual sediment reduction). Alternatively, if the goal is 6,300 tons of sediment reduction it would cost nearly $50,000 to achieve this through random approaches versus just $1,600 using a targeted strategy, which is 3.2 percent of the cost.

Figure 2.12 Sediment total cost curves for Targ_S_50 and Rand_S_50



The total cost curve data in Figure 2.12 can also be expressed marginally. That is, how does the average annual cost per ton change as more sediment is being reduced? Examining the marginal cost curves in Figure 2.13 for these same scenarios highlights more of the differences between strategies. The random approach yields a downward sloping somewhat variable marginal cost curve (the explanation for this can be found on page 72). This curve ranges from $10.00 to $5.00 per ton marginal cost values. The targeted strategy, on the other hand, is upward sloping climbing from $0.22 to $0.44 per ton of sediment reduction.

Figure 2.13 Sediment marginal cost curves for Targ_S_50 and Rand_S_50



A similar story results in the cases where nitrogen and phosphorus are the primary pollutants. Figure 2.14 and Figure 2.15 display the total cost curves for these cases. In the case of nitrogen, a $50,000 annual budget will result in 40,052 lbs of nitrogen reduction whereas a similar amount of nitrogen reduction can be achieved using a targeted approach for about $2,700 annually, or 5.5 percent of the cost. In the case of phosphorus, a $50,000 annual budget will result in 9,776 lbs of phosphorus reduction whereas a similar amount of phosphorus reduction can be achieved using a targeted approach for about $3,500 annually, or 7.0 percent of the cost.

Figure 2.14 Nitrogen total cost curves for Targ_N_50 and Rand_N_50

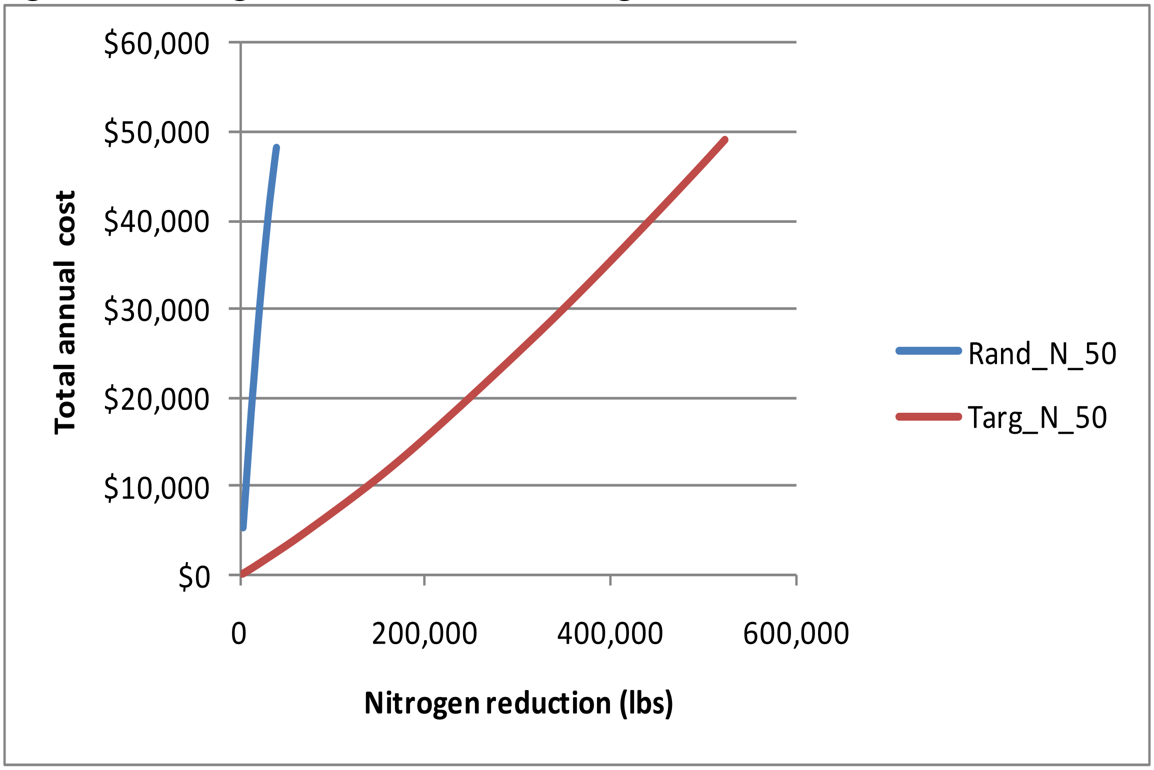
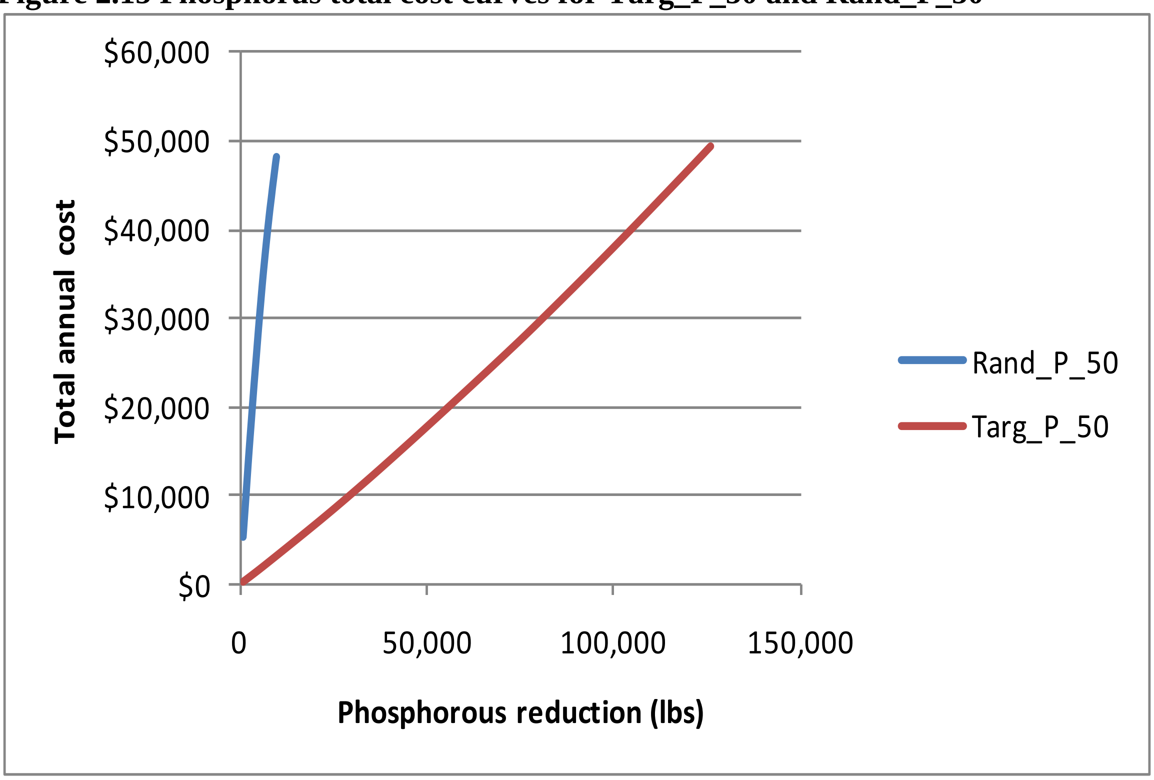


Figure 2.15 Phosphorus total cost curves for Targ_P_50 and Rand_P_50



Effects of the budget constraint

As the budget increases from \$50,000 to \$450,000, the total cost curve for the targeted case continues increasing at an increasing rate. This means that the primary pollutant reduction becomes more expensive as the most cost-effective BMPs are implemented. Thus, the marginal cost curve for the targeted case should continue to be upward sloping as the budget constraint increases.

Figure 2.16 shows how the total cost curve for the \$150,000 case essentially builds upon the total cost curve for the \$50,000 scenario. This continues as the budget constraint increases. However, upon closer inspection one can see that there is not a perfectly smooth transition between like scenarios with different budget constraints. Figure 2.17 shows that total cost curve for the lower budget constraint scenario deviates above the higher budget scenario as the budget constraint is approached. This is because “large” total cost projects, which may be the next best in terms of cost-effectiveness, may exceed the budget. Thus, lower total cost projects must be implemented even though they may not be the next best in terms of cost-effectiveness. This result occurs in each of the targeted scenarios as budget constraints change.

Figure 2.16 Sediment total cost curves for Targ_S scenarios

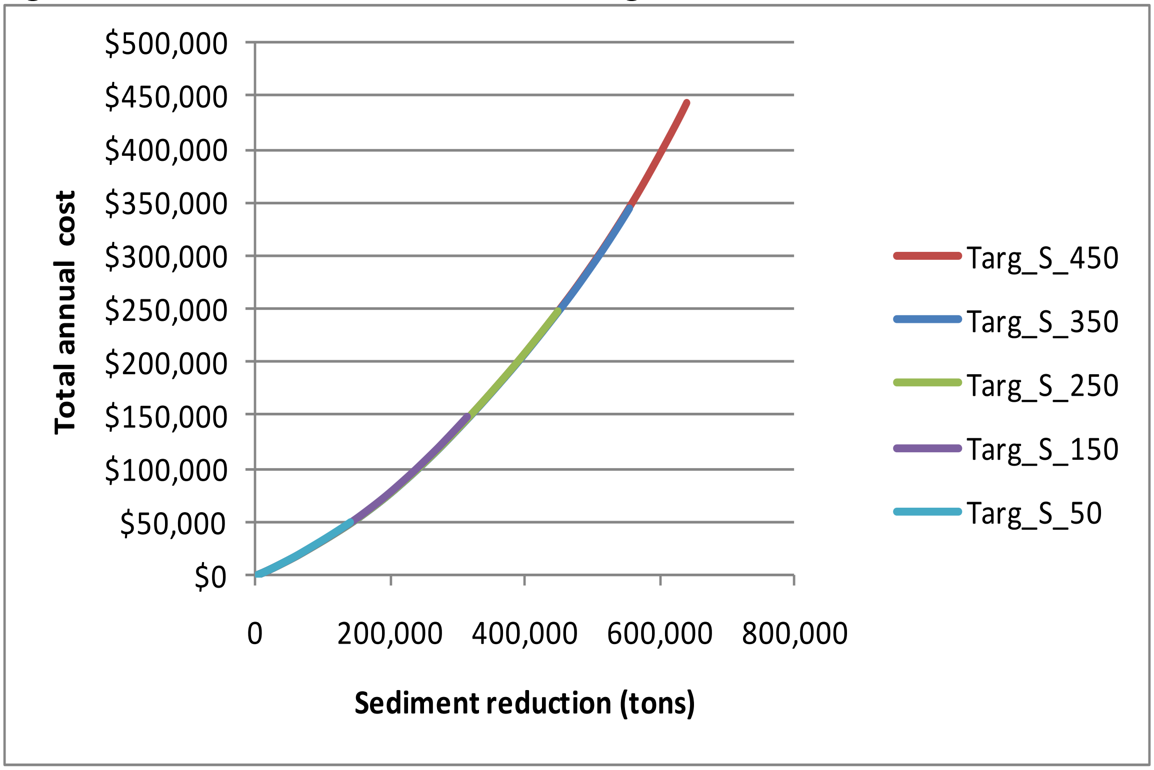
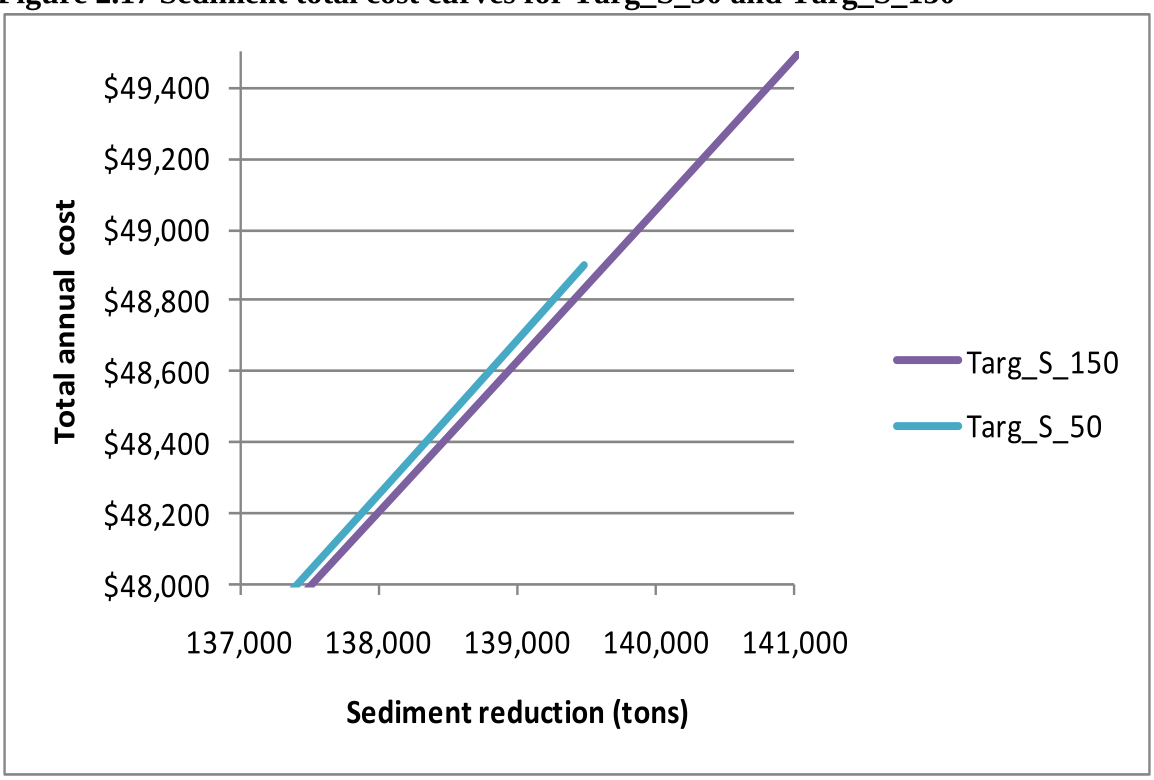
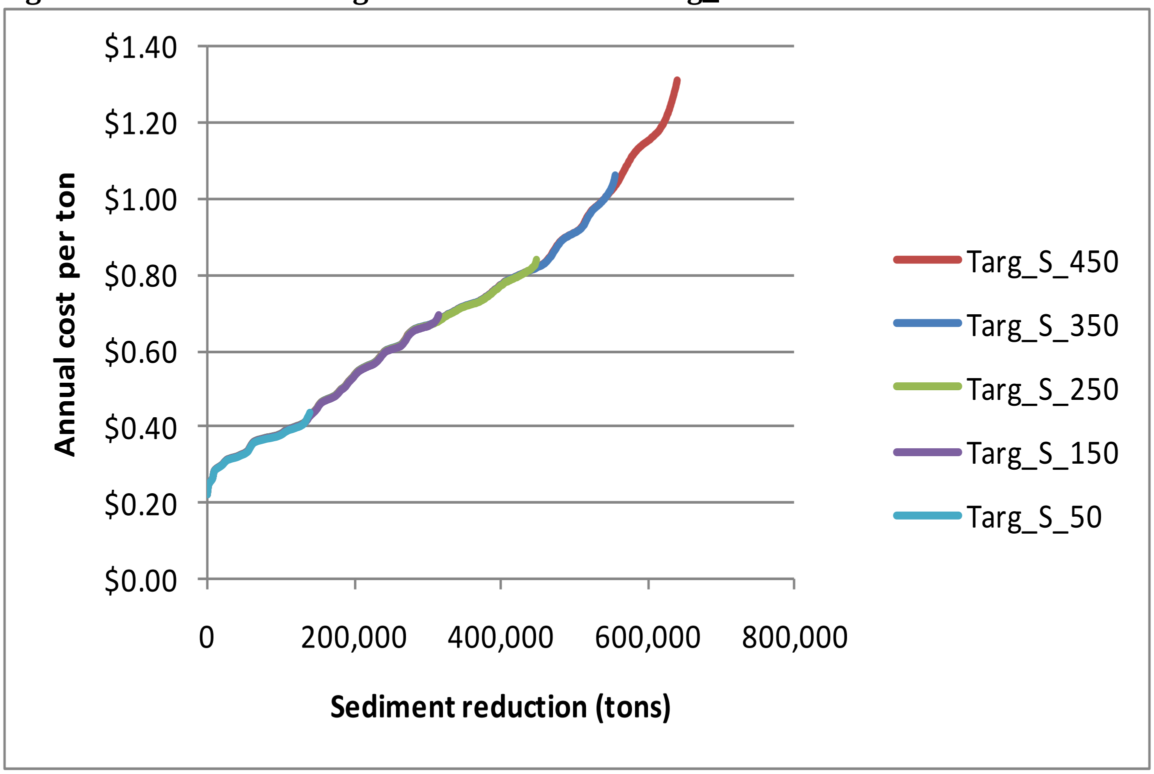


Figure 2.17 Sediment total cost curves for Targ_S_50 and Targ_S_150



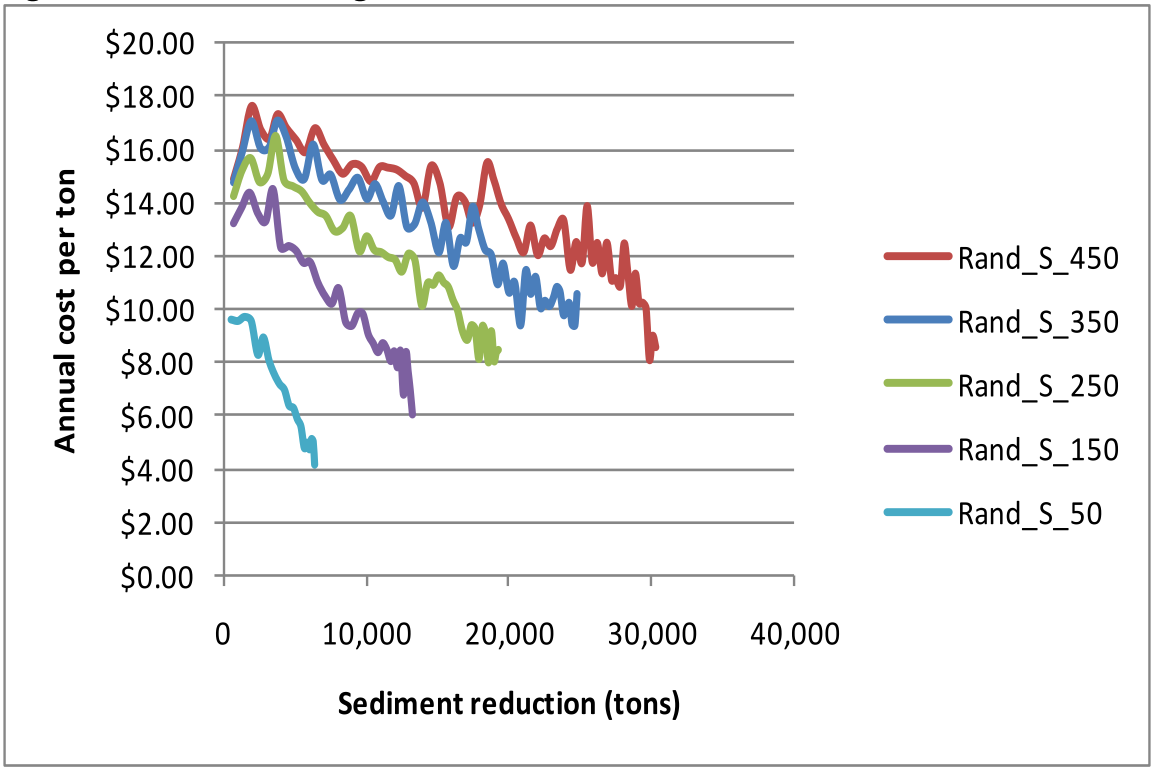
This result also is seen by analyzing the marginal cost curves. In Figure 2.18, the marginal cost curves are upward sloping and essentially build upon each other. In each scenario, the marginal cost curve turns nearly vertical as the budget constraint is reached. However, there is very little horizontal movement at those points, so the effects on total costs are minimal.

Figure 2.18 Sediment marginal cost curves for Targ_S scenarios



The marginal cost curves for the random scenarios do not build upon each other as the budget constraint increases. The average marginal cost of sediment reduction steadily increases from $7.65 to $14.13 per ton as the budget increases from $50,000 to $450,000 per year (Table 2.12). Figure 2.19 shows that the marginal cost curve for Rand_S_50 lies entirely below the other curves across the first 6,300 tons of sediment reduction. Apparently, there are some rather “large” total cost projects with high average sediment reduction costs that cannot be implemented because the budget constraint would be violated. As the budget constraint increases these high cost projects are feasible to be implemented. This is seen by looking at the marginal cost curves for Rand_S_150, Rand_S_250, Rand_S_350, and Rand_S_450 scenarios in Figure 2.19.

Figure 2.19 Sediment marginal cost curves for Rand_S scenarios



The reasons for the downward sloping trends of the curves in Figure 2.19 are related to the budget constraints. As the budget constraint is approached, many of the high average cost projects cannot be implemented for reasons stated previously. Thus, "lower" average cost projects ("lower" relative to the projects that would be implemented without the imposition of a budget constraint) are implemented causing the marginal cost curve to trend downwards. This point is illustrated by looking that the first 5,000 tons of reduction in Figure 2.19 for the relatively high budget scenarios, Rand_S_350 and Rand_S_450 and in the case of an infinite budget constraint shown later in Figure 2.22. The larger budget constraint scenarios generate somewhat flatter marginal cost curves (Figure 2.19).

The total cost curves for the secondary pollutants, nitrogen and phosphorus (note that sediment is still being targeted here), in Figure 2.20 and Figure 2.21 do not display the smooth convex curvature as the primary pollutant total cost curves. The secondary total cost curves exhibit much more variability. But, the curves are upward sloping and do build upon each other as the budget constraint increases.

Figure 2.20 Nitrogen total cost curves for Targ_S scenarios

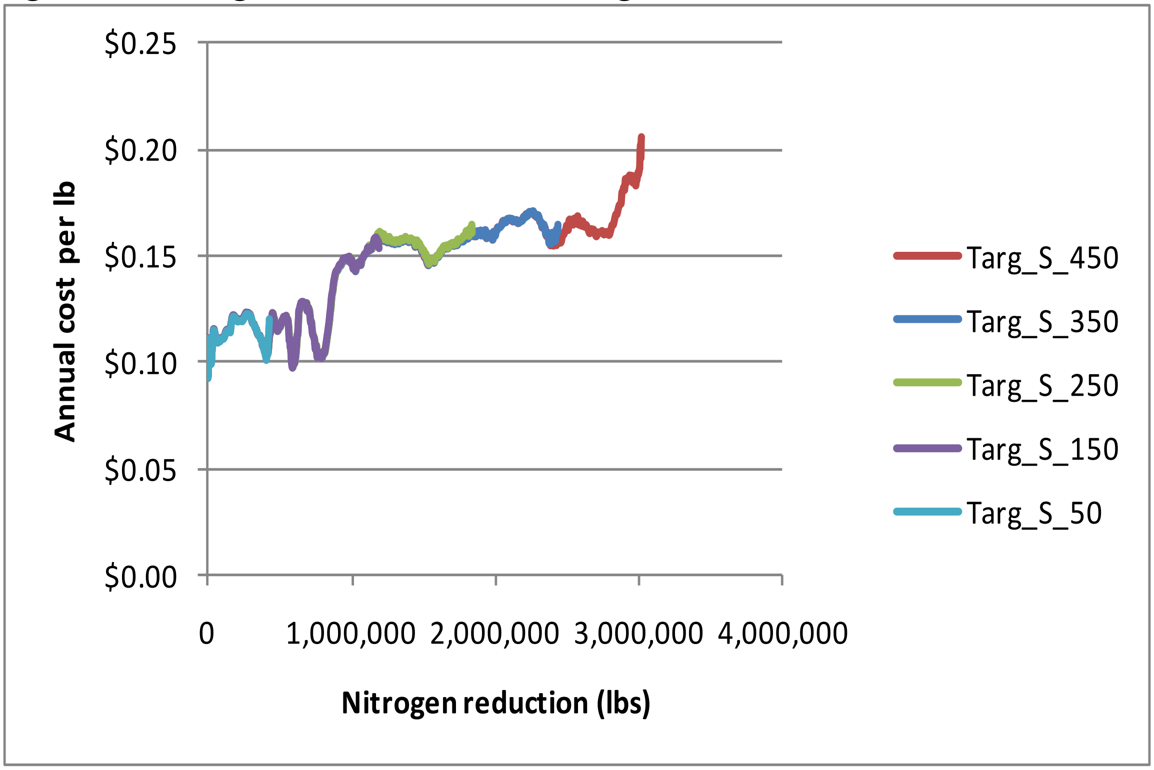
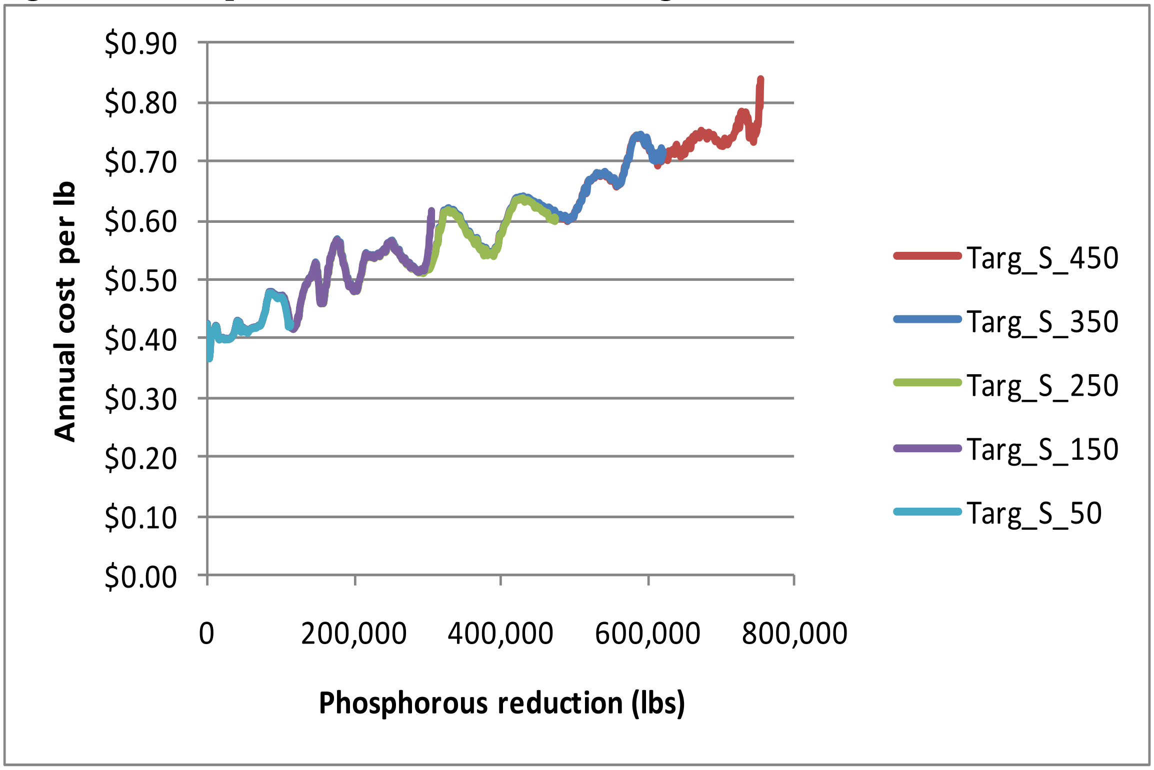


Figure 2.21 Phosphrous total cost curves for Targ_S scenarios



For purposes of illustration (and not realism), each of the targeted and random scenarios are run under an unlimited budget constraint and pollutant reduction goal. The results for these scenarios are displayed in Table 2.13. According to these results focusing on phosphorus will yield more overall pollution reduction across all pollutants than a strategy focused on sediment or nitrogen. The reason for this is that many of the no-till projects, if implemented, will reduce sediment and nitrogen, but actually increase the amount of phosphorus runoff. In the scenarios where sediment and nitrogen are targeted, these BMP projects can and will be implemented. But, when phosphorus is targeted, these projects are not an option due to the fact that phosphorus runoff will be increased. Under an unlimited budget scenario, the targeted approaches are approximately 10 times more cost effective than the random scenarios. Figure 2.22 shows the marginal cost curves for the targeted and random approaches for sediment, nitrogen, and phosphorus.

Table 2.13 Simulation results for the targeted and random scenarios with an unlimited budget and pollutant reduction goal

Scenario	Total annual cost of BMPs	Average S reduction cost for all land treated by BMPs (/ton)	Average N reduction cost for all land treated by BMPs (/lb)	Average P reduction cost for all land treated by BMPs (/lb)	Total # of BMP projects	# of Filter Strip Projects	# of No-till Projects	#of Perma-nent Vegeta-tion Projects	Total area of land treated by BMPs (ac)	Total annual amount of sediment reduction (tons)	Total annual amount of nitrogen reduction (lbs)	Total annual amount of phosphor us reductio n (lbs)
Targ_S_$$$	$3,429,944	$3.89	$0.61	$2.58	1,393	815	578	0	484,551	880,609	5,577,824	1,327,619
Targ_N_$$$	$3,885,785	$4.81	$0.65	$2.82	1,393	795	598	0	484,551	807,783	5,936,667	1,380,356
Targ_P_$$$	$4,371,890	$4.28	$0.63	$2.56	1,393	1,214	179	0	484,551	1,020,888	6,976,413	1,709,869
Rand_S_$$$	$30,230,696	$32.49	$5.13	$23.00	1,393	464	464	465	484,607	930,535	5,887,270	1,314,662
Rand_N_$$$	$32,535,051	$33.83	$5.17	$22.11	1,393	481	437	475	484,607	961,595	6,296,998	1,471,656
Rand_P_$$$	$37,407,025	$35.90	$5.38	$21.86	1,393	541	311	541	484,607	1,041,857	6,950,307	1,711,283

S = Sediment, N = Nitrogen, P = Phosphorus

Figure 2.22 Sediment marginal cost curves under an unlimited budget constraint

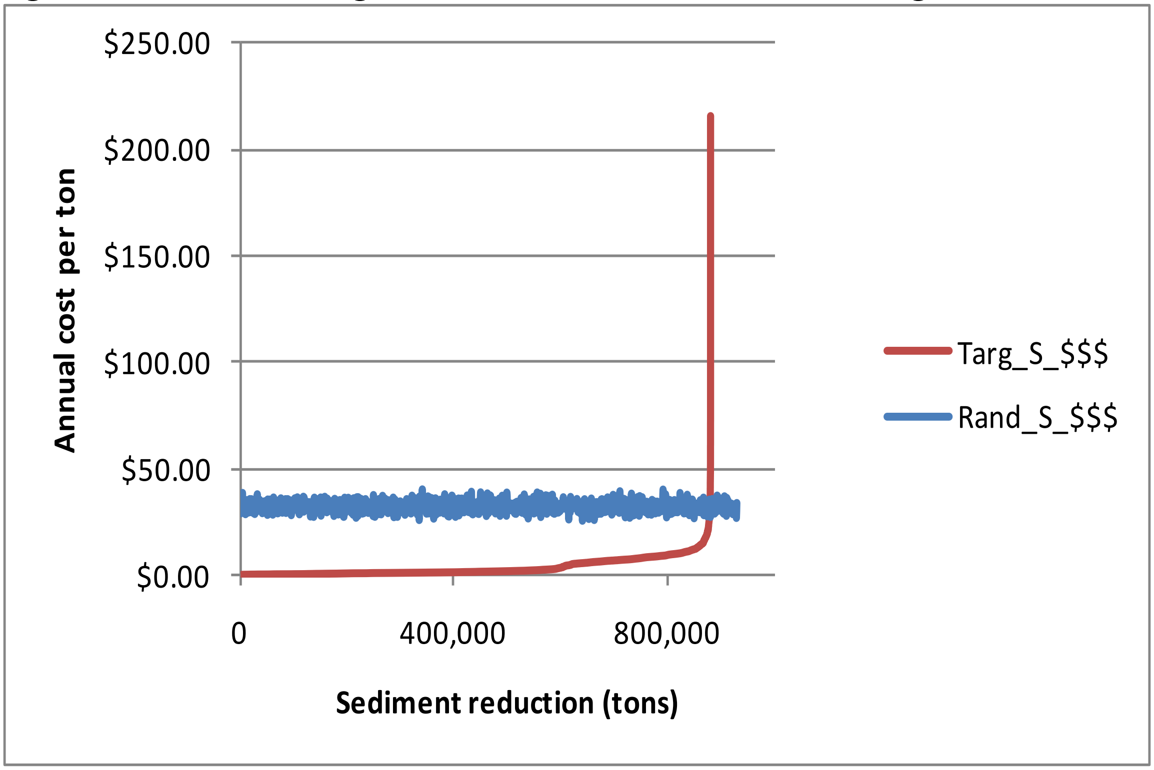


Figure 2.23 Nitrogen marginal cost curves under an unlimited budget constraint

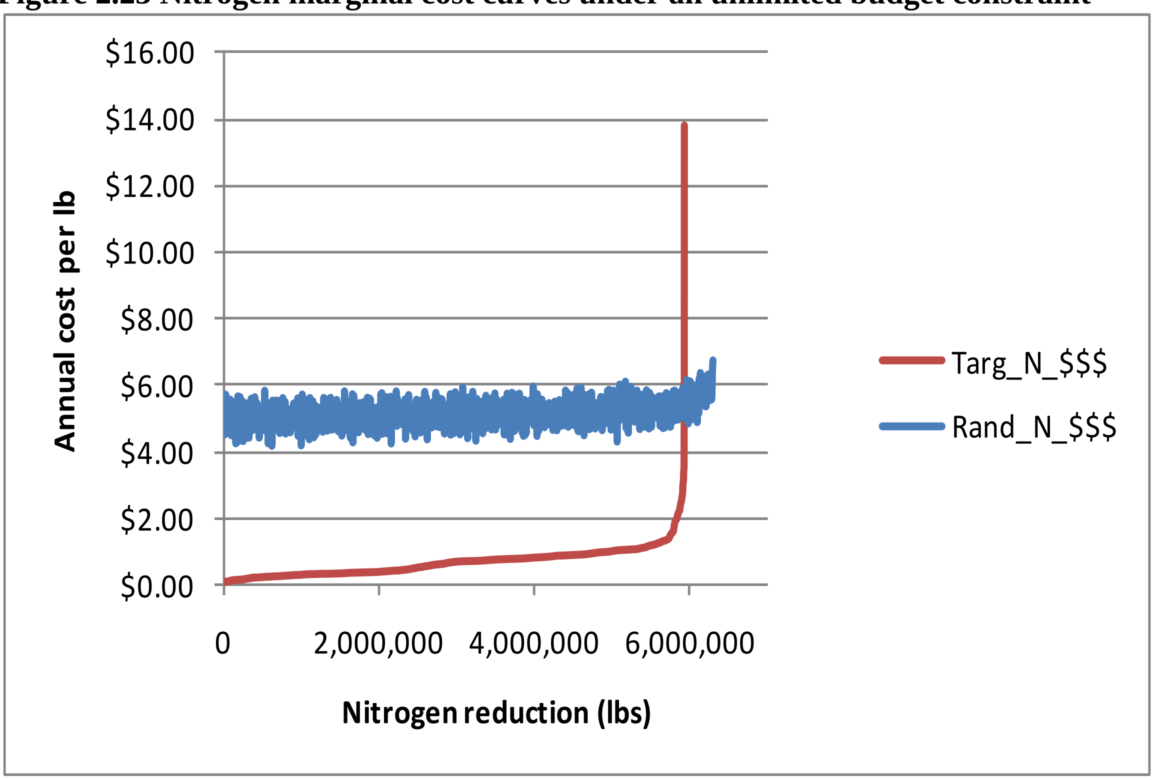
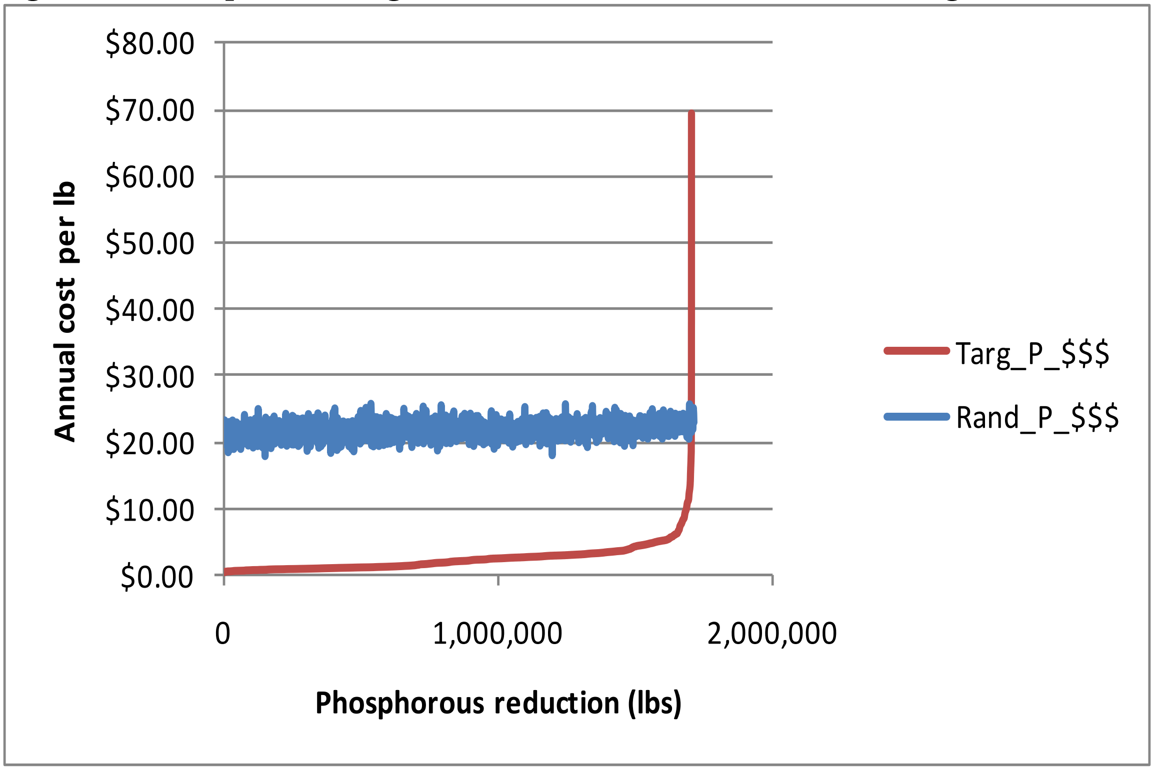


Figure 2.24 Phosphorus marginal cost curves under an unlimited budget constraint

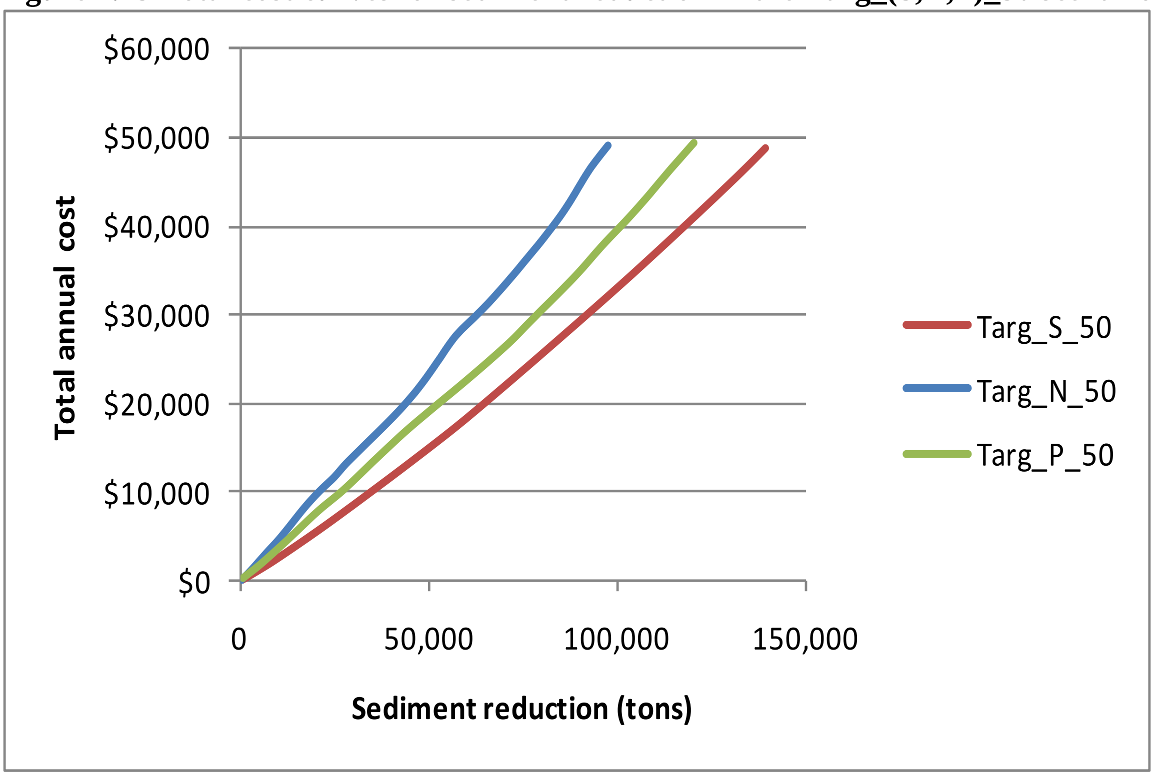


Primary pollutant of concern effects

Regardless of the pollutant targeted, all of the BMP projects implemented result in secondary pollutant reduction as well. While it is true that there are some individual BMP projects that increase pollutant runoff (i.e., some no-till projects increase phosphorus runoff), the vast majority result in pollutant reduction for sediment, nitrogen, and phosphorus. But, because all of the pollutants are not perfectly correlated in terms of reduction cost-effectiveness, assigning one pollutant as “primary” means that some BMP projects will be implemented that would otherwise not be if one of the secondary pollutants was chosen as “primary.” For example, if sediment is the targeted pollutant, it is likely that some BMP projects will be adopted that would otherwise not be if nitrogen or phosphorus was the “primary” pollutant. This is not to say that these BMPs result in increases (as opposed to reductions) in the other pollutants for reasons stated previously, but rather that they are not the most cost-effective BMPs across all of the pollutants.

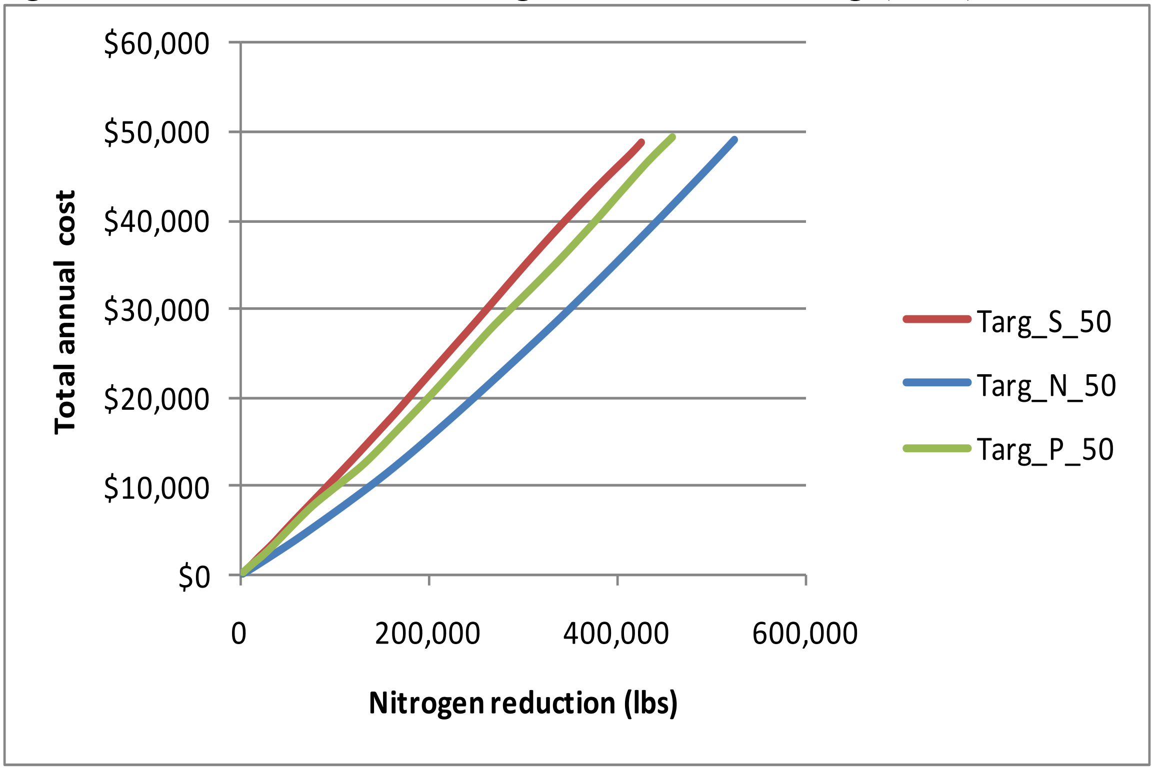
Figure 2.25 depicts this result. As expected, the most cost-effective sediment reduction is achieved when sediment is the primary pollutant. When sediment is the primary pollutant, the $50,000 annual budget results in nearly 140,000 tons of sediment reduction. On the other hand when nitrogen or phosphorus are the primary pollutants, only 97,500 (70 percent of the Targ_S_50 scenario) and 120,500 (86 percent of the Targ_S_50 scenario) tons of sediment reduction is achieved.

Figure 2.25 Total cost curves for sediment reduction in the Targ_(S,N,P)_50 scenarios



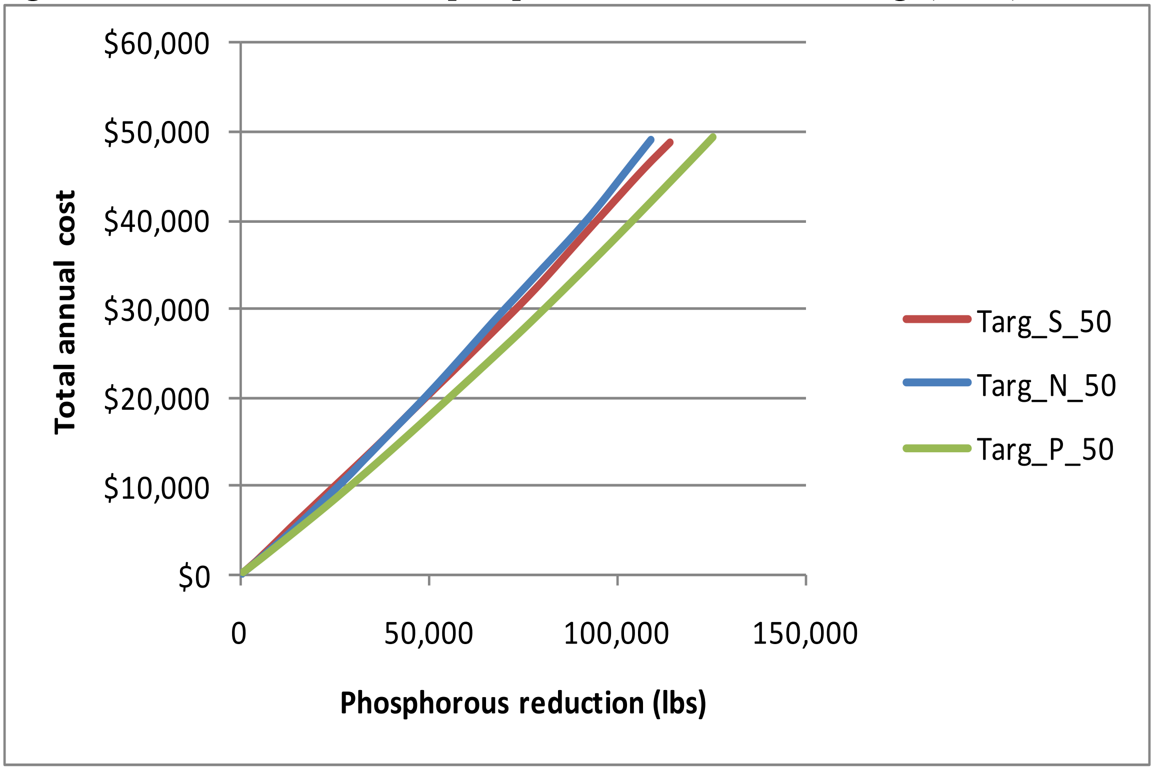
Similarly, when nitrogen is the primary pollutant, a $50,000 budget achieves 524,250 pounds of nitrogen reduction as seen in Figure 2.26. Targeting sediment or phosphorus yields a reduction or 427,350 (82 percent of the Targ_N_50 scenario) and 460,250 (88 percent of the Targ_N_50 scenario) pounds, respectively.

Figure 2.26 Total cost curves for nitrogen reduction in the Targ_(S,N,P)_50 scenarios



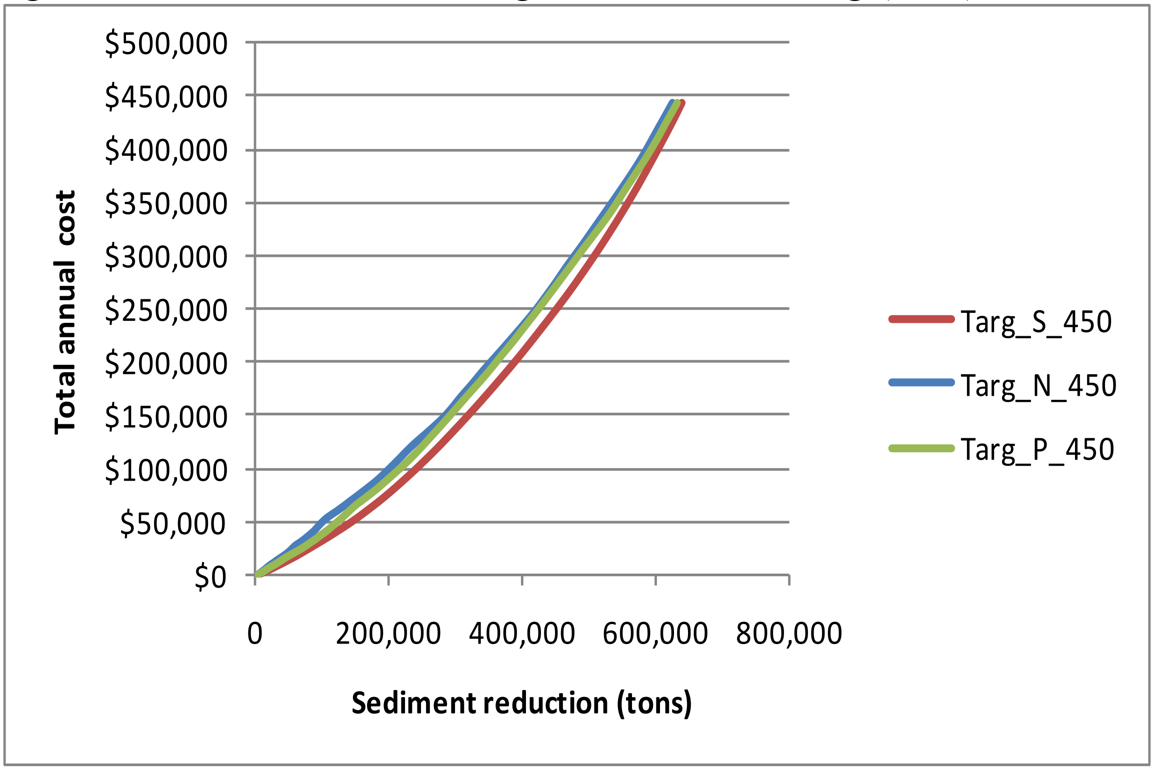
When phosphorus is the primary pollutant, the $50,000 budget results in 125,750 pounds of phosphorus reduction. This compares to 114,150 (91 percent of the Targ_P_50 scenario) and 108,750 (86 percent of the Targ_P_50 scenario) pounds of phosphorus reduction stemming the Targ_S_50 and Targ_N_50 scenarios, respectively. Figure 2.27 displays these results.

Figure 2.27 Total cost curves for phosphorus reduction in the Targ_(S,N,P)_50 scenarios



As the budget constraint increases, however, the effects of primary pollutant are gradually muted. As Figure 2.28 depicts, under a $450,000 budget the resulting sediment reduction for the Targ_S_450, Targ_N_450, and Targ_P_450 scenarios are 640,150, 624,500, and 630,750, respectively. Hence, focusing on nitrogen as the primary pollutant will still yield 97.6 percent of the sediment reduction as the scenario, which focuses primarily on sediment under a $450,000 budget constraint. This compares to a 70 percent reduction under a $50,000 budget (as shown previously). The same results hold for the other corresponding scenarios. Thus, under targeted scenarios, the determination and selection of the primary and secondary pollutants can have important effects on the expected loading reductions for each pollutant particularly under lower budget constraints.

Figure 2.28 Total cost curves for nitrogen reduction in the Targ_(S,N,P)_450 scenarios



As would be expected, when BMPs are implemented in a random fashion, the selection of the primary pollutant is nearly irrelevant. As Figure 2.29 shows, the three curves are nearly identical under a $50,000 budget. Taking the curves out further under a $450,000 budget, Figure 2.30, indicates that this relationship holds across all of the budget constraints considered.

Figure 2.29 Total cost curves for sediment reduction in the Rand_(S,N,P)_50 scenarios

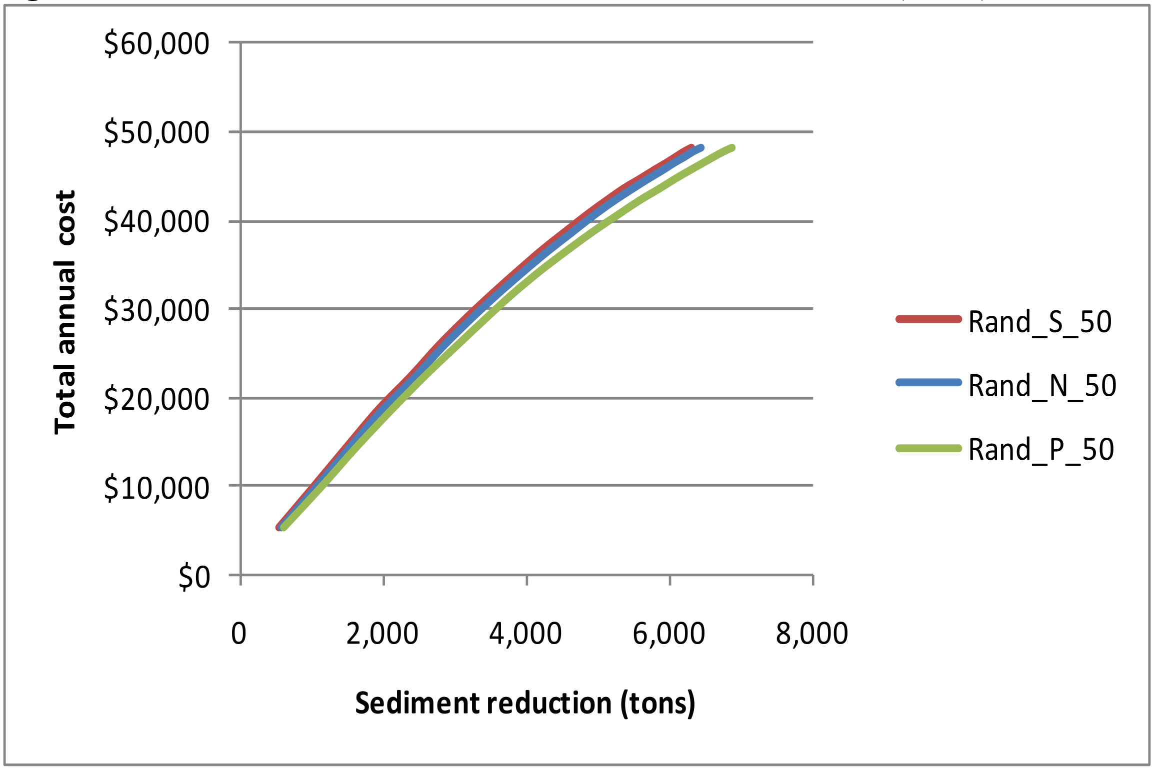
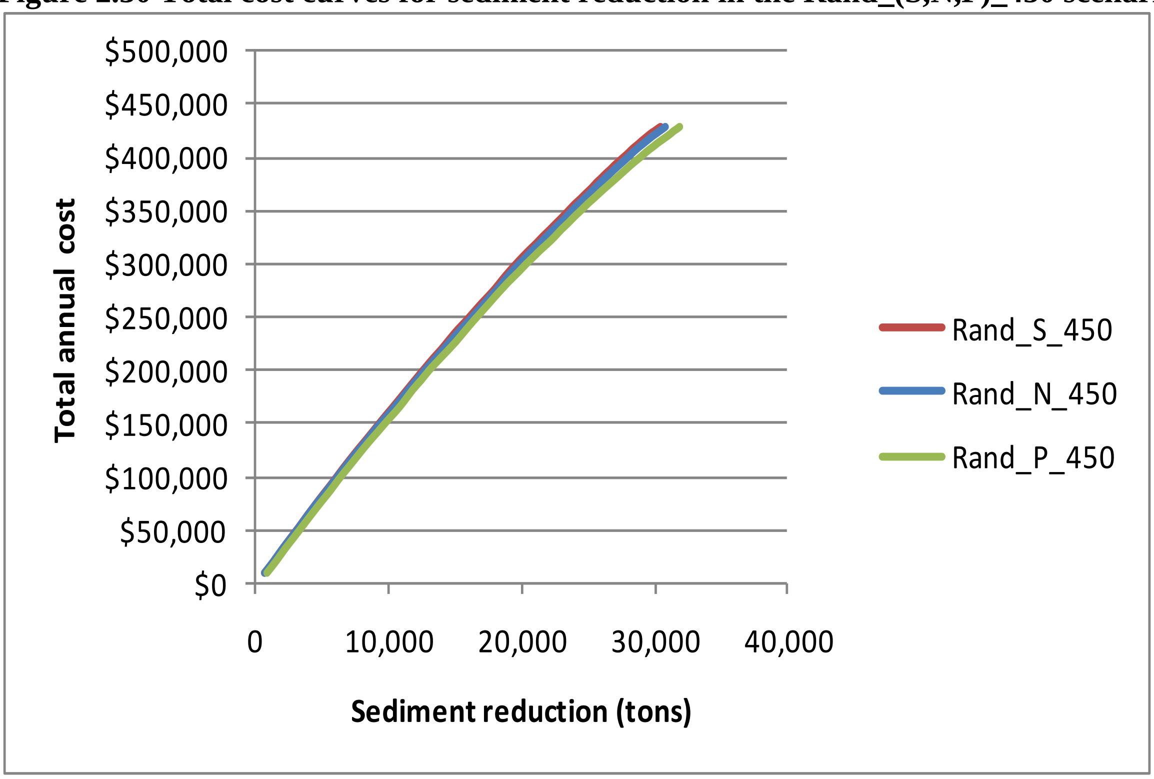


Figure 2.30 Total cost curves for sediment reduction in the Rand_(S,N,P)_450 scenarios



Effects of changing BMP costs

The BMP cost data displayed in Table 2.1 are based on 2009 values of cropland cash rent, CRP rents, and establishment and maintenance costs for filter strips and for converting cropland to permanent vegetation. Further, the costs of no-till are based on per acre incentive payments for converting to no-till established by the EQIP program in 2009 (KS EQIP 2009; NE EQIP 2009).

Recent upward swings in commodity prices and overall farm profitability are being capitalized into land values and rents. Thus, the opportunity costs associated with converting cropland to filter strips and permanent vegetation also increase. Increasing fuel prices also result in higher establishment costs for each of these BMPs. Meanwhile, higher fuel prices make no-till a more financially attractive option (all else being equal) to conventional or minimum tillage. For these reasons, adjustments to the 2009 BMP costs are made as follows.

The total annualized costs for filter strips and permanent vegetation are first increased by 150 percent to capture the increasing land opportunity costs and fuel prices. For no-till, the annualized costs were decreased by 50 percent to account for the higher fuel prices. Table 2.14 displays the annualized costs for each BMP over a 15-year time horizon. These cost scenarios will be denoted as the “X” scenarios to distinguish these from the original scenarios.

Table 2.14 Adjusted BMP Annualized costs over a 15-year time horizon - "X" scenarios

County, State	Annualized Cost ($/acre) for Filter Strips per cropland acre treated[1]	Annualized Cost ($/acre) for No-till	Annualized Cost ($/acre) for Permanent Vegetation
Clay, KS	$5.74	$6.50	$121.58
Gage, NE	$8.50	$10.00	$162.23
Jefferson, NE	$8.50	$10.00	$152.90
Marshall, KS	$7.06	$6.50	$133.85
Nemaha, KS	$7.18	$6.50	$138.69
Pawnee, NE	$8.21	$10.00	$158.28
Pottawatomie, KS	$6.47	$6.50	$129.87
Republic, KS	$5.82	$6.50	$114.95
Riley, KS	$6.82	$6.50	$122.81
Washington, KS	$6.83	$6.50	$124.61

[1] Annualized cost of filter strip divided by 25 cropland acres (treated)

Table 2.15 displays the results of the "X" scenarios. In general, the results for the "X" scenarios follow the same patterns as the original scenarios. In the targeted "X" scenarios, filter strips are again the only BMP implemented in the watershed. Even though the annualized costs for filter strips and no-till are very similar on a per acre basis, the greater pollutant reduction efficiencies achieved by filter strips makes this the more attractive BMP. In the random "X" scenarios, however, there is more balance between no-till and filter strip projects but less permanent vegetation projects compared to the original scenarios.

In all cases, the amount of pollutant reduction achieved by the "X" scenarios is less than the corresponding original scenarios. This is due to the higher costs of filter strips, which tend to still be more cost-effective than no-till (even with the reduced costs of no-till).

Table 2.15 Simulation results for the "X" scenarios

Scenario	Average sediment reduction cost for all land treated by BMPs (/ton)	Average nitrogen reduction cost for all land treated by BMPs (/lb)	Average phosphor-rous reduction cost for all land treated by BMPs (/lb)	Total # of BMP projects	# of Filter Strip Projects	# of No-till Projects	#of Permanent Vegetation Projects	Total area of land treated by BMPs (ac)	Total amount of sediment reduction (tons)	Total amount of nitrogen reduction (lbs)	Total amount of phosphorus reduction (lbs)
Targ_S_50_X	$0.50	$0.17	$0.62	59	59	0	0	7,124	99,591	287,113	79,608
Targ_S_150_X	$0.62	$0.17	$0.69	189	189	0	0	21,357	237,035	859,769	213,526
Targ_S_250_X	$0.73	$0.19	$0.74	264	264	0	0	35,701	338,541	1,299,917	334,169
Targ_S_350_X	$0.81	$0.20	$0.78	318	317	0	0	50,203	427,653	1,735,850	447,735
Targ_S_450_X	$0.88	$0.21	$0.81	369	369	0	0	64,140	503,141	2,134,228	548,622
Rand_S_50_X	$8.34	$1.37	$6.90	20	8	8	3	3,108	5,791	35,152	6,997
Rand_S_150_X	$12.07	$1.99	$9.71	32	12	12	7	6,389	11,956	72,505	14,871
Rand_S_250_X	$14.39	$2.36	$11.30	40	15	15	10	8,839	16,626	101,551	21,165
Rand_S_350_X	$15.87	$2.60	$12.32	48	18	18	13	11,053	21,050	128,465	27,109
Rand_S_450_X	$17.01	$2.78	$13.09	56	20	20	15	13,263	25,300	154,841	32,880
Targ_N_50_X	$0.72	$0.13	$0.65	86	86	0	0	7,143	68,595	375,152	75,943
Targ_N_150_X	$0.75	$0.16	$0.73	197	197	0	0	21,478	196,100	928,965	202,707
Targ_N_250_X	$0.82	$0.17	$0.77	283	283	0	0	35,574	300,861	1,408,522	319,485
Targ_N_350_X	$0.88	$0.19	$0.79	360	360	0	0	50,211	393,850	1,855,596	437,498
Targ_N_450_X	$0.94	$0.20	$0.82	426	426	0	0	64,163	471,594	2,254,543	539,930
Rand_N_50_X	$8.16	$1.31	$6.37	20	8	8	3	3,020	5,915	36,716	7,570
Rand_N_150_X	$11.90	$1.91	$8.98	32	13	12	7	6,143	12,122	75,470	16,057
Rand_N_250_X	$14.28	$2.28	$10.55	40	16	15	10	8,477	16,767	105,187	22,699
Rand_N_350_X	$15.75	$2.51	$11.51	48	18	17	13	10,634	21,260	133,211	29,080
Rand_N_450_X	$16.94	$2.70	$12.28	55	21	20	15	12,636	25,345	159,192	34,975
Targ_P_50_X	$0.58	$0.16	$0.56	63	63	0	0	7,099	84,922	313,976	87,605
Targ_P_150_X	$0.70	$0.18	$0.65	163	163	0	0	21,323	212,515	832,787	229,075
Targ_P_250_X	$0.80	$0.19	$0.70	224	224	0	0	35,336	308,546	1,282,136	351,387
Targ_P_350_X	$0.87	$0.20	$0.74	304	304	0	0	49,804	397,459	1,729,568	465,191
Targ_P_450_X	$0.93	$0.21	$0.78	353	353	0	0	63,879	476,897	2,165,517	568,319
Rand_P_50_X	$8.01	$1.28	$5.80	19	9	6	4	2,712	6,017	37,736	8,307
Rand_P_150_X	$11.87	$1.89	$8.35	30	13	9	8	5,452	12,132	76,238	17,232
Rand_P_250_X	$14.23	$2.25	$9.84	39	16	11	11	7,600	16,937	107,058	24,490
Rand_P_350_X	$15.80	$2.50	$10.83	46	19	13	13	9,514	21,316	134,816	31,115
Rand_P_450_X	$17.09	$2.70	$11.63	52	22	15	16	11,233	25,227	159,798	37,079

Next, the total annualized costs for filter strips and permanent vegetation are increased by 200 percent to capture a more drastic increase in land opportunity costs and fuel prices. For no-till, the annualized costs were decreased by 75 percent to account for the even higher fuel prices, and thus, a greater relative cost advantage of no-till (all else equal). Table 2.16 displays the annualized costs for each BMP over a 15-year time horizon. These cost scenarios will be denoted as the "Y" scenarios to distinguish these from the original (Table 2.1) and "X" scenarios (Table 2.14).

Table 2.16 Adjusted BMP Annualized costs over a 15-year time horizon - "Y" scenarios

County, State	Annualized Cost ($/acre) for Filter Strips per cropland acre treated[1]	Annualized Cost ($/acre) for No-till	Annualized Cost ($/acre) for Permanent Vegetation
Clay, KS	$7.66	$3.25	$162.10
Gage, NE	$11.34	$5.00	$216.30
Jefferson, NE	$11.34	$5.00	$203.86
Marshall, KS	$9.41	$3.25	$178.46
Nemaha, KS	$9.57	$3.25	$184.92
Pawnee, NE	$10.95	$5.00	$211.04
Pottawatomie, KS	$8.63	$3.25	$173.16
Republic, KS	$7.76	$3.25	$153.26
Riley, KS	$9.10	$3.25	$163.74
Washington, KS	$9.11	$3.25	$166.14

[1] Annualized cost of filter strip divided by 25 cropland acres (treated)

Table 2.17 displays the results of the "Y" scenarios. In general, the results for the "Y" scenarios follow the same patterns as the original and "X" scenarios. In all cases the amount of pollutant reduction achieved by the "Y" scenarios is less than the corresponding original and "X" scenarios.

A notable difference here is that in the targeted "Y" scenarios, both filter strips and no-till are implemented in each of the budget constraints considered. Based on the distribution of these two BMPs, it appears that no-till is relatively more cost-competitive at reducing nitrogen as compared to sediment or phosphorus. For example, under a $50,000 annual budget constraint, the Targ_N_50_Y scenario results in 156 total BMP projects, of which, 154 are no-till projects. On the other hand, the Targ_S_50_Y and Targ_P_50_Y scenarios result in a near even distribution of filter strips and no-till projects.

Table 2.17 Simulation results for the "Y" scenarios

Scenario	Average sediment reduction cost for all land treated by BMPs (/ton)	Average nitrogen reduction cost for all land treated by BMPs (/lb)	Average phosphor-rous reduction cost for all land treated by BMPs (/lb)	Total # of BMP projects	# of Filter Strip Projects	# of No-till Projects	#of Permanent Vegetation Projects	Total area of land treated by BMPs (ac)	Total amount of sediment reduction (tons)	Total amount of nitrogen reduction (lbs)	Total amount of phosphorus reduction (lbs)
Targ_S_50_Y	$0.63	$0.22	$0.86	62	32	30	0	7,297	79,092	221,238	57,737
Targ_S_150_Y	$0.78	$0.23	$0.95	181	107	75	0	22,255	189,131	654,387	155,535
Targ_S_250_Y	$0.92	$0.25	$1.02	266	165	101	0	36,695	270,298	1,004,966	243,851
Targ_S_350_Y	$1.02	$0.26	$1.05	311	198	113	0	48,945	340,221	1,313,930	328,689
Targ_S_450_Y	$1.11	$0.27	$1.09	359	228	131	0	61,382	401,990	1,634,355	407,518
Rand_S_50_Y	$8.39	$1.42	$7.67	21	8	10	3	3,375	5,774	34,212	6,318
Rand_S_150_Y	$13.02	$2.16	$10.99	32	12	14	7	6,328	11,147	67,119	13,201
Rand_S_250_Y	$15.77	$2.61	$12.91	40	14	17	9	8,458	15,321	92,592	18,713
Rand_S_350_Y	$17.99	$2.95	$14.42	46	16	19	11	10,228	18,720	113,964	23,355
Rand_S_450_Y	$19.53	$3.21	$15.44	52	18	21	13	11,945	22,181	135,088	28,055
Targ_N_50_Y	$1.30	$0.13	$1.19	156	2	154	0	15,065	37,944	378,335	41,627
Targ_N_150_Y	$1.20	$0.18	$1.39	310	29	281	0	39,188	123,904	817,404	106,742
Targ_N_250_Y	$1.22	$0.21	$1.35	410	75	335	0	57,906	203,797	1,170,024	182,941
Targ_N_350_Y	$1.28	$0.23	$1.32	456	102	355	0	71,519	271,321	1,484,817	261,627
Targ_N_450_Y	$1.35	$0.25	$1.33	500	125	375	0	84,228	330,137	1,776,426	334,959
Rand_N_50_Y	$8.35	$1.36	$6.94	21	8	10	3	3,202	5,803	35,746	6,984
Rand_N_150_Y	$12.96	$2.08	$10.09	32	12	14	7	6,008	11,207	69,815	14,393
Rand_N_250_Y	$15.78	$2.53	$11.97	40	14	16	9	7,997	15,348	95,796	20,221
Rand_N_350_Y	$17.94	$2.86	$13.38	46	17	18	11	9,740	18,845	118,307	25,260
Rand_N_450_Y	$19.48	$3.11	$14.42	52	19	20	13	11,401	22,302	139,683	30,118
Targ_P_50_Y	$0.76	$0.19	$0.72	58	38	20	0	6,401	64,564	264,917	68,113
Targ_P_150_Y	$0.89	$0.23	$0.83	157	116	41	0	17,765	165,654	652,979	178,616
Targ_P_250_Y	$0.99	$0.24	$0.90	210	158	52	0	28,831	248,743	1,016,077	275,697
Targ_P_350_Y	$1.09	$0.26	$0.94	267	203	64	0	39,964	316,663	1,341,790	364,237
Targ_P_450_Y	$1.17	$0.26	$0.99	320	250	70	0	51,933	380,819	1,696,268	449,598
Rand_P_50_Y	$8.42	$1.35	$6.32	20	9	8	3	2,723	5,776	35,965	7,698
Rand_P_150_Y	$13.25	$2.10	$9.47	30	12	11	7	5,145	10,997	69,284	15,375
Rand_P_250_Y	$16.14	$2.56	$11.34	37	15	13	9	6,867	15,020	94,647	21,370
Rand_P_350_Y	$18.35	$2.90	$12.74	43	17	14	11	8,415	18,466	116,906	26,600
Rand_P_450_Y	$20.01	$3.16	$13.79	48	19	15	13	9,800	21,737	137,474	31,527

Figure 2.31 and Figure 2.32 display the marginal and total cost curves for sediment, respectively, as the costs of BMPs change from the original case to the "X" case and finally to the "Y" case. Across the first 100,000 tons of sediment reduction, each of the marginal cost curves appear to have similar slopes (only different y-intercepts). But, after 100,000 tons of reduction, the slope of scenario "Y" increases at a much faster rate than the original scenario.

Figure 2.33 depicts the total acreage being treated by BMPs across total sediment reduction for each of the different scenarios. It can be seen that the curves for the original and "X" scenarios perfectly overlay across the first 503,000 tons of reduction. From this figure, it is evident that the original and "X" scenarios consist of the same 426 BMP projects. In each of these scenarios, only filter strips are applied. Because filter strip costs are higher in the Targ_S_450_X scenario, the acreage-sediment reduction curve ends after when the $450,000 constraint is met at 503,000 tons of reduction.

The Targ_S_450_Y scenario, on the other hand, follows closely to the original and "X" scenario curve across the first 100,000 tons of reduction. It is likely that the same filter strips are being applied in each case. After 100,000 tons of reduction, no-till becomes the most cost-effective BMP and more of these projects are implemented in the "Y" scenario. However, no-till is not as environmentally effective on a per acre basis as filter strips. Therefore, more acres need to be treated to achieve the same amount of sediment reduction as compared to the other two scenarios. In the "Y" scenario, 350,000 tons of sediment reduction requires 50,500 acres of BMP treatment, whereas, only 37,500 acres need to be treated in the "X" scenario to achieve a similar reduction.

Figure 2.31 Sediment marginal cost curves for different BMP cost levels

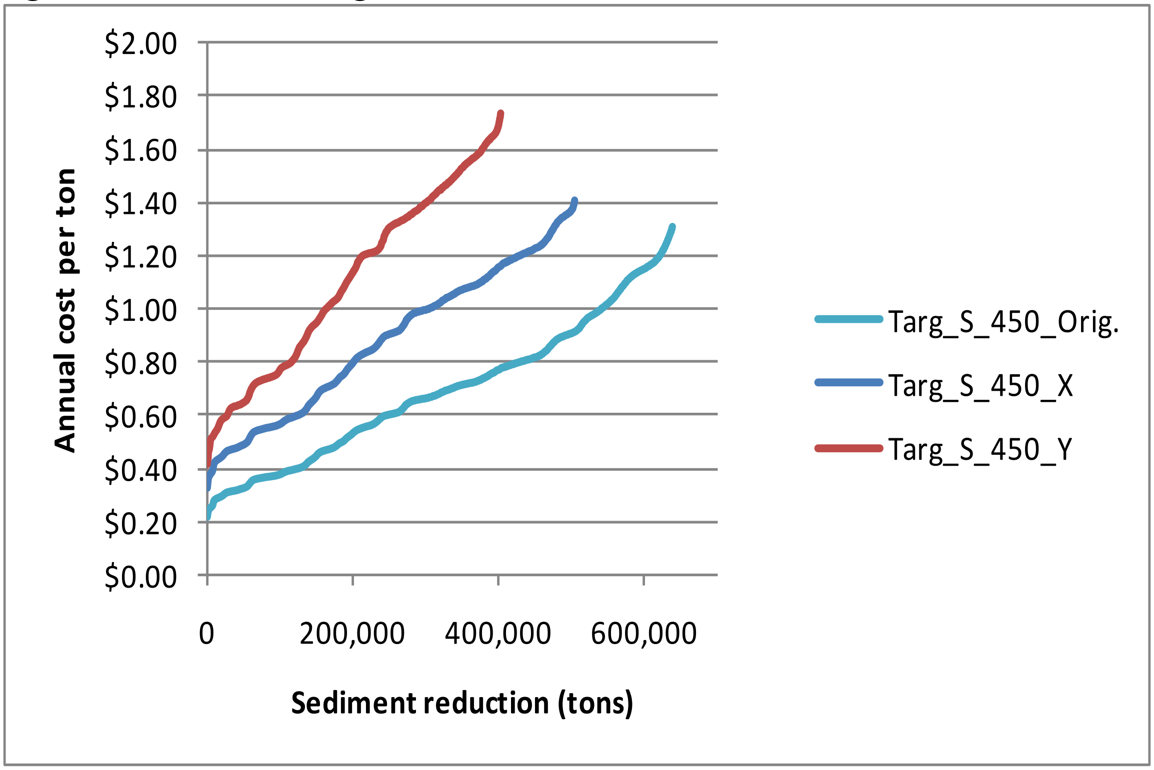


Figure 2.32 Sediment total cost curves for different BMP cost levels

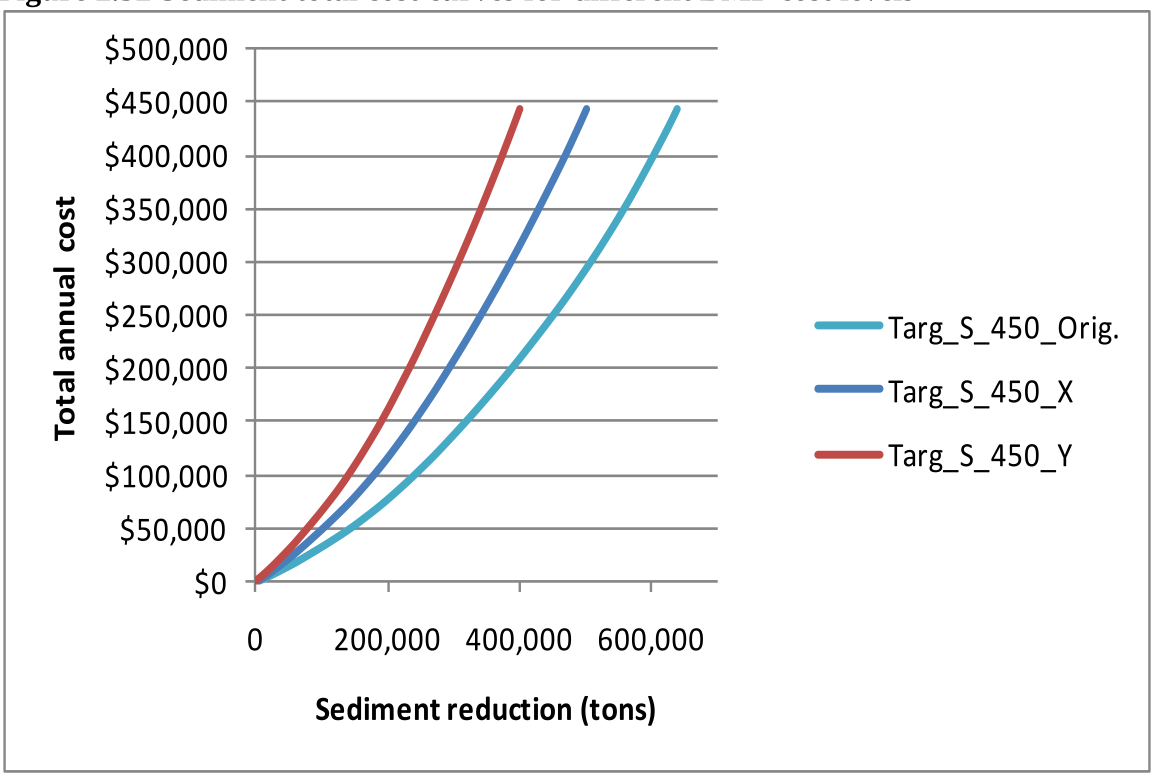
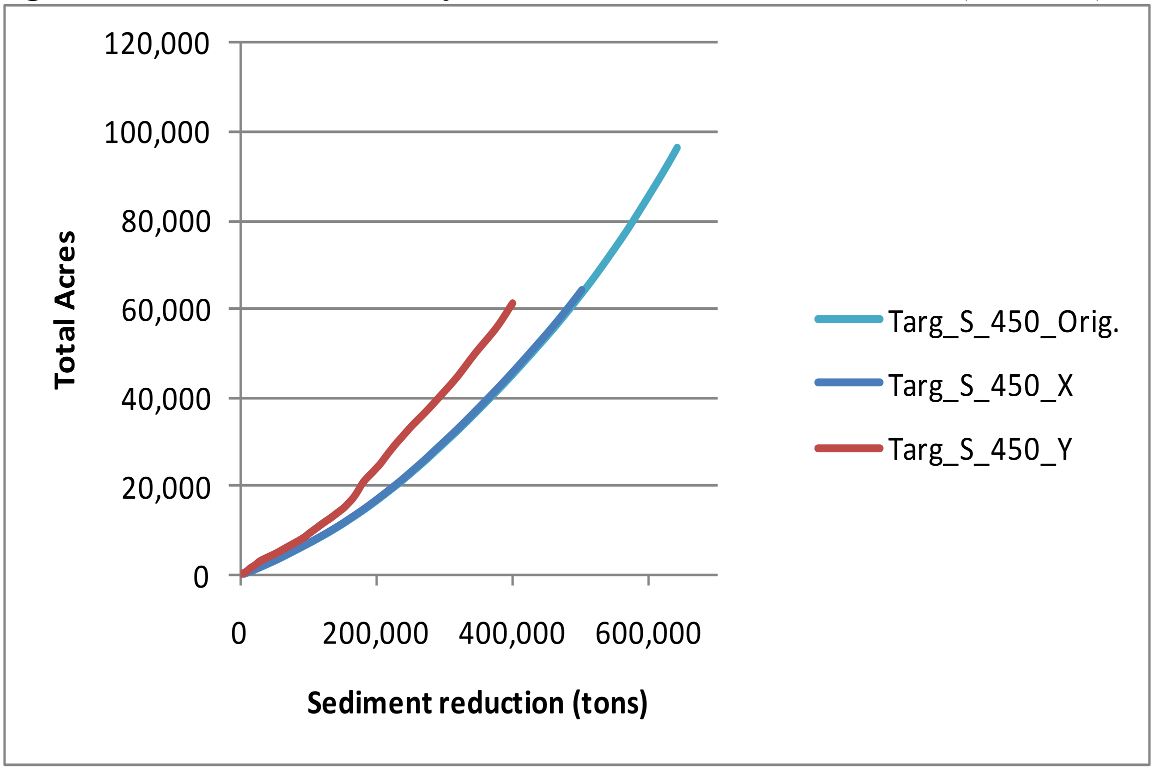


Figure 2.33 Total acres treated by BMPs for different BMP cost levels (Sediment)



The targeted nitrogen cost curves (Figure 2.34 and Figure 2.35) depict a different story as compared to the sediment examples discussed above. As with the sediment case, the original and "X" scenario exhibit a similar shape due to the fact that the same BMP projects are implemented in each case as shown in Figure 2.36 (across the first 2,250,000 lbs of nitrogen reduction). However, the relatively high cost of filter strips and low cost of no-till in Targ_N_450_Y results in a quite differently shaped marginal cost curve (Figure 2.34). Here, the marginal costs are lower than the "X" case across the first 250,000 lbs of nitrogen reduction. In terms of total cost, this translates to about $30,000. Evidently, the reduced cost of no-till combined with the moderate effectiveness of nitrogen reduction resulting from no-till adoption makes certain no-till projects more cost-effective than filter strips in the Targ_N_450_X scenario. As Table 2.17 shows, 99 percent of the BMPs implemented in the Targ_N_50_Y scenario compared to 48 and 34 percent of the BMPs in the Targ_S_50_Y and Targ_P_50_Y scenarios, respectively. Still, more acres need to be treated in the “Y” scenario to achieve the same amount of nitrogen reduction as compared to the other two scenarios. In the “Y” scenario, 1,776,426 lbs of nitrogen reduction requires 84,228 acres of BMP treatment, whereas, only 47,500 acres need to be treated in the original scenario to achieve a similar reduction.

Figure 2.34 Nitrogen marginal cost curves for different BMP cost levels

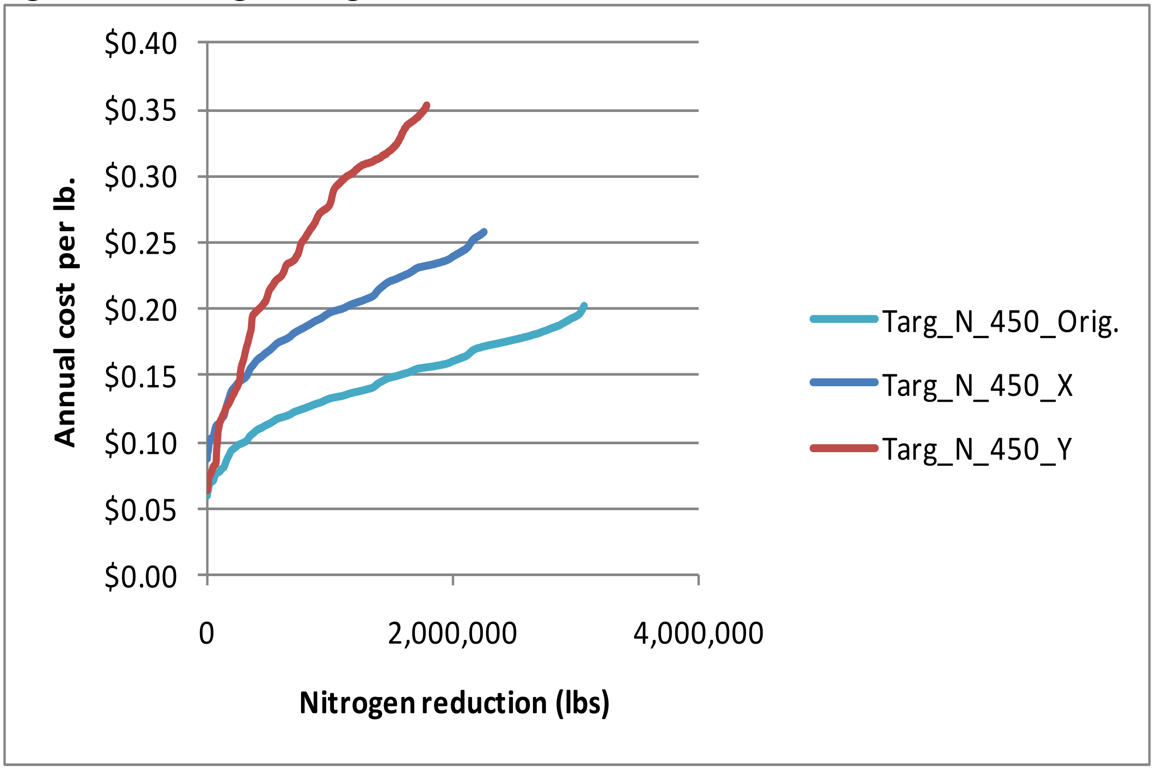


Figure 2.35 Nitrogen total cost curves for different BMP cost levels

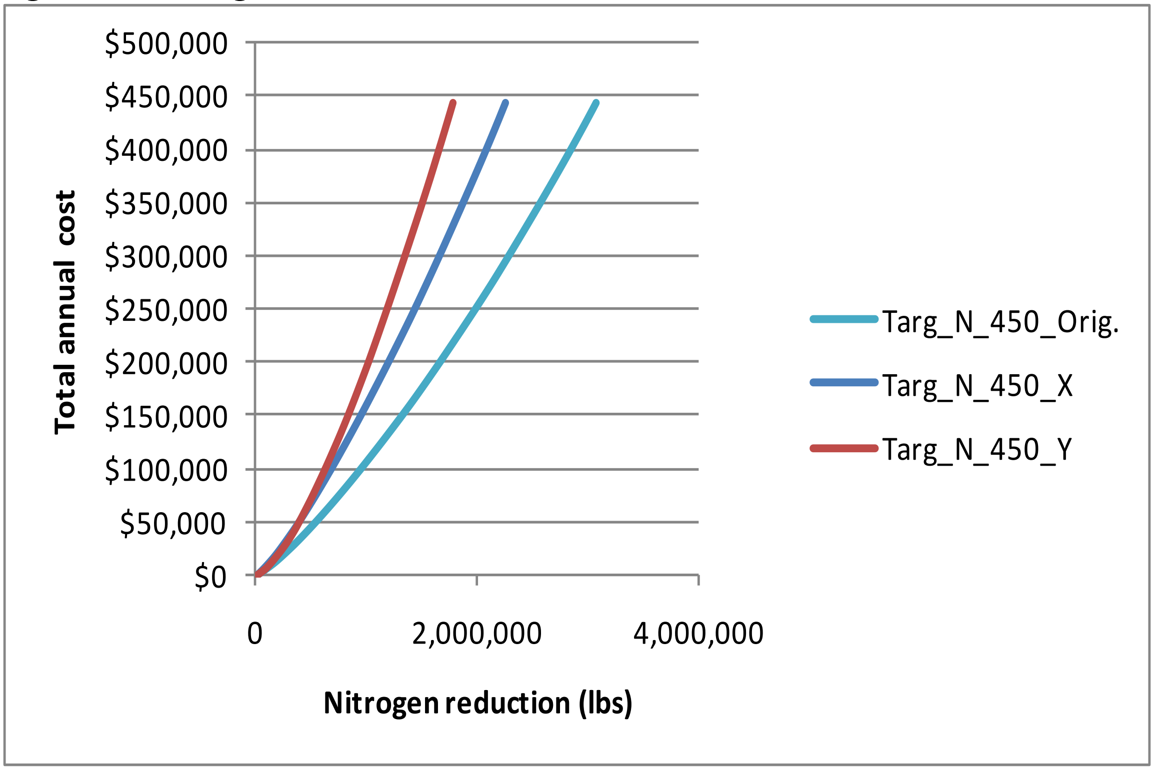
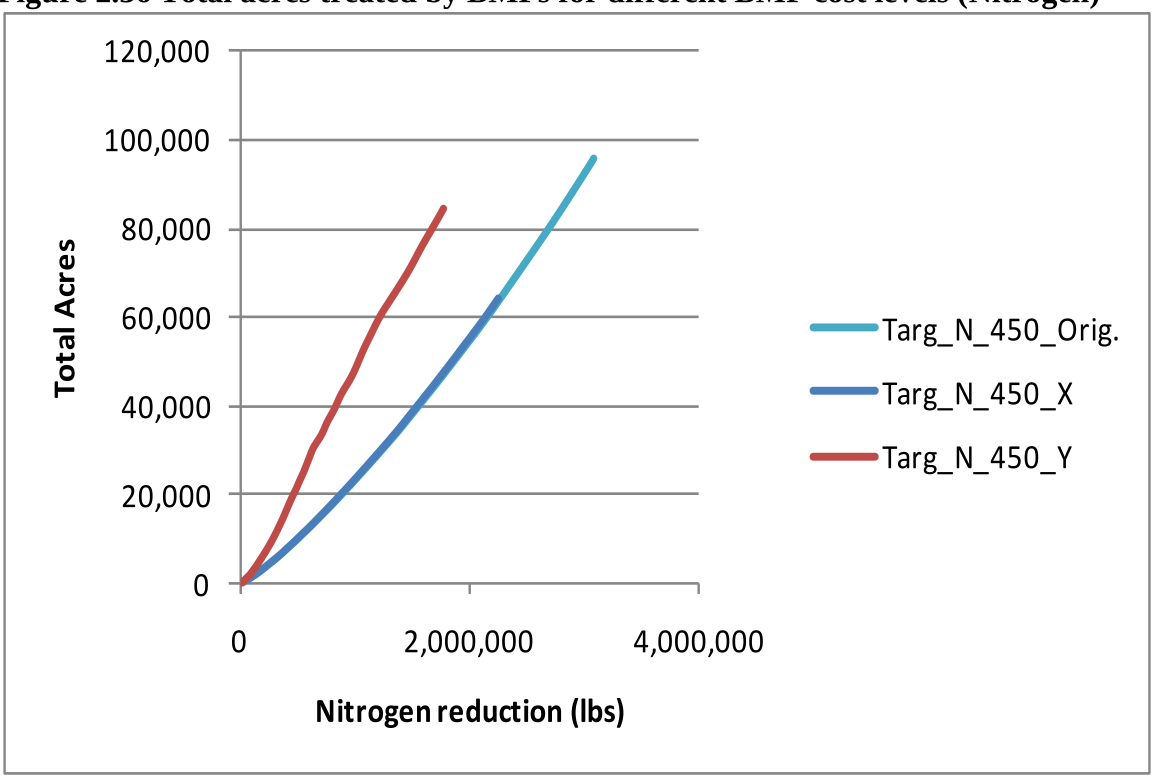


Figure 2.36 Total acres treated by BMPs for different BMP cost levels (Nitrogen)



In the case of targeting phosphorus, the cost curves behave much as they do in the case of targeting sediment (Figure 2.37 and Figure 2.38). The marginal cost curves in Figure 2.37 are all very similar in shape with the main differences being in the y-intercept. Examining Figure 2.39, one can see that again the same BMP projects are being implemented for the original and "X" scenarios. However, unlike the cases of targeting sediment or nitrogen, the acre-reduction curve for the Targ_P_450_Y scenario comes very close to matching the other two scenarios. Upon closer inspection, it is evident that the projects are not being implemented in the exact same order. However, the filter strip and no-till BMP projects are matching the acres per sediment reduction values of the other two scenarios closely. Across all of the considered budget constraints, the ratio of filter strip projects to no-till projects is approximately 3:1 (Table 2.17).

Figure 2.37 Phosphorus marginal cost curves for different BMP cost levels

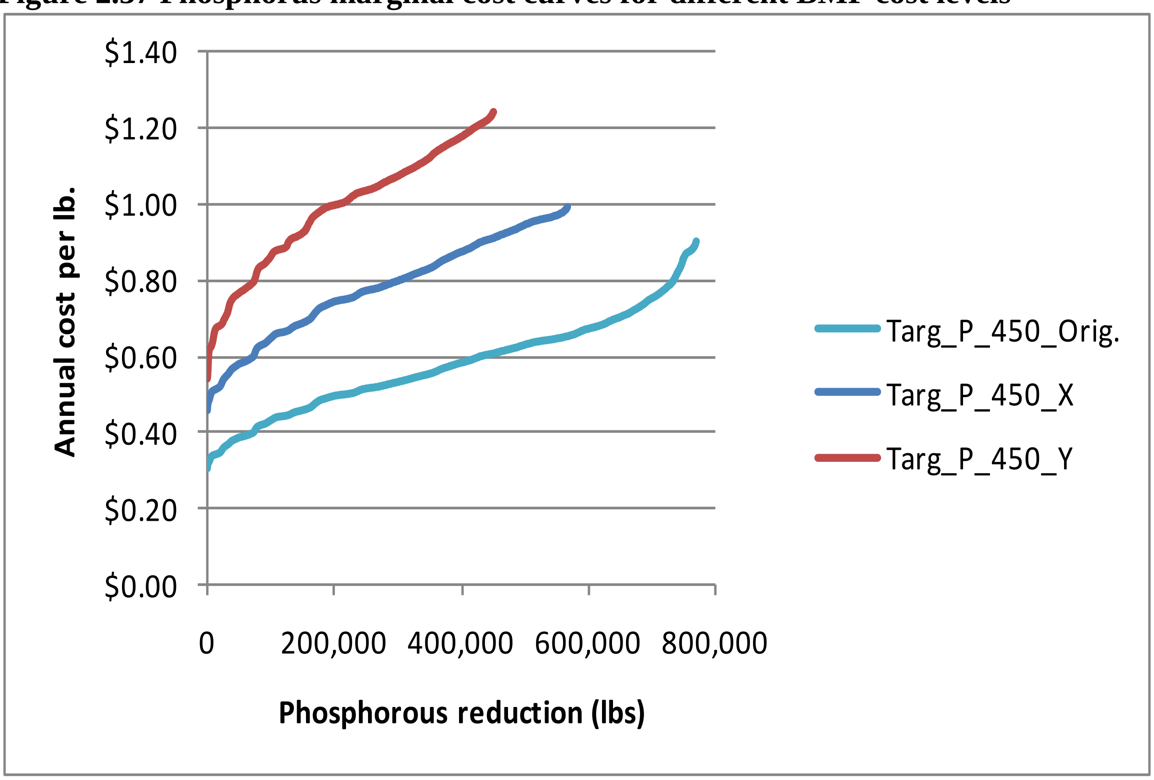


Figure 2.38 Phosphorus total cost curves for different BMP cost levels

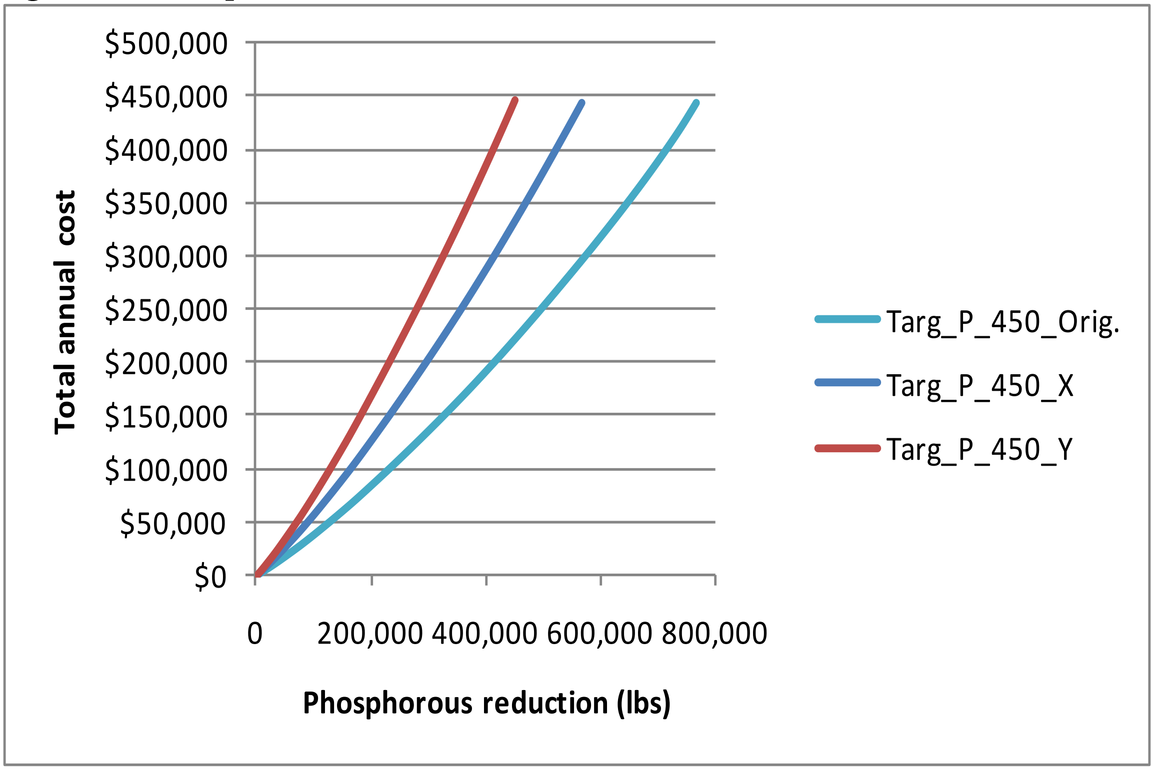
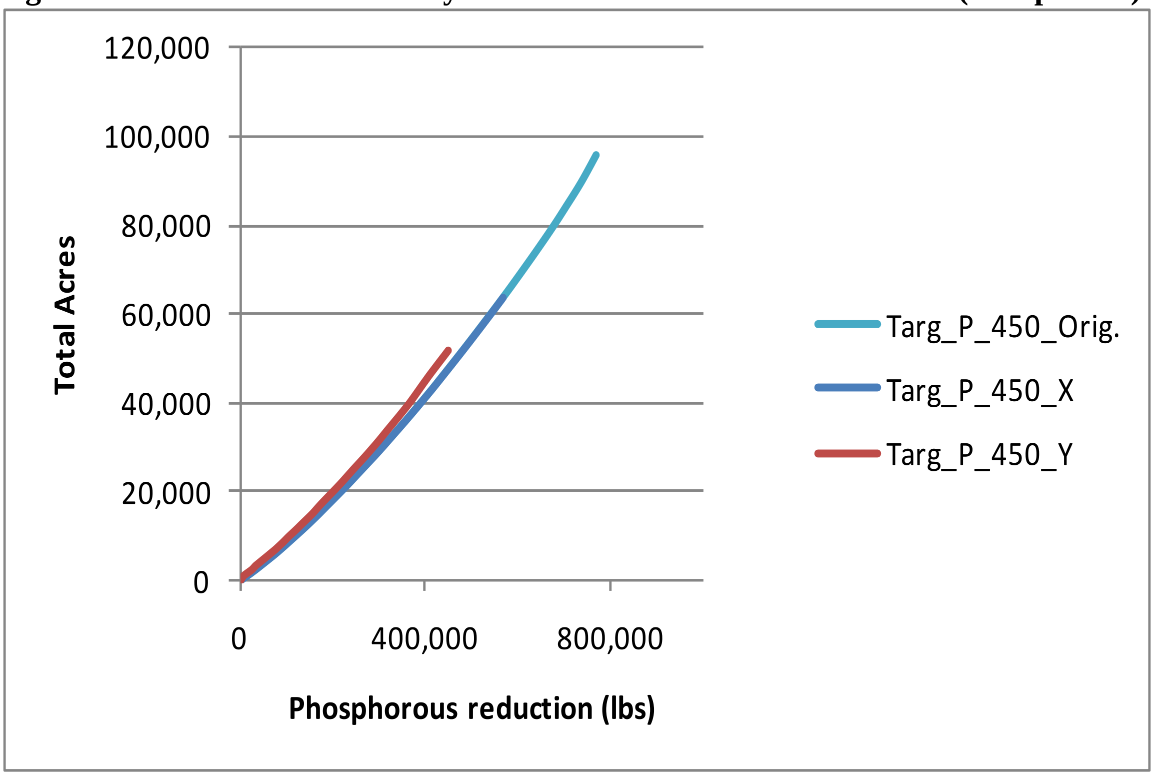


Figure 2.39 Total acres treated by BMPs for different BMP cost levels (Phosphorus)



Cost-effective spatial targeting for conservation

Spatial targeting occurs all of the time in our daily life. Consider a person who leaves the house on a shopping trip with their billfold in hand and returns to their house two hours later without it. A "wise" person will begin searching in areas in which they have just been in the past two hours. Retracing steps and focusing the search to these areas is a more efficient use of one's time than just searching randomly across the countryside. In principle, spatial conservation targeting is no different. It is the deliberate focus of BMP implementation on a particular geographical area. Implementing BMPs in areas that exhibit the most potential for erosion and/or nutrient loads is a good first step in efficient targeting. This approach to targeting could simply rely on baseline sediment and nutrient loading maps as shown in Figure 2.40, Figure 2.41, and Figure 2.42.

Figure 2.40 Baseline sediment losses from cropland by subwatershed

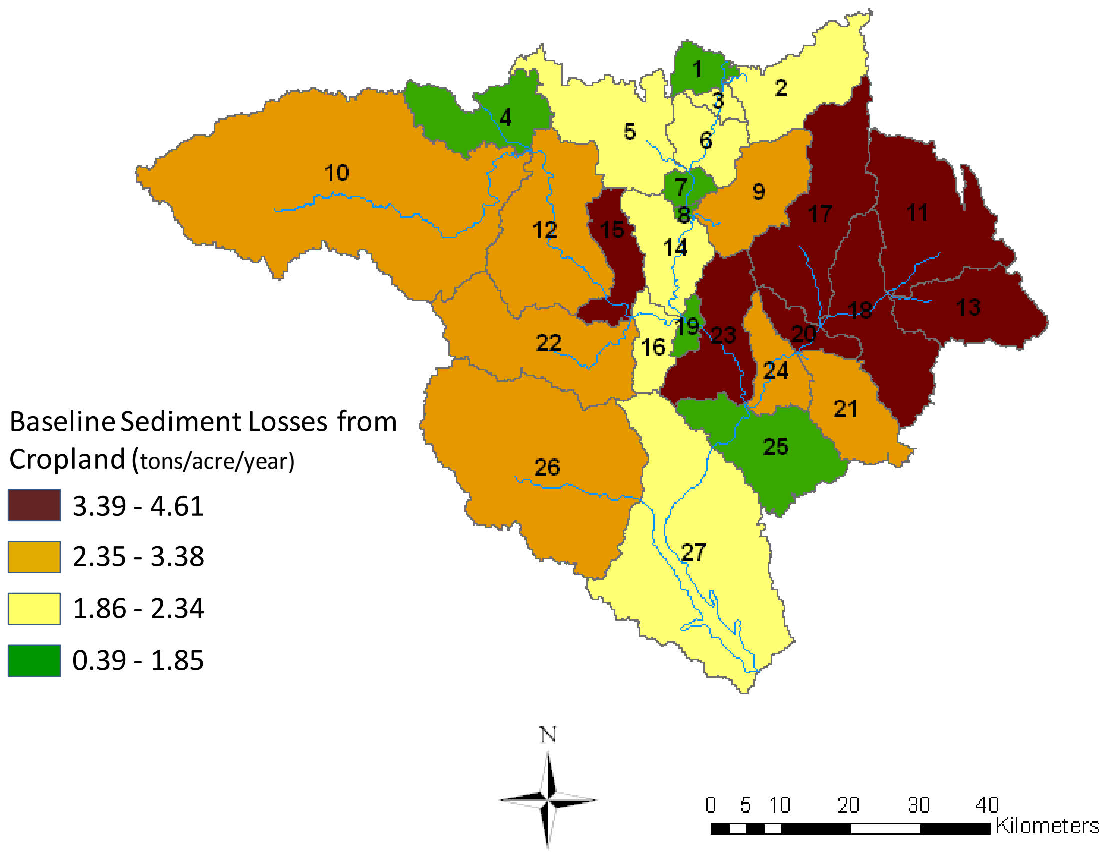


Figure 2.41 Baseline nitrogen losses from cropland by subwatershed

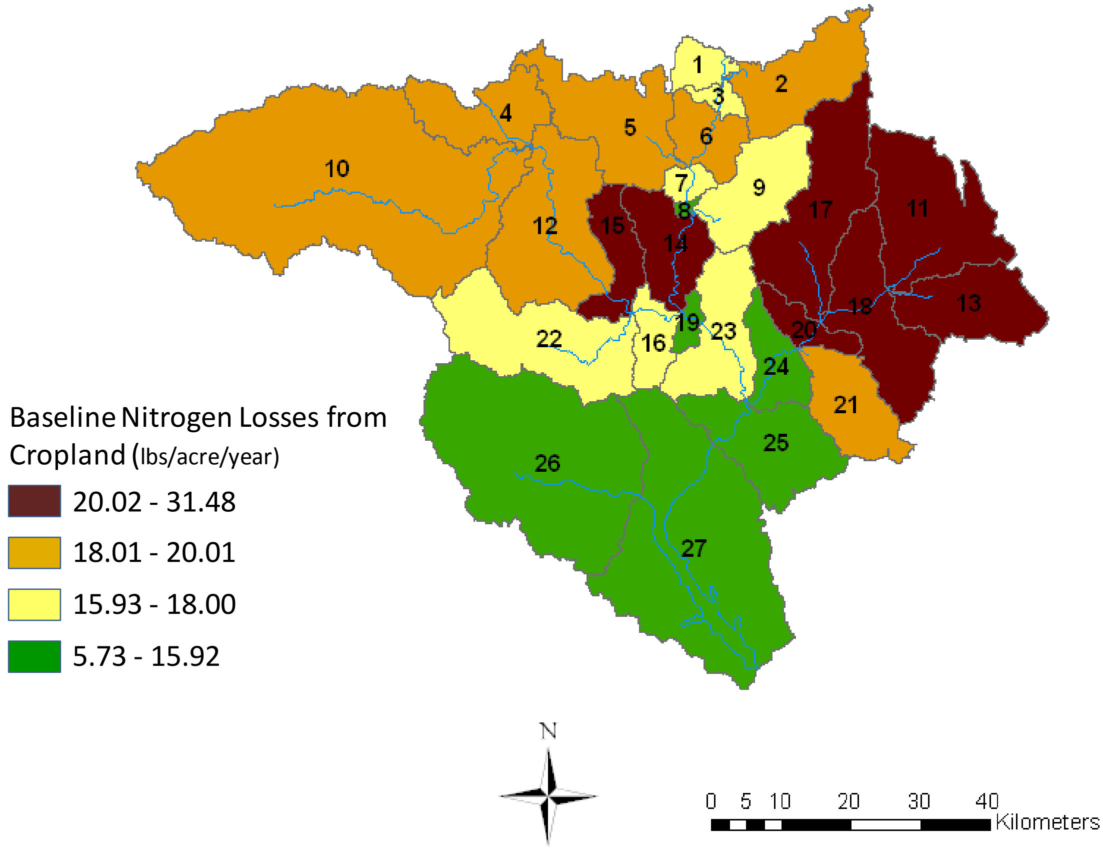
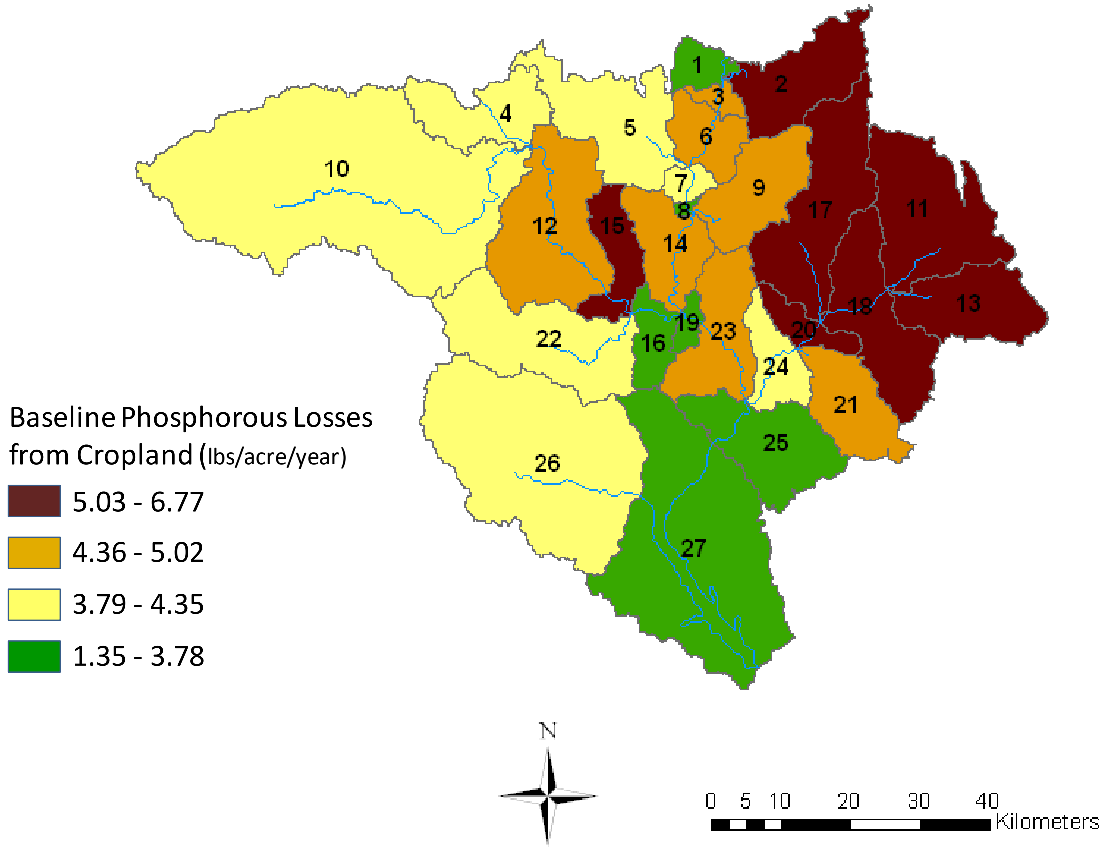


Figure 2.42 Baseline phosphorus losses from cropland by subwatershed



However, this may not be the most cost-effective technique because costs are not being considered. Cost-effective conservation spatial targeting includes the economics of pollutant reduction and focuses BMPs in areas of the watershed, which deliver the greatest benefits (pollutant reduction) for the cost.

Using the targeted approach discussed in previous sections, prescriptions for cost-effective spatial targeting can be derived. The process for determining target areas is described next.

The spatial targeting approach described here answers the question: Where in the watershed will a given BMP (i.e., filter strips, no-till, or permanent vegetation) provide the most cost-effective pollutant (i.e., sediment, nitrogen, or phosphorus) reduction? This targeting approach is performed with the original BMP costs as well as for the adjusted BMP costs used in the “Y” scenarios described previously. For obvious reasons, only the targeted scenarios (not the random) are used. No farms are deleted or eliminated from the choice set. The budget constraint and pollutant reduction goals are both set infinitely high, so that all possible BMPs are implemented. Only one iteration is run to produce the results necessary to determine the cost-effective spatial targeting prescriptions.

The results from one iteration provide information on the costs and pollution reduction achieved by implementing a given BMP on a farm. Each farm is located in one of the 27 subwatersheds. Using the cost, pollution reduction, and the acreage being treated by the BMP, acre-weighted averages are calculated for each subwatershed. A $6.69/ton sediment acre-weighted average reduction costs for subwatershed 1 reported in the first cell of Table 2.18 indicates that for an average acre in this subwatershed, sediment can be reduced for $6.69/ton. This is more cost-effective than implementing BMPs in subwatershed 8, which exhibits $16.69/ton sediment reduction costs, but not near as cost-effective as investing in filter strips in subwatershed 17.

While subwatershed 17 possesses the most cost-effective sediment reduction via filter strips, this subwatershed does not exhibit the most cost-effective nitrogen reduction via filter strips. Table 2.18 also displays the acre-weighted average costs of reducing nitrogen and phosphorus by subwatershed. Filter strips on subwatershed 17 results in an average cost of $0.26/lb of nitrogen reduction compared to just $0.20/lb for the same BMP on subwatershed 13 - nearly 25 percent more cost-effective. While the difference in cost-effectiveness is just $0.06/lb, this 25 percent increase in cost-effectiveness adds up greatly across thousands of pounds of nitrogen reduction. Table 2.18 also displays the weighted average costs of pollution reduction for no-till and permanent vegetation.

The targeting calculations also are performed for the “Y” scenarios. The “Y” scenarios represent the case where the total annualized costs for filter strips and permanent vegetation are increased by 200 percent to capture a more drastic increase in land opportunity costs and fuel prices. For no-till, the annualized costs were decreased by 75 percent to account for the even higher fuel prices, and thus, a greater relative cost advantage of no-till (all else equal). The results for the “Y” scenarios are displayed in Table 2.19.

Table 2.18 Acre-weighted average pollutant reduction costs for Targ_S_$$$_Orig. scenarios for each BMP

Subwatershed	Filter Strips			No-till			Permanent vegetation		
	Sediment ($/ton)	Nitrogen ($/lb)	Phosphorus ($/lb)	Sediment ($/ton)	Nitrogen ($/lb)	Phosphorus ($/lb)	Sediment ($/ton)	Nitrogen ($/lb)	Phosphorus ($/lb)
1	$6.69	$0.47	$2.09	$78.82	$5.03	$52.99	$98.00	$7.30	$31.27
2	$3.24	$0.35	$1.23	$32.84	$4.74	$25.73	$47.63	$5.51	$18.64
3	$3.43	$0.37	$1.41	$31.99	$4.25	$31.57	$50.48	$5.84	$21.14
4	$3.63	$0.35	$1.64	$35.45	$3.07	$28.74	$50.30	$5.23	$23.24
5	$3.45	$0.33	$1.49	$33.07	$2.60	$22.57	$49.93	$5.04	$21.99
6	$3.39	$0.33	$1.35	$30.77	$3.22	$28.40	$49.73	$5.20	$20.07
7	$3.90	$0.39	$1.65	$35.82	$3.70	$32.44	$56.96	$6.16	$24.61
8	$16.69	$1.16	$4.79	$158.06	$16.36	$161.36	$238.95	$23.35	$71.24
9	$2.53	$0.38	$1.31	$23.49	$6.11	$19.63	$37.41	$5.93	$19.67
10	$2.20	$0.32	$1.46	$21.16	$2.62	$23.54	$31.12	$4.77	$21.07
11	$1.43	$0.26	$0.95	$12.42	$2.41	$14.28	$21.16	$4.24	$14.47
12	$2.07	$0.31	$1.41	$18.72	$2.37	$17.28	$29.00	$4.73	$20.01
13	$1.81	$0.20	$0.97	$14.49	$1.08	$7.67	$26.34	$3.27	$14.68
14	$2.81	$0.32	$1.38	$25.75	$2.39	$14.84	$41.13	$4.93	$20.45
15	$1.83	$0.29	$1.28	$17.06	$2.06	$15.62	$26.53	$4.35	$18.74
16	$2.95	$0.38	$1.69	$27.17	$3.28	$24.15	$43.05	$5.95	$24.91
17	$1.36	$0.26	$0.93	$11.15	$2.42	$13.66	$19.86	$4.10	$13.90
18	$1.48	$0.27	$1.00	$13.55	$2.76	$16.59	$21.50	$4.32	$14.99
19	$4.47	$0.53	$2.32	$41.41	$4.80	$47.46	$65.19	$8.38	$34.53
20	$1.65	$0.30	$1.09	$14.28	$3.29	$26.23	$23.81	$4.64	$16.26
21	$1.61	$0.29	$1.09	$15.20	$3.09	$18.10	$23.80	$4.64	$16.67
22	$2.52	$0.34	$1.51	$23.02	$2.93	$23.21	$35.31	$5.08	$21.48
23	$1.56	$0.35	$1.31	$14.39	$3.24	$13.95	$23.04	$5.46	$19.60
24	$2.38	$0.41	$1.52	$20.52	$5.14	$41.06	$34.31	$6.27	$22.77
25	$2.62	$0.34	$1.61	$22.81	$2.56	$16.49	$39.05	$5.73	$24.99
26	$2.36	$0.37	$1.46	$21.86	$3.60	$20.49	$33.58	$5.50	$21.12
27	$2.29	$0.38	$1.51	$17.55	$3.65	$25.26	$32.85	$6.03	$22.33

Table 2.19 Acre-weighted average pollutant reduction costs for Targ_S_$$$_Y scenarios for each BMP

	Filter Strips			No-till			Permanent vegetation		
Subwatershed	Sediment ($/ton)	Nitrogen ($/lb)	Phosphorus ($/lb)	Sediment ($/ton)	Nitrogen ($/lb)	Phosphorus ($/lb)	Sediment ($/ton)	Nitrogen ($/lb)	Phosphorus ($/lb)
1	$13.37	$0.94	$4.19	$19.70	$1.26	$13.25	$196.00	$14.61	$62.54
2	$6.47	$0.69	$2.47	$8.21	$1.19	$6.43	$95.26	$11.01	$37.27
3	$6.86	$0.73	$2.82	$8.00	$1.06	$7.89	$100.95	$11.67	$42.28
4	$7.25	$0.71	$3.29	$8.86	$0.77	$7.19	$100.61	$10.46	$46.47
5	$6.89	$0.65	$2.98	$8.27	$0.65	$5.64	$99.86	$10.07	$43.97
6	$6.78	$0.66	$2.70	$7.69	$0.80	$7.10	$99.46	$10.40	$40.15
7	$7.80	$0.77	$3.31	$8.96	$0.93	$8.11	$113.91	$12.32	$49.21
8	$33.37	$2.32	$9.57	$39.52	$4.09	$40.34	$477.90	$46.69	$142.49
9	$5.06	$0.75	$2.61	$5.87	$1.53	$4.91	$74.81	$11.87	$39.35
10	$4.40	$0.63	$2.92	$5.29	$0.66	$5.89	$62.25	$9.54	$42.14
11	$2.86	$0.53	$1.91	$3.10	$0.60	$3.57	$42.32	$8.49	$28.94
12	$4.15	$0.63	$2.82	$4.68	$0.59	$4.32	$58.01	$9.45	$40.03
13	$3.62	$0.39	$1.94	$3.62	$0.27	$1.92	$52.68	$6.54	$29.35
14	$5.63	$0.64	$2.77	$6.44	$0.60	$3.71	$82.26	$9.85	$40.90
15	$3.67	$0.57	$2.55	$4.26	$0.52	$3.90	$53.06	$8.70	$37.47
16	$5.91	$0.77	$3.38	$6.79	$0.82	$6.04	$86.10	$11.90	$49.82
17	$2.72	$0.52	$1.85	$2.79	$0.60	$3.42	$39.73	$8.20	$27.80
18	$2.96	$0.55	$2.00	$3.39	$0.69	$4.15	$43.00	$8.64	$29.98
19	$8.95	$1.05	$4.65	$10.35	$1.20	$11.86	$130.38	$16.77	$69.07
20	$3.31	$0.60	$2.19	$3.57	$0.82	$6.56	$47.62	$9.28	$32.51
21	$3.22	$0.58	$2.18	$3.80	$0.77	$4.53	$47.61	$9.27	$33.33
22	$5.04	$0.69	$3.02	$5.75	$0.73	$5.80	$70.61	$10.15	$42.95
23	$3.13	$0.69	$2.62	$3.60	$0.81	$3.49	$46.09	$10.93	$39.19
24	$4.77	$0.82	$3.05	$5.13	$1.28	$10.26	$68.63	$12.55	$45.54
25	$5.24	$0.69	$3.23	$5.70	$0.64	$4.12	$78.11	$11.46	$49.99
26	$4.71	$0.74	$2.92	$5.47	$0.90	$5.12	$67.15	$11.01	$42.24
27	$4.59	$0.77	$3.03	$4.39	$0.91	$6.31	$65.71	$12.05	$44.66

The data in Table 2.18 and Table 2.19 may be better represented in map form. Dividing each of the scenario's results into "quartiles," cost-effective conservation spatial targeting maps are created. [17] In other words, sorting the average costs for a given scenario in ascending order and then dividing the data into four groups of seven subwatersheds each is a useful way of presenting the results cartographically. Individual maps are created for each of the 18 scenarios covered in Table 2.18 and Table 2.19. Upon closer inspection, the spatial priority ranking of the subwatersheds is identical across the original cost scenarios and the adjusted "Y" cost scenarios. For this reason, only the maps for the "Y" scenarios (which correspond with Table 2.19) will be analyzed here. The remaining maps for the original cost scenarios can be found in Appendix C.

Figure 2.43 has been included to give the reader an indication of which watercourses are located in the economically derived priority areas. It displays the locations of the major rivers and creeks in the Kansas portion of the TCL watershed. Figure 2.44 shows the priority areas in the TCL watershed for reducing sediment via filter strips. According to this figure, the most cost-effective sediment reducing locations for placing filter strips is in the east-northeast portion of the watershed. Particularly, subwatersheds 11, 13, 17, 18, 20, 21, and 23. Here, sediment can be reduced for $2.72 to $3.62/ton annually. The poorest places (from a cost-effectiveness standpoint) for sediment reducing filter strips are subwatersheds 1, 4, 5, 7, 8, and 19. Here, sediment reduction costs are much higher ranging from $6.87/ton up to $33.37/ton annually. In general, the north-central portion of the TCL watershed is the least cost-effective region to place filter strips for sediment reduction.

Figure 2.45 and Figure 2.46 display the nitrogen and phosphorus reduction costs via filter strips by subwatershed. Many of the subwatersheds are prioritized in similar fashion to the

[17] The word "quartiles" is in quotes because the number 27 is not perfectly divisible by 4. So, the quartiles used here contain 7, 7, 7, and 6 subwatersheds in the high, medium-high, medium-low, and low categories.

sediment case. For example, subwatersheds 11, 13, 18, 20, and 21 are labeled as the highest priority areas across all of the pollutants for filter strips. Sediment can be reduced for $2.72 to $3.62/ton annually, nitrogen reduction for $0.39 to $0.60/lb annually, and phosphorus can be reduced for $1.85 to $2.47/lb annually. Alternatively, subwatersheds 1, 7, 8, and 19 are identified as being the least cost-effective across all of the pollutants for filter strips. Sediment, nitrogen, and phosphorus annual reduction costs can approach $33.37/ton, $2.32/lb, and $9.57/lb, respectively.

Figure 2.43 Major watercourses and subwatershed delineation for the TCL watershed

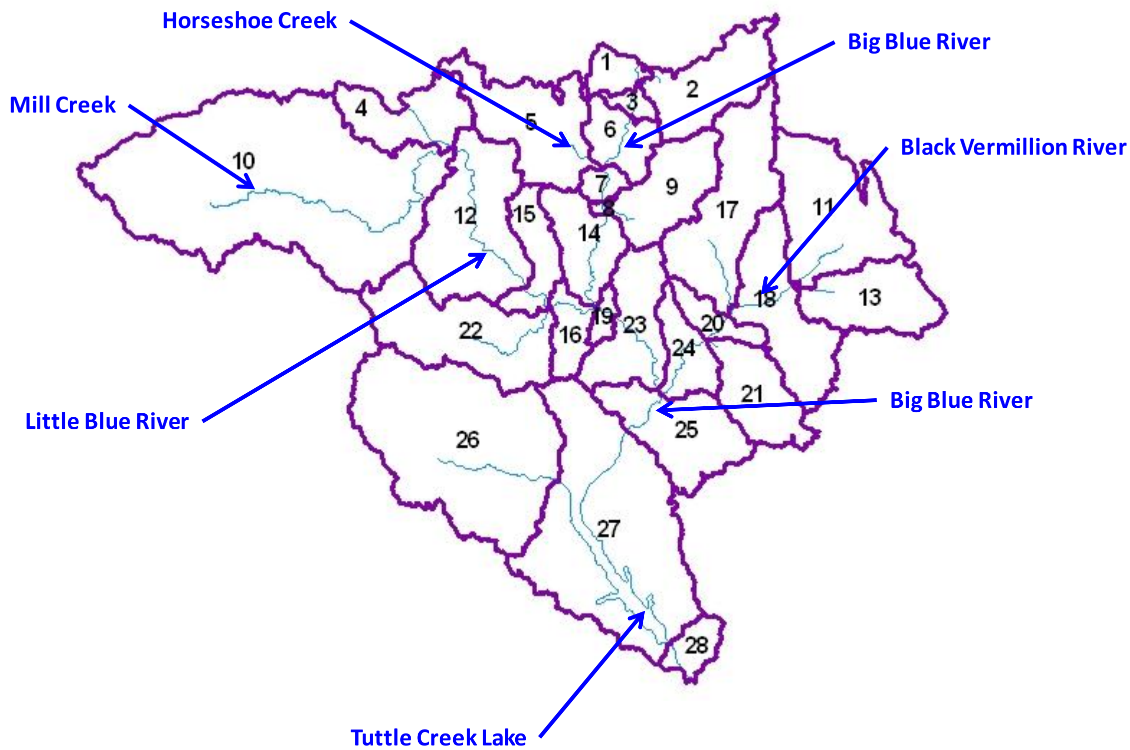


Figure 2.44 Spatial average sediment reduction costs under adjusted ("Y") costs with filter strips

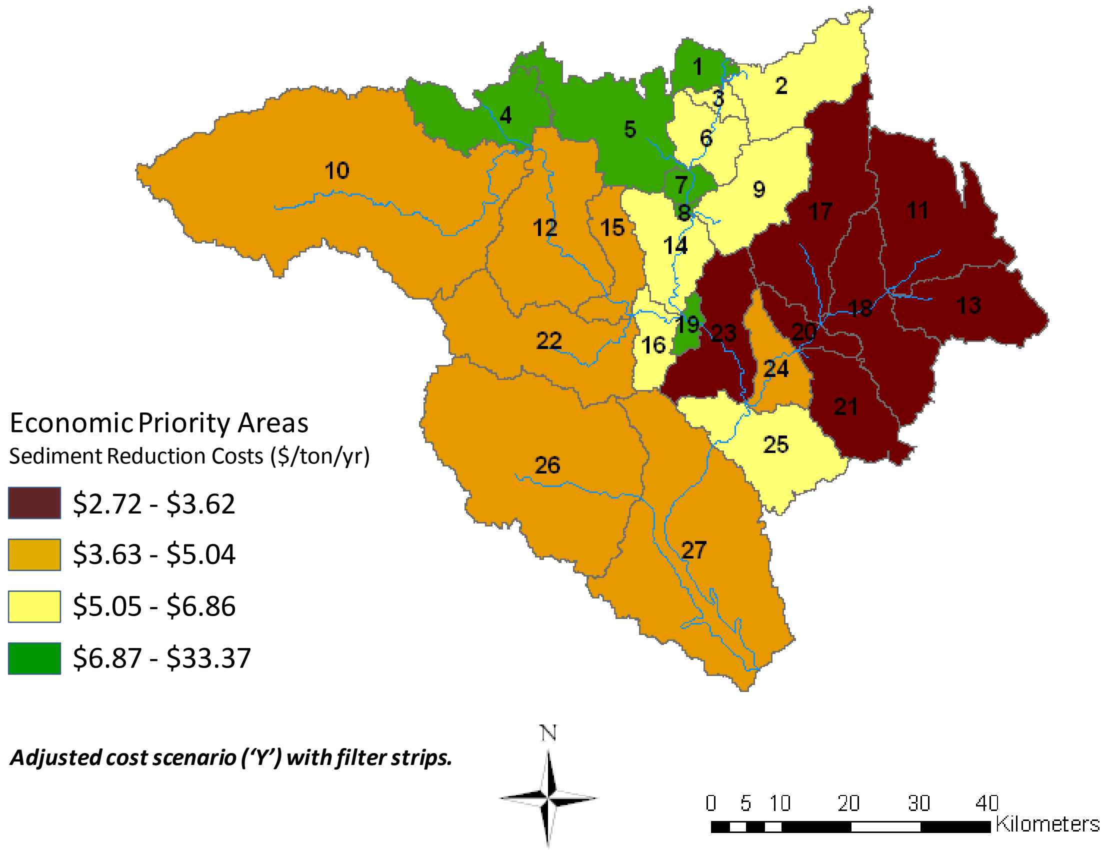


Figure 2.45 Spatial average nitrogen reduction costs under adjusted ("Y") costs with filter strips

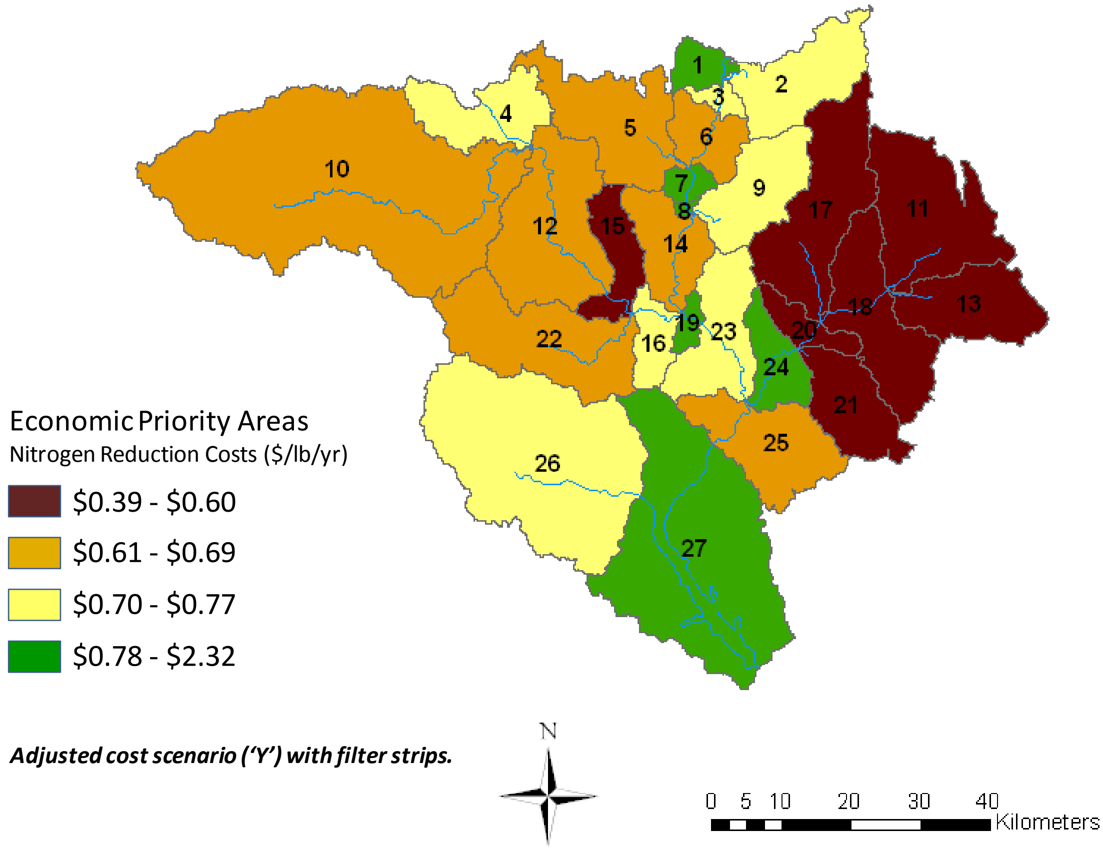


Figure 2.46 Spatial average phosphorus reduction costs under adjusted ("Y") costs with filter strips

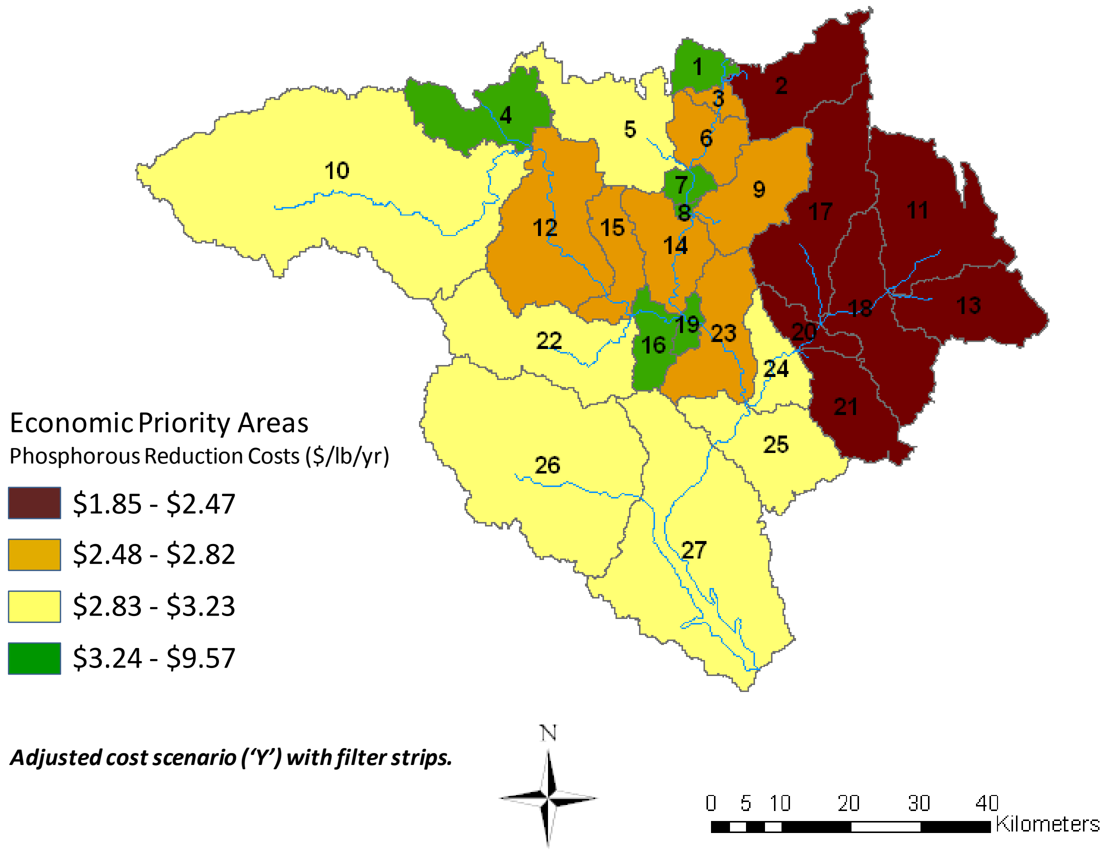


Figure 2.47, Figure 2.48, and Figure 2.49 display the average annual pollutant reduction costs when no-till is applied in each of the subwatersheds. According to Figure 2.47, the most cost-effective sediment reducing locations for placing no-till is again in the east-northeast portion of the watershed. Particularly, subwatersheds 11, 13, 17, 18, 20, 21, and 23. Here, sediment can be reduced for $2.79 to $3.80/ton annually. The poorest places (from a cost-effectiveness standpoint) for sediment reducing no-till are subwatersheds 1, 4, 5, 7, 8, and 19. Here, sediment reduction costs are much higher ranging from $8.22/ton up to $39.52/ton annually. In general, the north-central portion of the TCL watershed is the least cost-effective region to place no-till for sediment reduction.

Figure 2.48 displays the nitrogen reduction costs via no-till. The prioritization, here, differs quite a little bit from the sediment case. For example, only three of the subwatersheds are identified as high-priority in both cases - subwatersheds 11, 13, and 17. In addition, some of the subwatersheds that are identified as medium-high priority regarding sediment are labeled as high priority in the nitrogen case. This occurs with subwatersheds 12, 15, and 25.

Figure 2.49 shows the annual phosphorus reduction costs for no-till adoption in the TCL watershed. Again, some of the subwatersheds that are identified as medium-high priority with sediment are characterized as high priority with phosphorus. Subwatersheds 15 and 25 fall into this category. Alternatively, several of the subwatersheds identified as high priority under sediment are medium-high priority regarding phosphorus - subwatersheds 18 and 21, in particular.

Considering no-till as a BMP for cost-effectively reducing all of the pollutants simultaneously, would indicate that subwatersheds 11, 13, and 17 as the highest priority for no-till adoption. Here, sediment can be reduced for $2.79 to $3.80/ton annually, nitrogen reduction for $0.27 to $0.64/lb annually, and phosphorus can be reduced for $1.92 to $4.12/lb annually. On the flip side, subwatersheds 1, 8, and 19 are identified as being the least cost-effective across all of the pollutants for no-till. Sediment, nitrogen, and phosphorus annual reduction costs can approach $39.52/ton, $4.09/lb, and $40.34/lb, respectively.

Figure 2.47 Spatial average sediment reduction costs under adjusted (“Y”) costs with no-till

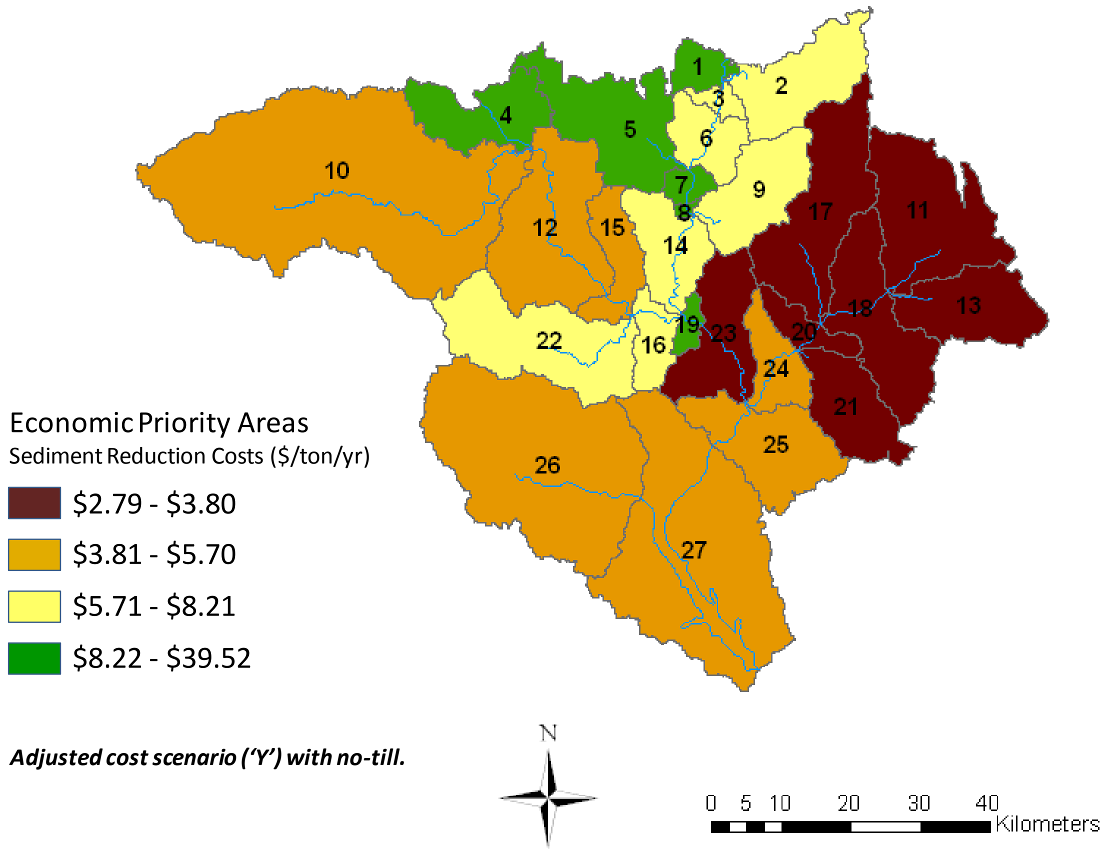


Figure 2.48 Spatial average nitrogen reduction costs under adjusted ("Y") costs with no-till

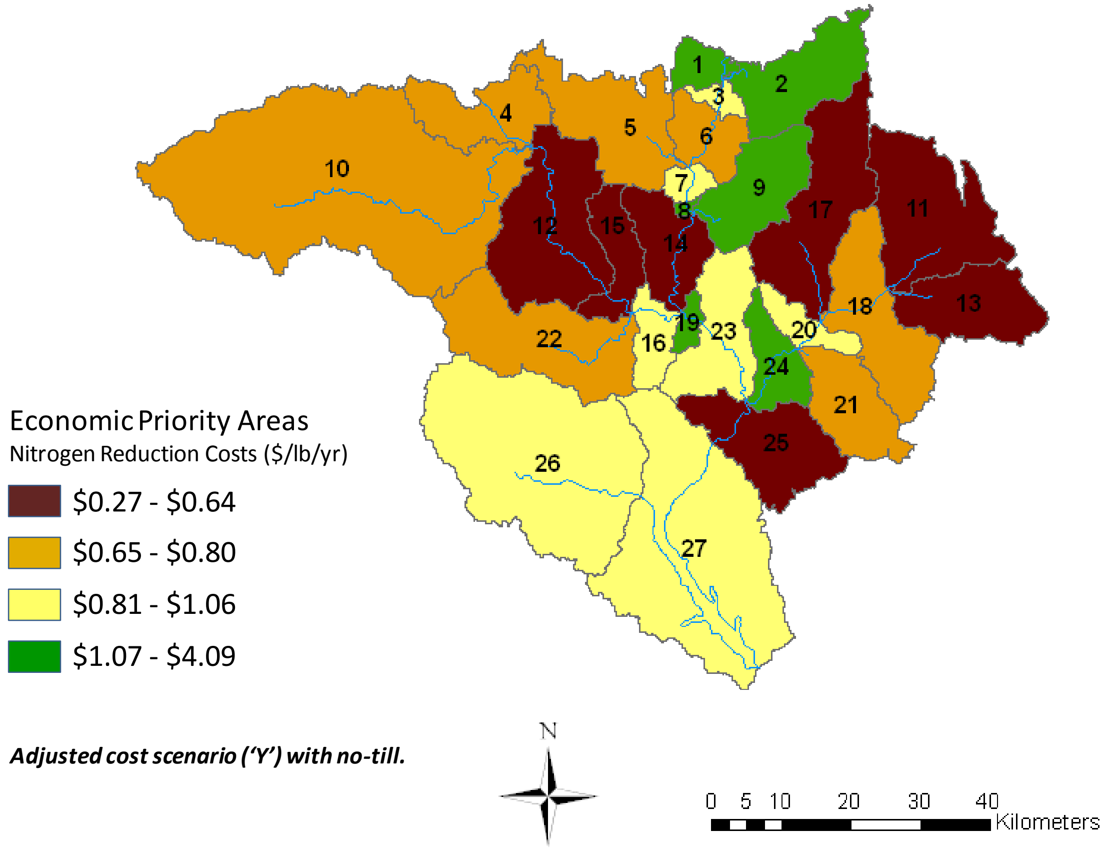


Figure 2.49 Spatial average phosphorus reduction costs under adjusted (“Y”) costs with no-till

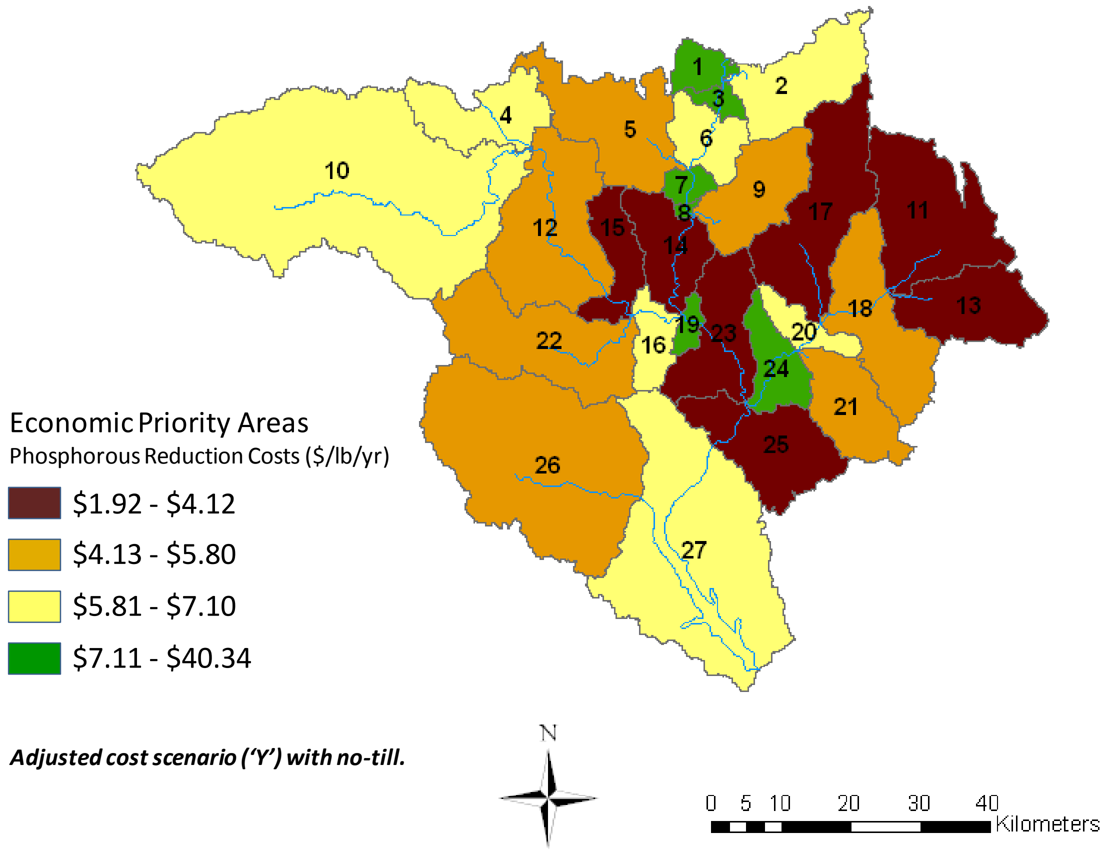


Figure 2.50, and Figure 2.51, and Figure 2.52 display the annual average pollutant reduction costs with permanent vegetation. In general, there are less difference between these maps as compared to the differences seen with the other two BMPs discussed previously. In other words, subwatersheds that are identified as high economic priority for sediment are generally identified as high economic priority for nitrogen and phosphorus as well. For each of the pollutants, subwatersheds 11, 13, 17, 18, 20, and 21 are all labeled as high priority. In similar fashion, subwatersheds 1, 7, 8, and 19 are all identified as low priority for permanent vegetation reduction of each of the pollutants. Subwatersheds 24 and 27 are low priority for nitrogen via

permanent vegetation whereas these are considered medium-high priority areas for sediment reduction.

Figure 2.50 Spatial average sediment reduction costs under adjusted ("Y") costs with permanent vegetation

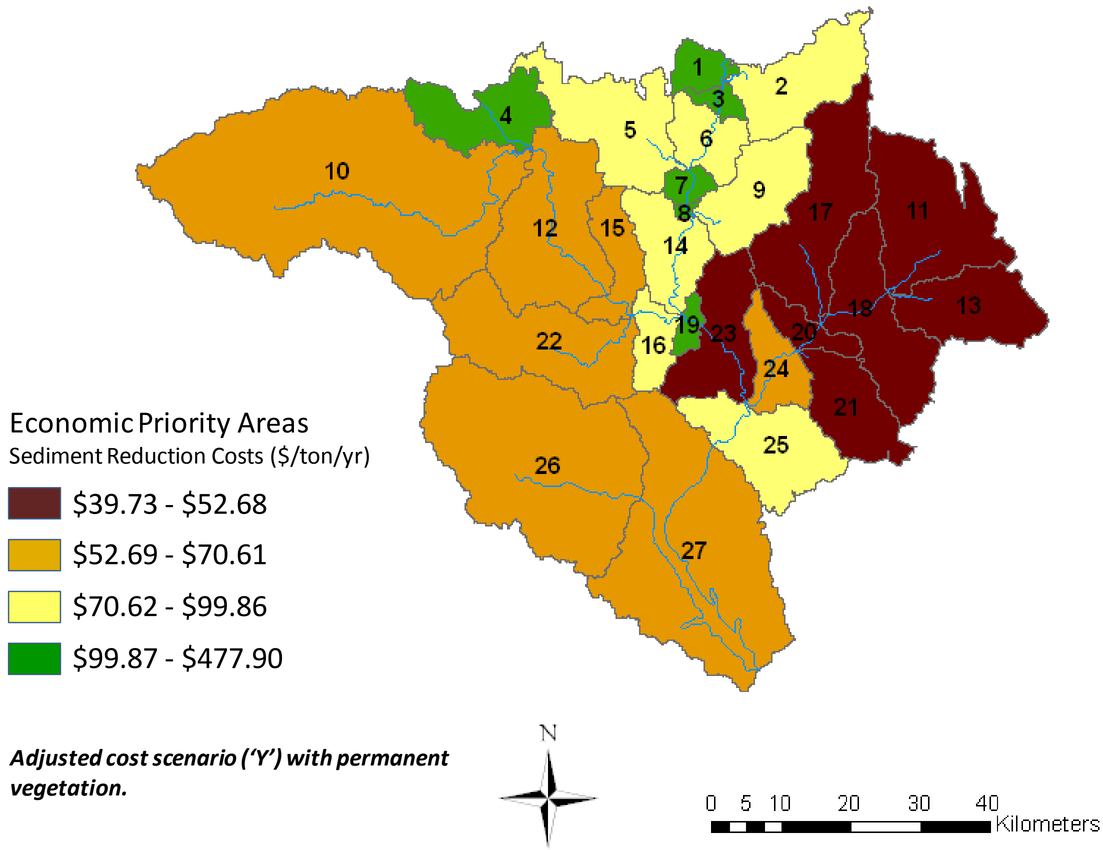


Figure 2.51 Spatial average nitrogen reduction costs under adjusted ("Y") costs with permanent vegetation

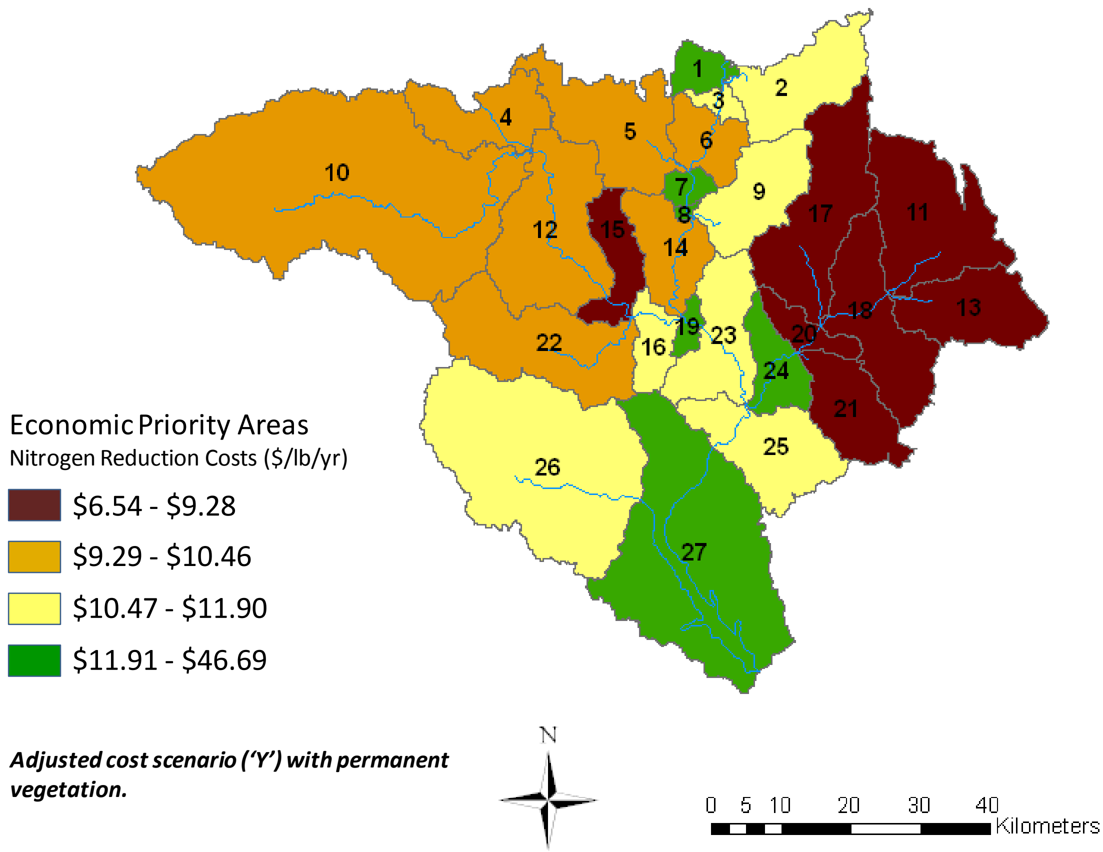
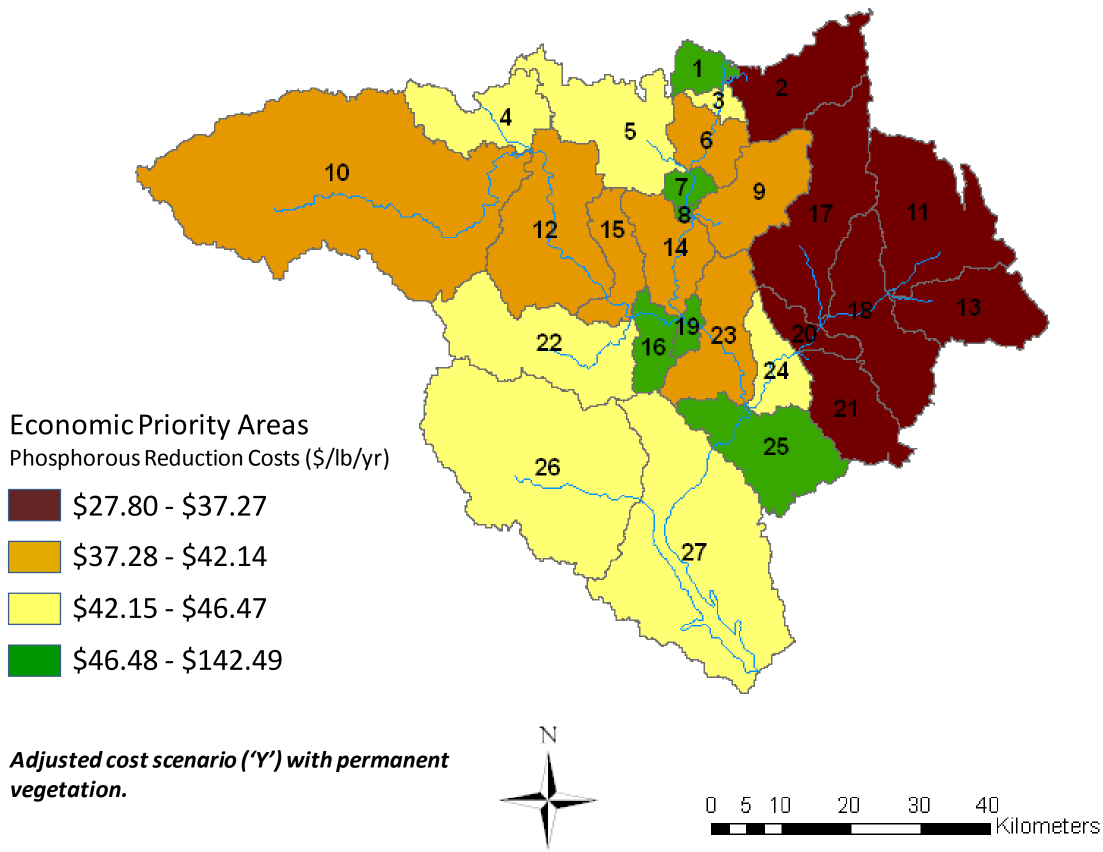


Figure 2.52 Spatial average phosphorus reduction costs under adjusted ("Y") costs with permanent vegetation



From a cost-effective conservation spatial targeting standpoint, certain areas of the TCL watershed should be prioritized higher than others. Depending on which BMP and which pollutant is under consideration the subwatersheds may be ranked differently. In other words, if sediment is the concern and filter strips are expected to be promoted and adopted the focus should be on subwatersheds 11, 13, 17, 18, 20, 21, and 23. However, if nitrogen is the main concern and no-till will be the primary BMP promoted and financed, then the focus should be on subwatersheds 11, 12, 13, 14, 15, 17, and 25.

If one were to place equal weighting on each of the three BMPs and pollutants, two prescriptions can be made based on the previous maps. First, the most cost-effective pollutant reduction will likely be achieved in subwatersheds 11 and 13. These subwatersheds were identified as high priority across all of the BMPs and pollutants. Secondly, subwatersheds 1, 8, and 19 exhibit the least potential (relatively speaking) for cost-effectively reducing any of the pollutants in regards to any of the BMPs considered. The remaining 22 subwatersheds fall somewhere in between these two bounds. In other words, depending on the BMP/pollutant focus, these subwatersheds may exhibit some potential for cost-effective conservation.

Characteristics of economically targeted areas

As described previously, the economically targeted areas take into account both the physiographical and the economic characteristics of the farm (or HRU) and the BMP. In general, the three primary physiographical factors affecting sediment and nutrient runoff and contribution to TCL for a given farm and BMP are land slope, hydrologic soil group, and delivery ratio (for sediment). Thus, it would be expected that subwatersheds 11 and 13 would exhibit different physiographical characteristics than subwatersheds 1, 8, and 19.

Based on information in Table 2.4, subwatershed 19 actually has a much greater percentage of land with slopes greater than 6 percent than either subwatershed 11 or 13. However, only 49.6 percent of the land in subwatershed 19 is classified as being in hydrologic soil group D.[18] This compares to 96.7 and 93.5 percent of the land in subwatersheds 11 and 13. Subwatersheds 1 and 8 have 0.0 and 50.3 percent of land with "D" soils, respectively. In terms of delivery ratios for sediment (Table 2.9), subwatershed 19 has the highest at 1.00 while subwatersheds 1, 8, 11, and 13 have sediment delivery ratios of 0.56, 0.69, 0.69, and 0.66,

[18] Which represents areas with higher risks for runoff generating potential.

respectively. From this, it appears that soil type is driving much of the differences in sediment and nutrient contribution to TCL. However, the physiographical characteristics that make up each subwatershed only put into picture part of the story. The economic characteristics help to explain the other part.

Each of the five subwatersheds described previously are contained completely or partially in Marshall County, Kansas. Subwatersheds 8 and 19 lay completely in Marshall County. Over 90 percent of subwatershed 1 is contained in Gage County, Nebraska with the remaining 10 percent in Marshall County. Subwatershed 11 is 64 and 36 percent in Marshall and Nemaha Counties, respectively. Subwatershed 13 is 27 and 73 percent in Marshall and Nemaha Counties, respectively. Of the counties in Kansas, Nemaha County exhibits the highest annualized costs for filter strips and land retirement with permanent vegetation. Gage County, Nebraska exhibits the highest annualized costs across all of the counties considered here. Thus, it appears that while high land opportunity costs make subwatersheds 11 and 13 less attractive, the relatively large pollutant loading and levels of BMP effectiveness make these subwatersheds prime spots for cost-effective BMP investments.

According to Figure 2.41, subwatershed 2 would be a higher priority area for reducing nitrogen than subwatershed 26. This is likely due to the fact that 98.5 percent of the land in subwatershed 2 is "D" soils compared to just 38 percent of subwatershed 26. However, as Table 2.19 shows, no-till investments are nearly 25 percent more cost-effective when applied to subwatershed 26 as opposed to subwatershed 2. Part of the reason for this is that the annualized costs of no-till are approximately 25 percent less for subwatershed 26 compared to subwatershed 2.

What does all of this mean for cost-effective targeting? Cost-effective targeting is not as simple as looking at just one factor such as land slope or land opportunity costs. While soil type appears to be a good indicator of targeting, relying heavily on it can even be misleading. For example, 99 percent of the soils in subwatershed 9 are hydrologic group D. This subwatershed ranks number one in this respect. However, this subwatershed should be low priority for nitrogen reduction via no-till and should be medium-low priority for sediment reduction with filter strips. At least in the case of TCL watershed, cost-effective targeting can only occur when all relevant physiographical and economic factors are considered.

Distribution of BMP types across subwatersheds

The spatial targeting analysis performed previously focused on one BMP at a time across the TCL watershed. Building on this, another important aspect may be the distribution of the different BMP types across the watershed when cost-effective targeting is performed and all BMPs are available for adoption. In other words, what is the optimal ratio of filter strips to no-till to permanent vegetation projects across subwatersheds in the TCL watershed? In order to determine this, the following procedures are used.

Targeted simulations are run focusing on sediment, nitrogen, and phosphorus. The pollution reduction goal is set infinitely high and the annual budget constraint is set at $450,000. No farms (HRUs) are deleted from the choice set. The BMP costs are from the "Y" scenarios (Table 2.16). One iteration of each scenario is run and the simulation results are tabulated and further analyzed.

The total number of BMP projects implemented is equal to 1,770 in each scenario. It is not equal to 1,858 (total number of cropland farms or HRUs) because 88 farms exhibit zero or negative primary pollutant reduction and are eliminated from the possible choice set. In regards to the 1,770 BMP projects, specific information about the subwatershed location/identification and BMP type (i.e., filter strip, no-till, or permanent vegetation) is known and tabulated. From this data, Figure 2.53, Figure 2.54, and Figure 2.55 are created which show the proportion of the total BMP projects that fall into each subwatershed by type of BMP. These three figures represent the cases when sediment, nitrogen, or phosphorus are the primary pollutants of concern, respectively. The total number of BMP projects implemented under each scenario are 400, 580, and 343.

To briefly summarize these figures, one can see that permanent vegetation projects are not implemented in any scenario. In general, more filter strips are applied in the targeted sediment and phosphorus cases as compared to when nitrogen is the primary concern. No-till projects are predominantly implemented when nitrogen is the focus pollutant (Figure 2.54). Across all scenarios, subwatershed 10 has the greatest number of projects mainly due to its relative large area. Focusing on subwatersheds 11 and 13 (which were identified as very high priority in the previous subsections), there is approximately an equal distribution of filter strips and no-till when sediment is the main focus. However, under a targeted nitrogen strategy, there is about a 3.5 to 1 ratio of no-till to filter strips in these two subwatersheds. Under a targeted phosphorus strategy, there is approximately a 2.5 to 1 ratio of filter strips to no-till in subwatersheds 11 and 13. In terms of least cost-effective subwatersheds, very little to zero BMP activity occurs across subwatersheds 8 and 19.

Figure 2.53 Distribution of the different BMPs across subwatersheds, Targ_S_450_Y

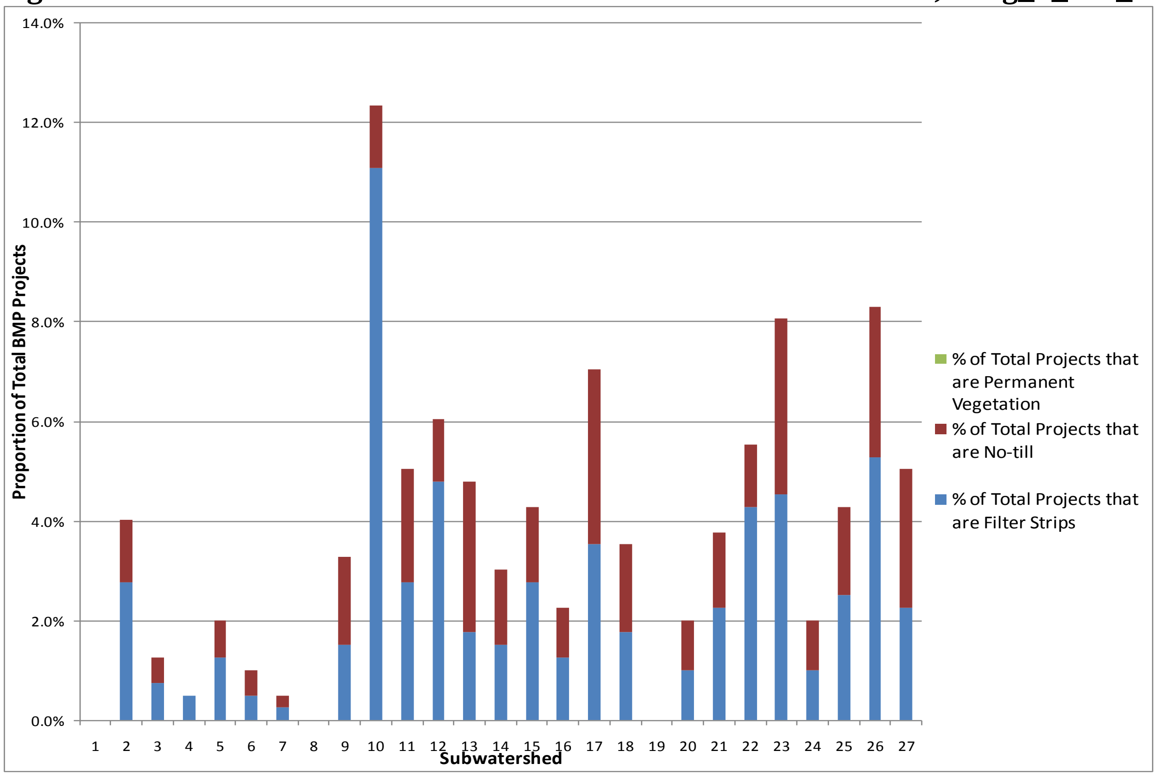


Figure 2.54 Distribution of the different BMPs across subwatersheds, Targ_N_450_Y

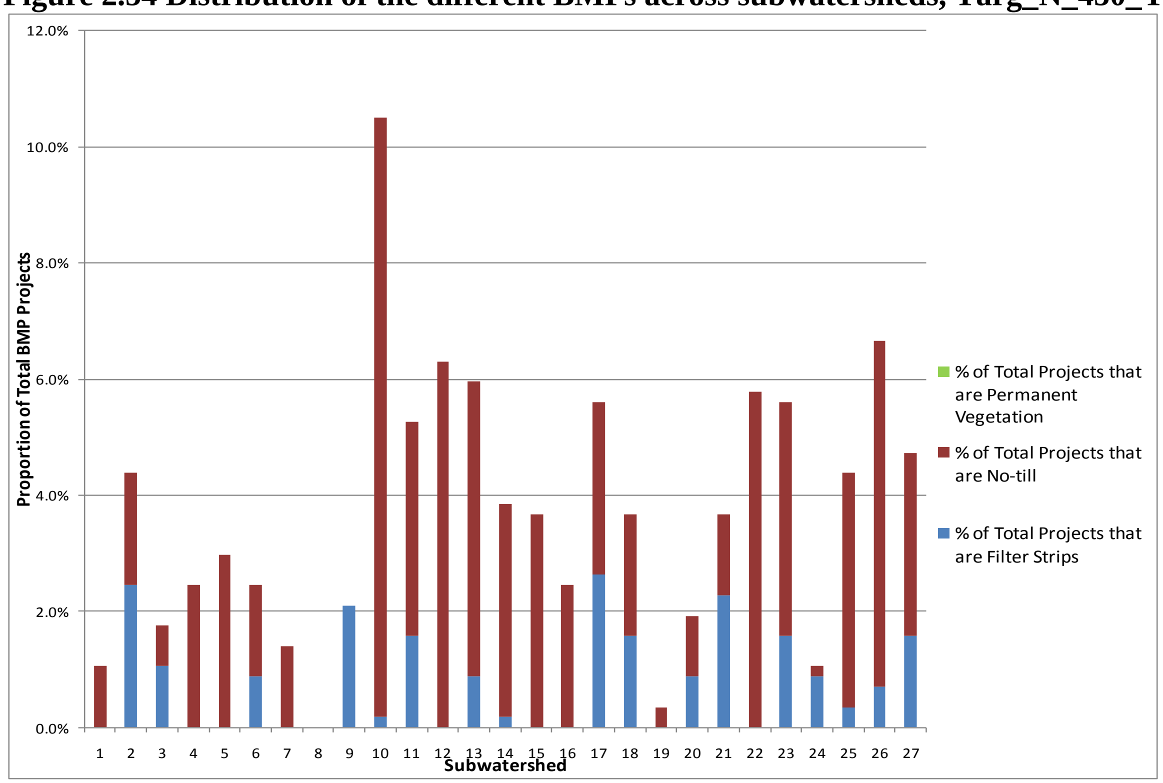
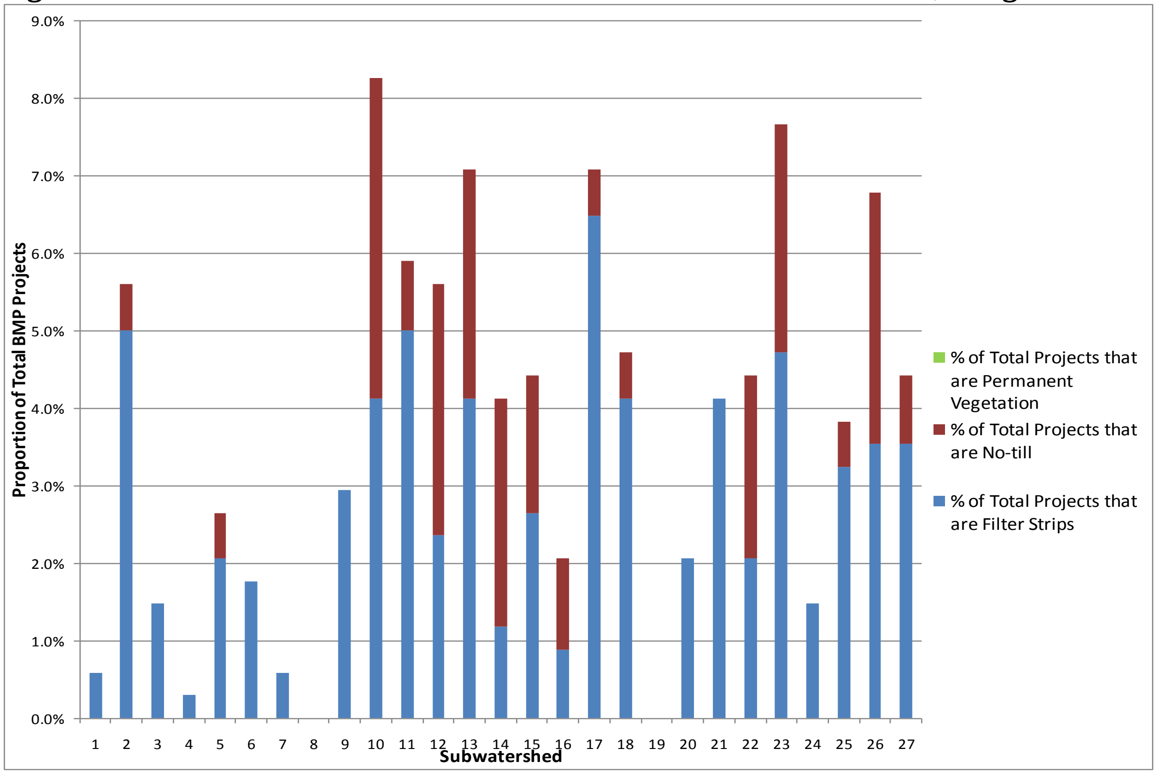


Figure 2.55 Distribution of the different BMPs across subwatersheds, Targ_P_450_Y



For reasons stated previously, it may be the case that many producers have already adopted some of these BMPs on their farms. It also possible (and maybe even probable) that many of these BMPs have been adopted on farms (HRUs) that exhibit the most cost-effective pollutant reduction. In other words, the BMPs have been adopted on fields which have great erosion and runoff potential and/or have a low cost of implementation. If we make this assumption, then the stochastic "search and deletion of farms" process used previously may not be the most accurate. In order to mimic this assumption, the data used to generate Figure 2.53, Figure 2.54, and Figure 2.55 are used with one important modification. That is, the most cost-effective 25 percent BMP projects/farms are removed. Figure 2.56, Figure 2.57, and Figure 2.58 show the proportion of the total BMP projects that fall into each subwatershed by type of BMP under this assumption for sediment, nitrogen, and phosphorus cases.

In these scenarios, the number of BMP projects in subwatersheds 11 and 13 tend to decrease. For example, when all farms are considered no-till projects in subwatershed 13 make up over 5 percent of all projects across the TCL watershed when nitrogen is the pollutant of concern. However, when the most cost-effective 25 percent of BMPs are removed, this amount drops to below 2 percent. Meanwhile, the percentage of filter strips attributable to subwatershed 11 increases from 1.6 to 2.1 percent as the most cost-effective farms are removed (when nitrogen is the pollutant of concern).

Figure 2.56 Distribution of the different BMPs across subwatersheds, Targ_S_450_Y with the most cost-effective 25 percent of farms removed

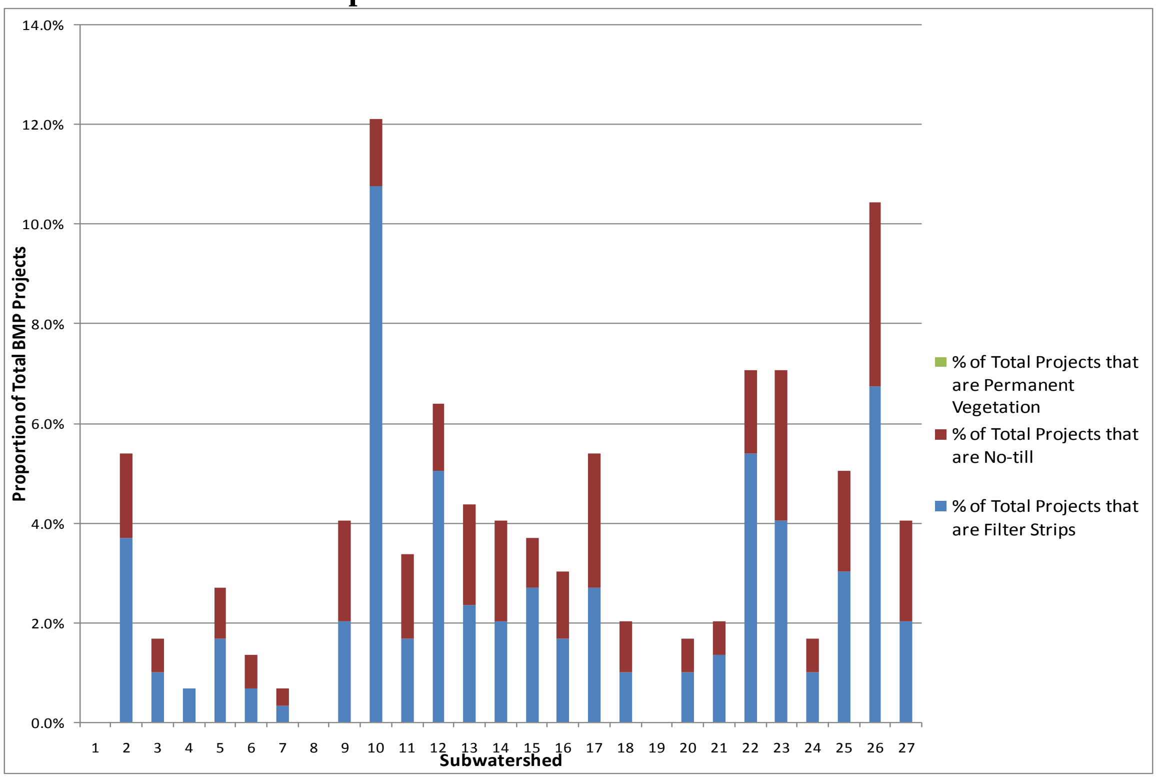


Figure 2.57 Distribution of the different BMPs across subwatersheds, Targ_N_450_Y with the most cost-effective 25 percent of farms removed

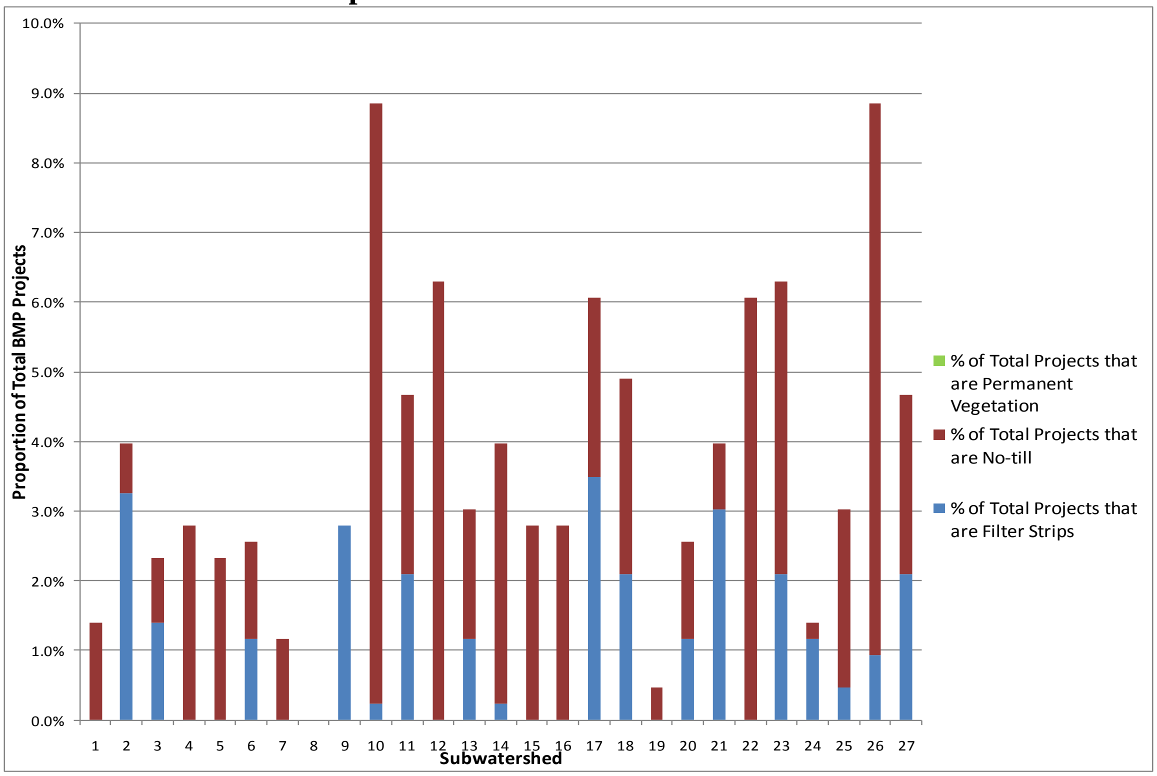
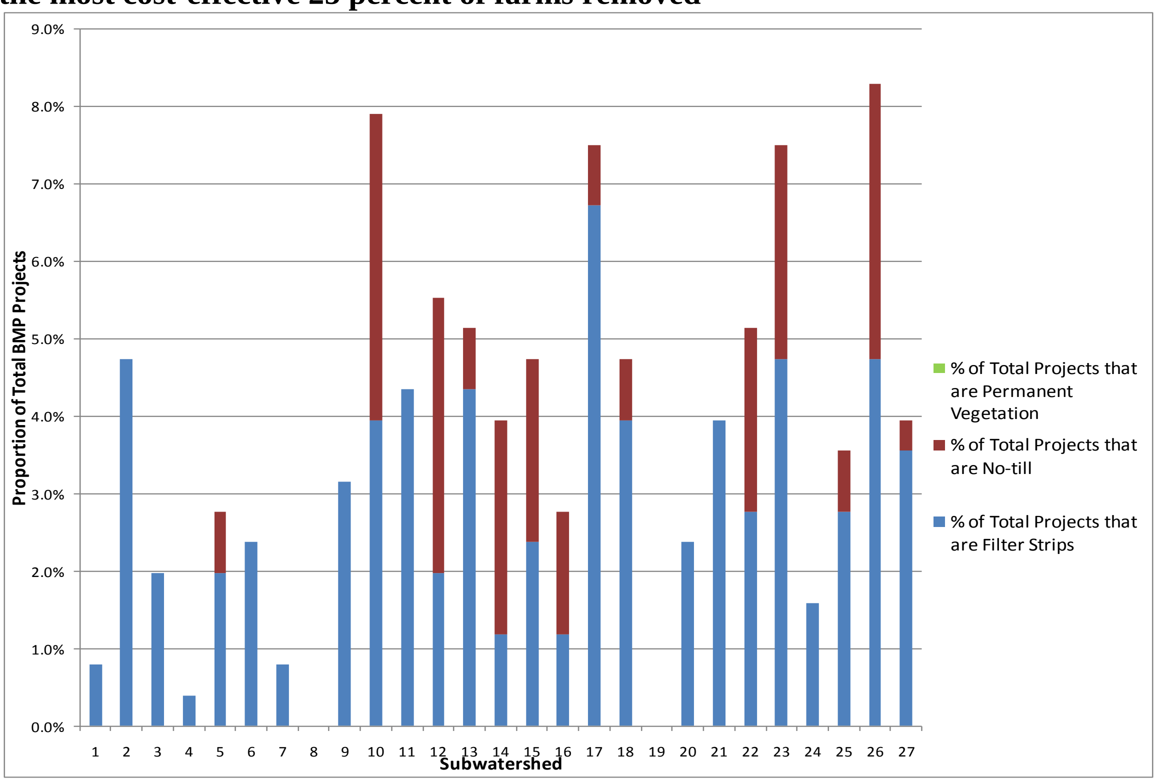


Figure 2.58 Distribution of the different BMPs across subwatersheds, Targ_P_450_Y with the most cost-effective 25 percent of farms removed



An alternative method of selecting farms that have already adopted BMPs

Up to this point in the analysis, it has been assumed that any existing BMP adoption in the TCL watershed was random in nature. That is, a random 25 percent of the farms in the watershed are assumed to have already implemented BMPs, and therefore, are eliminated from the choice set in the simulation routines. The reason behind this is that given the available data that exists there is no way of precisely determining which farms have or have not implemented BMPs in the past.

Perhaps a more realistic assumption would be to assume that BMPs have already been adopted by farms which have the greatest potential for soil erosion.[19] In cases where soil erosion is severe, farmers will often install BMPs either with or without cost-share funding in an effort to save significant losses of top soil and/or prevent gullies from forming in their fields. To simulate this alternative approach, the following assumption is made within the simulation program. Prior to any simulation the 25 percent of farms that exhibit the greatest amount of baseline soil erosion (on a per acre basis) are eliminated from the possible choice set. More specifically, the top 465 farms out of 1,858 in total are assumed to have already implemented BMPs and are removed from the selection pool. The simulation processes proceed in the same manner as described in previous sections. It should be noted that the adjusted "Y" costs are used in these analyses and the primary pollutant is sediment (i.e., scenarios in which nitrogen and phosphorus are "primary" are not presented or discussed). Also of importance, the text "_alt" is included at the end of the scenario description to indicate that this alternative method of selecting farms that have already adopted BMPs is used.

[19] Soil erosion is used as opposed to nitrogen or phosphorus loss because of the visible nature of erosion.

Table 2.20 presents the results attained by using the alternative method of selecting farms that have already adopted BMPs. Comparing these results to those in Table 2.17 (which uses the “random” method of selecting the 25 percent of farms already adopting BMPs), there is an “across-the-board” increase in the average pollutant reduction costs. In terms of sediment under a \$50,000 annual budget, the average reduction costs increase from \$0.63 per ton to \$1.75 per ton. This is equal to a difference of \$1.12 per ton and a 277 percent increase in average costs. As the budget constraint increases, the difference between the two corresponding sets of scenarios (in Table 2.20 and Table 2.17) remains around \$1.12 per ton, but the percentage increase decreases from 277 percent in the case of a \$50,000 budget to just over 200 percent increase in the case of a \$450,000 budget.

Table 2.20 Simulation results for the "Y" scenarios with alternative method of selecting farms already having adopted BMPs

Scenario	Average sediment reduction cost for all land treated by BMPs (/ton)	Average nitrogen reduction cost for all land treated by BMPs (/lb)	Average phosphor-rous reduction cost for all land treated by BMPs (/lb)	Total # of BMP projects	# of Filter Strip Projects	# of No-till Projects	#of Permanent Vegetation Projects	Total area of land treated by BMPs (ac)	Total amount of sediment reduction (tons)	Total amount of nitrogen reduction (lbs)	Total amount of phosphorus reduction (lbs)
Targ_S_50_Y_alt	$1.75	$0.30	$1.54	59	16	43	0	9,484	28,215	165,381	31,993
Targ_S_150_Y_alt	$1.91	$0.31	$1.50	107	44	63	0	23,172	78,022	486,589	99,385
Targ_S_250_Y_alt	$2.03	$0.32	$1.49	168	82	87	0	36,957	122,876	789,159	166,956
Targ_S_350_Y_alt	$2.14	$0.33	$1.50	236	123	113	0	50,915	163,063	1,062,330	232,647
Targ_S_450_Y_alt	$2.26	$0.34	$1.55	318	175	142	0	63,790	198,542	1,307,531	289,801
Rand_S_50_Y_alt	$14.24	$1.81	$10.86	20	7	10	3	3,672	3,408	26,767	4,470
Rand_S_150_Y_alt	$21.71	$2.74	$15.11	30	11	14	6	6,805	6,675	52,828	9,590
Rand_S_250_Y_alt	$26.88	$3.38	$17.91	37	13	16	8	8,837	9,005	71,585	13,511
Rand_S_350_Y_alt	$29.84	$3.75	$19.45	43	15	18	10	10,792	11,341	90,275	17,399
Rand_S_450_Y_alt	$32.45	$4.07	$20.83	48	17	19	11	12,549	13,411	106,902	20,887

Figure 2.59 and Figure 2.60 graphically display the total and marginal cost curves for the targeted and random cases for both methods of selecting farms that have already adopted BMPs. The random BMP implementation scenarios do not appear to be significantly different (i.e., comparing the total cost curves for Rand_S_50_Y and Rand_S_50_Y_alt). For example, the Rand_S_50_Y scenario reduces 5,774 tons of sediment annually compared to 3,408 tons in the Rand_S_50_Y_alt scenario. Much of the noticeable divergence between these two random scenarios occurs after the first $25,000 in funding is used.

On the other hand, the targeted scenarios differ significantly. The "alternative" method of selecting the 25 percent of farms already adopting BMPs (Targ_S_50_Y_alt) results in only 28,215 tons of annual sediment reduction compared to nearly 80,000 tons in the Targ_S_50_Y scenario.

As stated in a previous section, the targeted approach to BMP implementation can be 20 to 23 times more cost-effective than a random approach. Under the assumption of this "alternative" method of selecting the 25 percent of farms already adopting BMPs, we find that targeted BMP strategies are 8 to 14 times more cost-effective than random methods. While this is significantly lower than the previous findings, there still appears to be a vast advantage in terms of cost-effectiveness to targeting.

Figure 2.59 Sediment total cost curves including alternative method of selecting farms already adopting BMPs

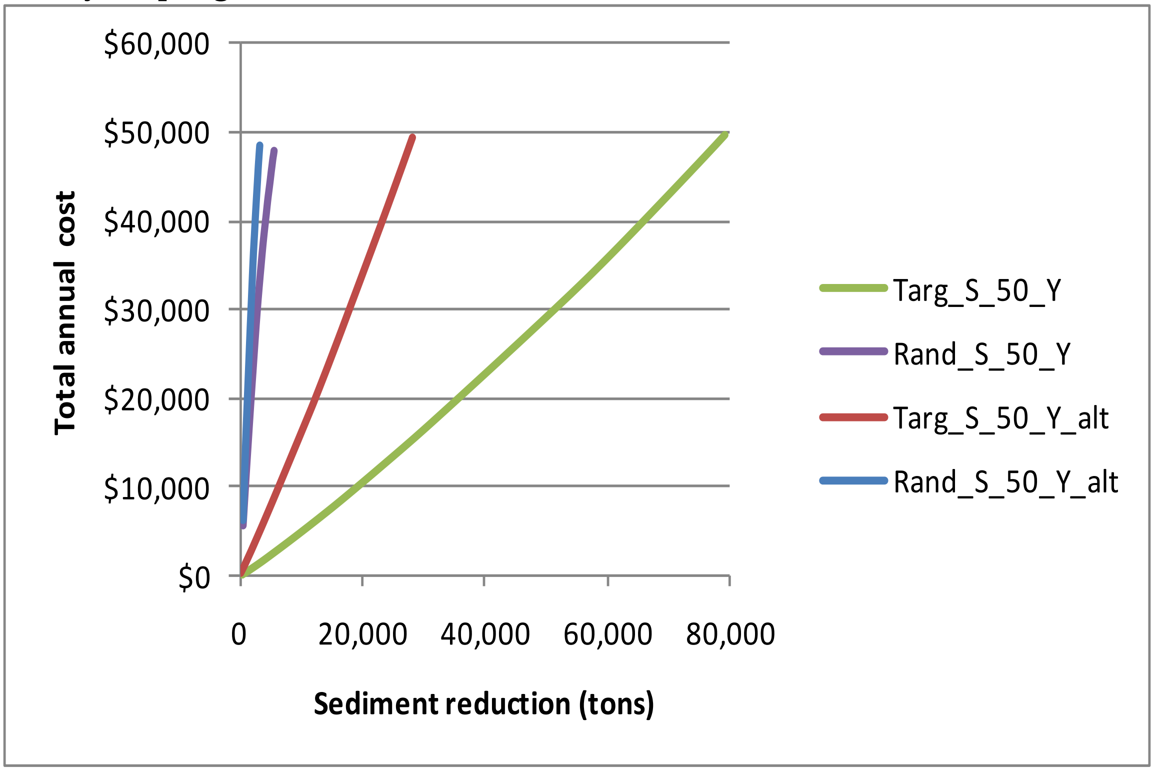
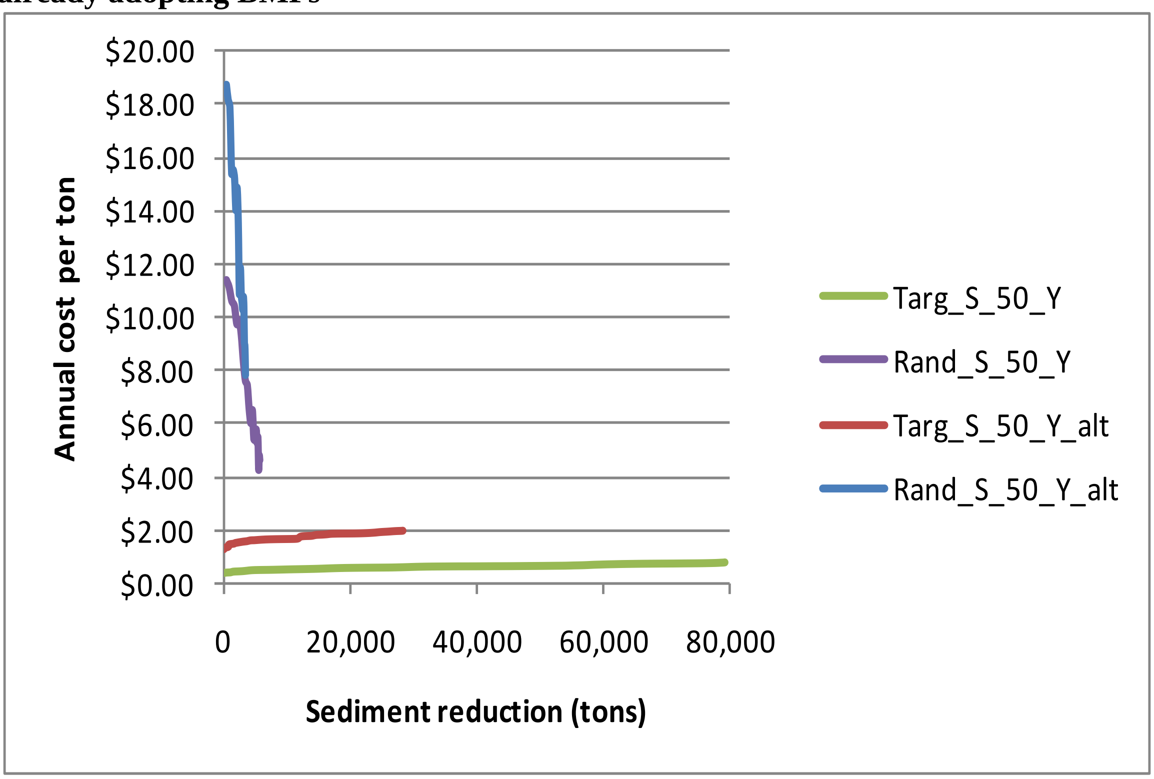
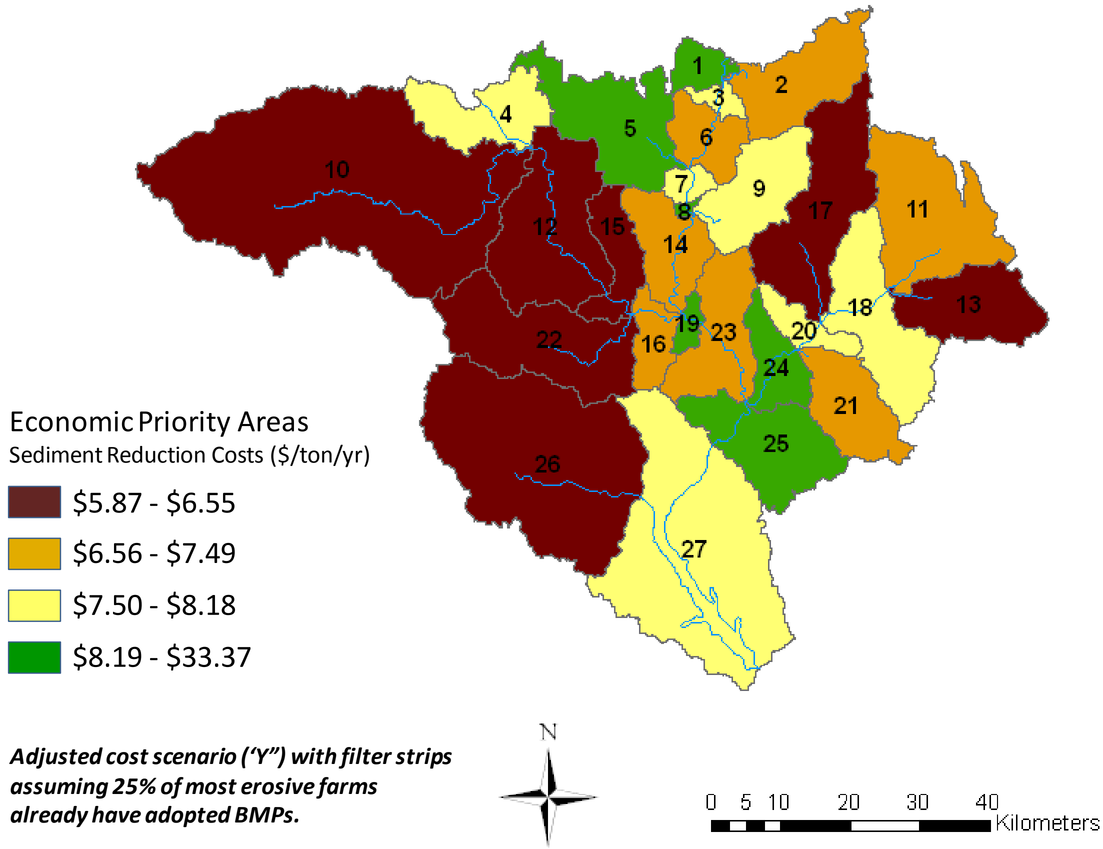


Figure 2.60 Sediment marginal cost curves including alternative method of selecting farms already adopting BMPs



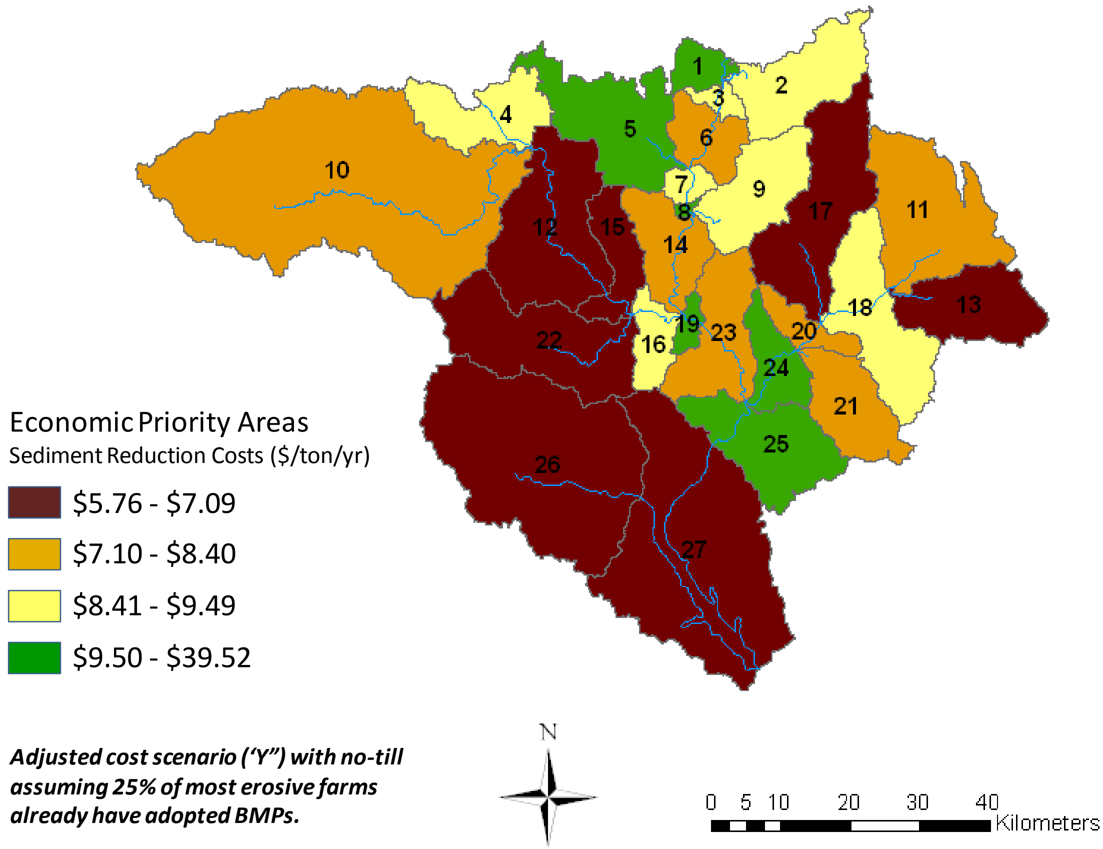
Assuming 25 percent of the most erosive farms in TCL have already adopted BMPs results in fairly significant changes in terms of cost-effective spatial targeting prescriptions. Comparing Figure 2.44 to Figure 2.61, we can see that the economic priority areas move from the eastern portion of TCL watershed to the western portion (when considering sediment and filter strips). Only subwatersheds 13 and 17 remain as a high priority in each case.

Figure 2.61 Spatial average sediment reduction costs with filter strips and assuming 25% of most erosive farms in TCL watershed have already adopted BMPs



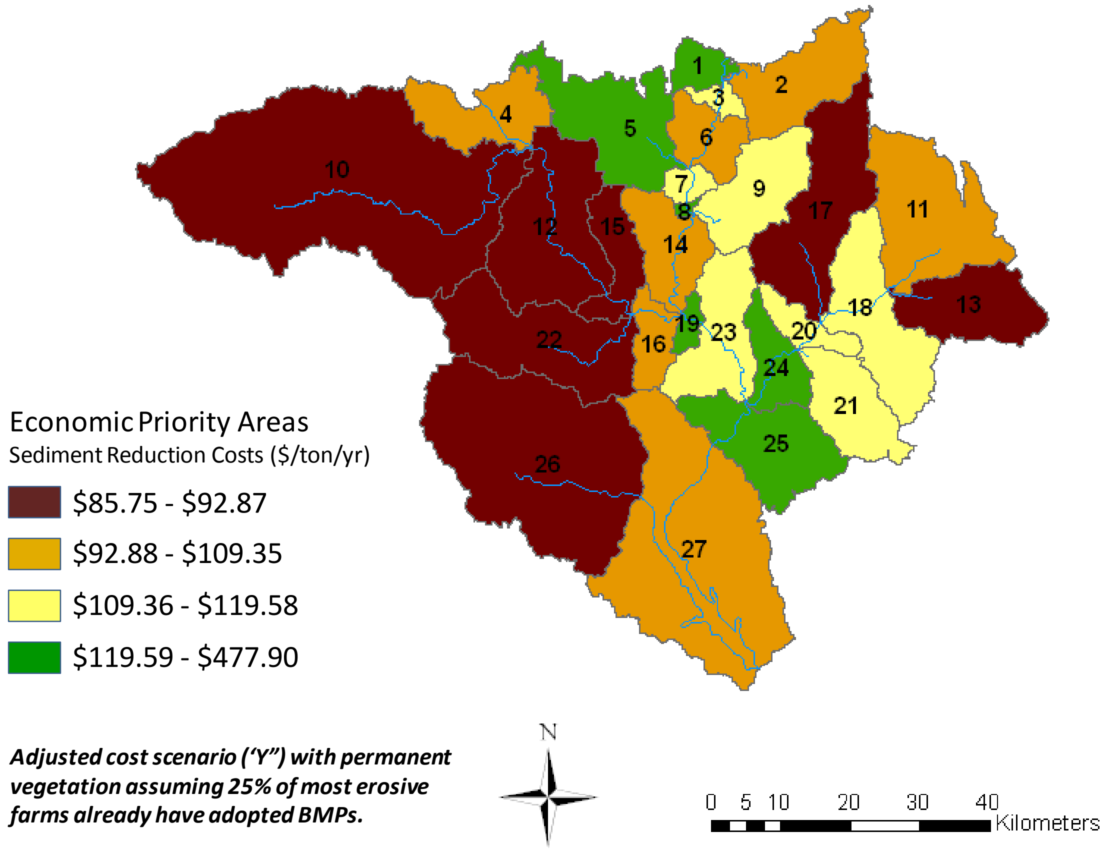
Comparing Figure 2.47 to Figure 2.62 we see a similar shift of economic priority from the northeastern part of TCL watershed to the southwest region. Again, subwatersheds 13 and 17 are the only two that remain classified as "high" in each case. Perhaps most significant here is the finding that subwatersheds 24 and 25 move from being "medium-high" priority to "low" priority under this alternative method of selection. The reason for this is that there are a few highly erosive farms in each of these subwatersheds. If these few farms have already adopted BMPs, there is not much relative value in funding additional BMPs such as no-till in these two subwatersheds.

Figure 2.62 Spatial average sediment reduction costs with no-till and assuming 25% of most erosive farms in TCL watershed have already adopted BMPs



The east to west change of focus is again evident when comparing Figure 2.63 to Figure 2.50 for controlling sediment with permanent vegetation. Again, subwatersheds 11 and 17 are the only two that remain a "high" economic priority in each case. Comparing Figure 2.63 (with permanent vegetation) to Figure 2.61 (with filter strips) one can see that all of the "high" and "low" priority subwatersheds are the same across the two scenarios.

Figure 2.63 Spatial average sediment reduction costs with permanent vegetation and assuming 25% of most erosive farms in TCL watershed have already adopted BMPs



Dredging versus BMPs

TCL and its watershed are used as a case-study to examine the economics of watershed protection and reservoir rehabilitation including dredging. TCL exhibits, perhaps, one of the most critical cases of reservoir sedimentation in Kansas and throughout the Midwest. As of 2009, which was 47 years since the reservoir was completed, TCL contained 180,378 acre-feet of sediment. With over 42 percent (Table 2.21) of its total original conservation (sediment plus multi-purpose) storage capacity (425,312 acre-feet) lost to sediment accumulation, TCL provides a unique and fitting case-study example for this analysis.

Table 2.21 Tuttle Creek Lake and watershed characteristics and dredging costs

Characteristics	
Original conservation storage pool (acre-feet)	425,312
Sediment deposited as of 2009 (acre-feet)	180,378
Sediment deposited as of 2009 (cubic yards)	291,009,849
Sediment deposited as of 2009 (tons)	291,009,849
Total drainage area (square miles)	9,628
Total drainage area (acres)	6,161,920
Kansas portion of Tuttle Creek watershed	
Portion of drainage area - KS portion (%)	25%
Drainage area - KS portion (square miles)	2,377
Drainage area - KS portion (acres)	1,521,554
Pastureland/Rangeland - KS portion (%)	42%
Pastureland/Rangeland - KS portion (acres)	646,639
Cropland - KS portion (%)	43%
Cropland - KS portion (acres)	649,548
Other - KS portion (%)	15%
Other - KS portion (acres)	225,367
Dredging costs in 2009	
Cost per cubic yard or ton	$4.11
Dredging and disposal cost per acre foot	$6,631
Sediment deposited as of 2009 (acre-feet)	180,378
Cost to remove sediment deposited until 2009	$1,196,050,480
Onetime equivalent costs	
Cost per total watershed-acre	$194.10
Cost per cropland acre (total watershed)	$269.59

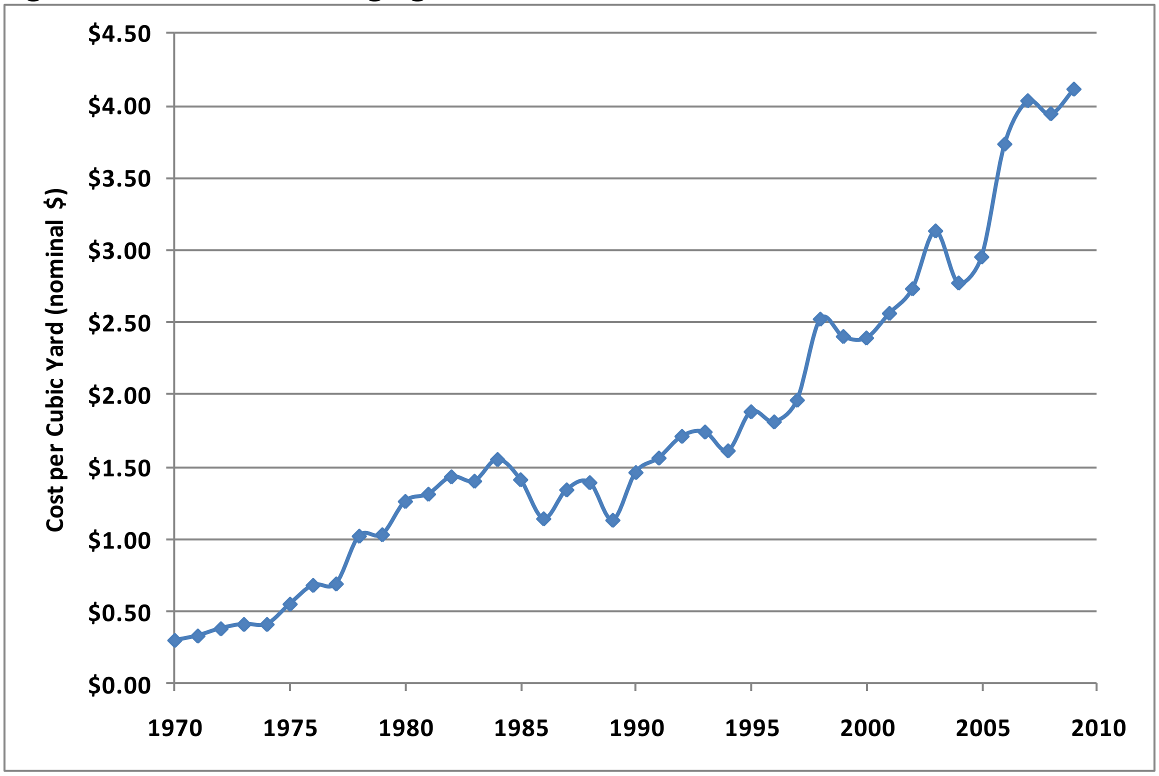
Dredging

Dredging is the removal of accumulated lake bottom sediments. This removal process can take place through mechanical, hydraulic, or pneumatic means (Hudson 1998). Sediments are frequently removed from our nation's rivers and ports for navigation and boating purposes. Although less common, dredging can also take place in lakes and reservoirs as a way of reclaiming water storage capacities. While there are many aspects to consider with dredging projects, one important consideration is cost.

As Williams and Smith (2008) point out, the decision on whether or not to dredge will depend on sediment source, sedimentation rate with and without management practices, effectiveness and cost of management practices, dredging cost inflation, the planning horizon, and the discount rate used to calculate present values. If accumulated sediment has not negatively impacted current reservoir services (e.g., recreation, flood control), then it might be reasonable to forego dredging in favor of investing in additional in-field and in-stream conservation practices to reduce the need for future dredging.

As part of this process, dredging cost data were collected from the U.S. Army Corps of Engineers historical dredging database (USACE 2011). These costs include the cost of maintenance dredging, as well as mobilization of equipment and costs of disposal. The smaller the project the larger the mobilization cost is as a percent of overall costs. Both Corps and industry managed projects are included in the calculations. Figure 2.64 displays the historical trend in dredging costs in nominal dollars. From a low of $0.30/$yd^3$ in 1970 to a high of $4.11/$yd^3$ in 2009, dredging costs have exhibited an average inflation rate of 6.94 percent over this 39 year period.

Figure 2.64 Historical dredging costs in nominal dollars



The cost of constructing TCL in 1962 dollars was $80,051,031. Given an annual inflation rate of 6.94 percent (consistent with the average inflation of dredging costs) in construction costs, the cost in 2009 dollars is $1,096,699,225. If $6.45/yd^3 were spent to dredge 291,009,874 cubic yards from the lake, it would approximately equal the construction cost in 2009 dollars. At a dredging cost of $4.11/yd^3, it would cost $1,196,050,480 (or $194 per total watershed-acre) to restore TCL to its original storage capacity (Table 2.21). Clearly, dredging is an expensive option.

While reservoir sedimentation and dredging data are typically in acre-feet or cubic yards units, soil erosion figures are typically reported in tonnage. Since each of these processes will be compared in this analysis, a common unit of measurement is needed. According to Holland (1971), past sediment samples from Kansas reservoirs exhibited (dry) soil bulk densities of approximately 0.82 tons/yd^3. Other studies have specified cropland soil bulk densities in the ranges of 0.94 to 1.43 tons/yd^3 (NYSSESC 2005) and 1.01 to 1.35 tons/yd^3 (Hillel 1998) depending on the soil characteristics (i.e., more clay content yields lower soil bulk density values). For simplicity, we will assume a ratio of 1 ton per 1 cubic yard. Thus, a 2009 dredging cost of $4.11 per cubic yard is equal to $4.11 per ton. This will be used as a starting point for the following analysis.

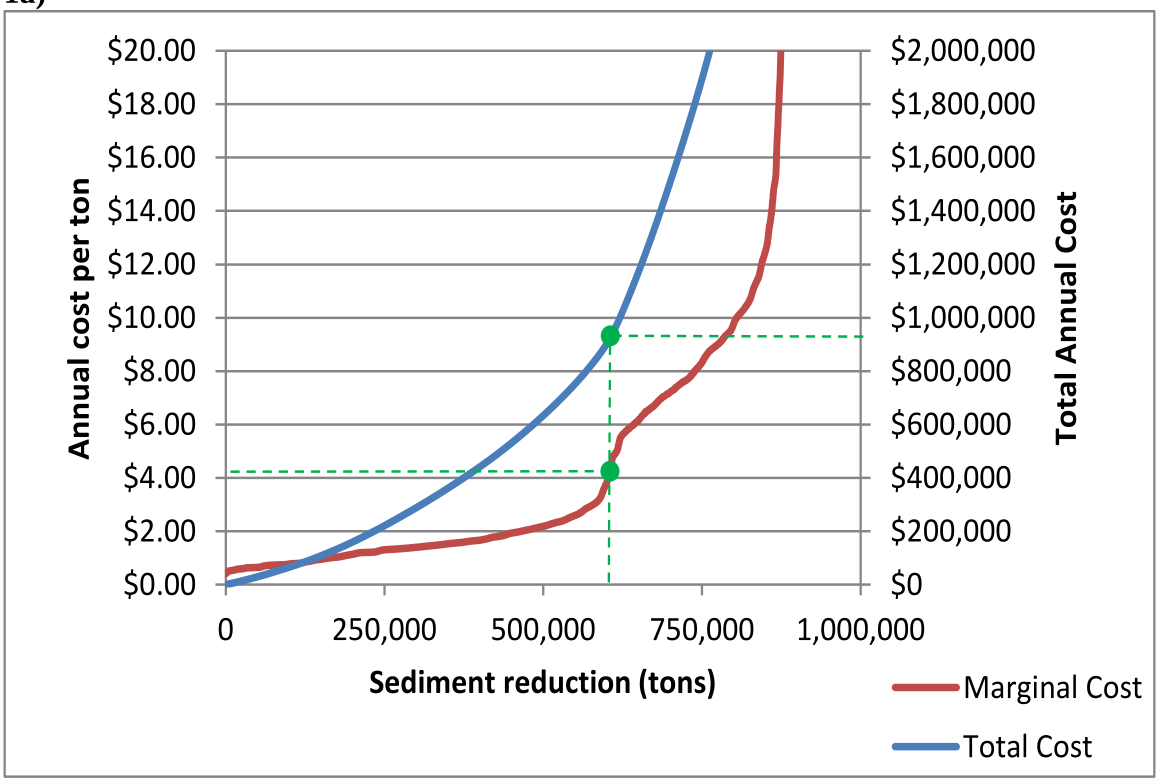
Under the adjusted BMP cost assumptions, Table 2.17 shows that all of the targeted "Y" scenarios up to a $450,000 annual budget result in average sediment reduction costs of much less than $4.11/ton. But, the marginal cost curves were increasing at an increasing rate. While dredging is expensive, there may be some point at which it becomes more feasible than spending additional money on BMP implementation. What is the transition point at which it becomes more cost-effective to dredge (either now or in the future) rather than spend more money on BMP implementation?

Case 1a: Implement BMPs and/or dredge beginning in year 1 (i.e., year 2009) assuming a random 25% of farms have already adopted BMPs

Several simplifying assumptions are made in the following case study. This case assumes perfect substitutability and equality between preventing a ton of soil from reaching TCL via BMP implementation and dredging a ton of sediment from TCL. Each results in one less ton of sediment in TCL at the end of each year. While there are other non-monetary benefits and costs associated with each of the BMP methods, these are not directly accounted for in this analysis.

The cost of dredging in year 1 is equal to $4.11 per ton. The average annual cost preventing sediment from reaching TCL via the three BMPs analyzed previously is $1.11 per ton for a $450,000 budget. Graphing the marginal and total cost curves for sediment reduction according to the assumptions of Targ_S_$$$_Y (i.e., targeted sediment reduction scenario with adjusted BMP costs and unlimited budget) shows that BMP implementation is economically preferred to dredging for the first 603,414 tons of sediment per year or $915,274 annual budget. This is equal to reducing 32.4 percent of the baseline sediment loading into TCL each year (from the Kansas portion of the watershed). Stated differently, all funds should be directed towards BMP implementation if operating under an annual budget of less than $915,274 per year. Or, if there are more than $915,274 in funding available for the restoration and/or protection of TCL, then the first $915,274 should be spent on BMPs and any remaining funds should be directed towards dredging (note, this is ignoring any other possible benefits provided by watershed BMPs). Figure 2.65 graphically shows the points of transition.

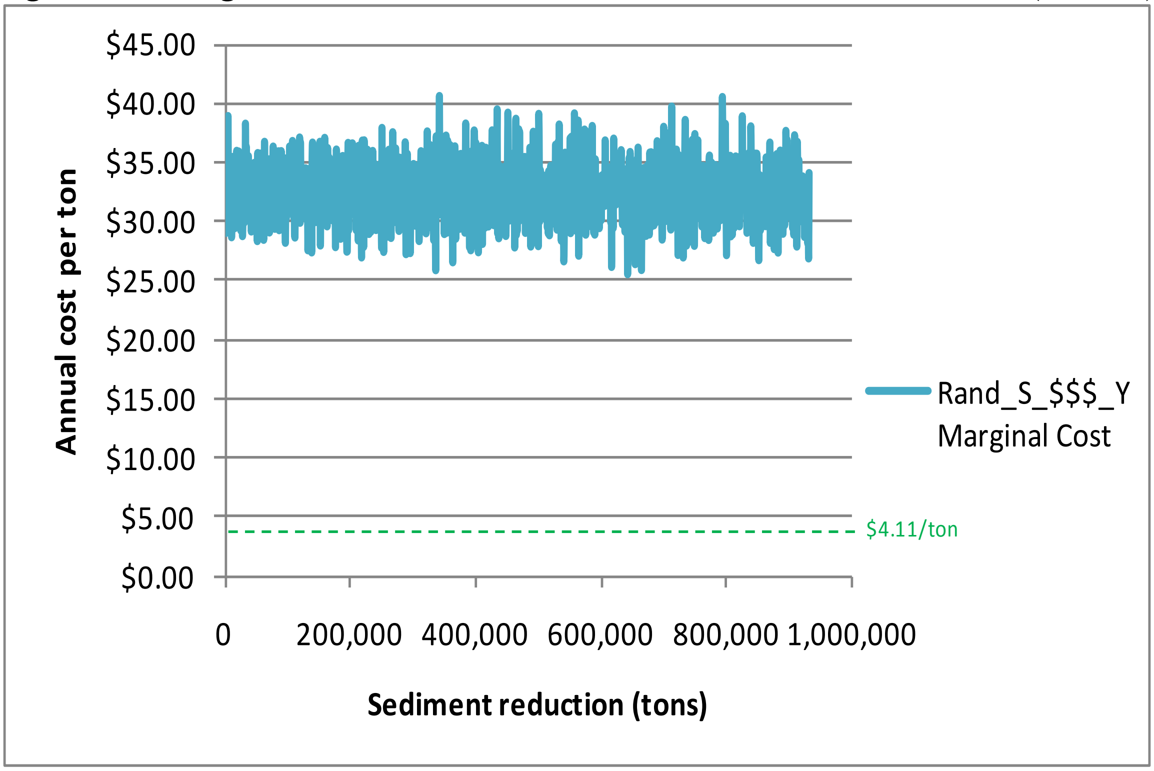
Figure 2.65 Marginal and total cost curves for sediment reduction for Targ_S_$$$_Y (Case 1a)



The above prescription assumes that BMPs are implemented in a highly targeted or "optimal" approach. If targeting of BMPs is not an option, then the prescription here would be to immediately spend the funds dredging. This is based on Figure 2.66, which shows the

Rand_S_$$$_Y scenario along with a line equal to the constant marginal cost curve of dredging at $4.11 per ton. The average cost of reducing sediment via BMPs without any targeting is $32.49 per ton, which is nearly 8 times higher than the cost of dredging.

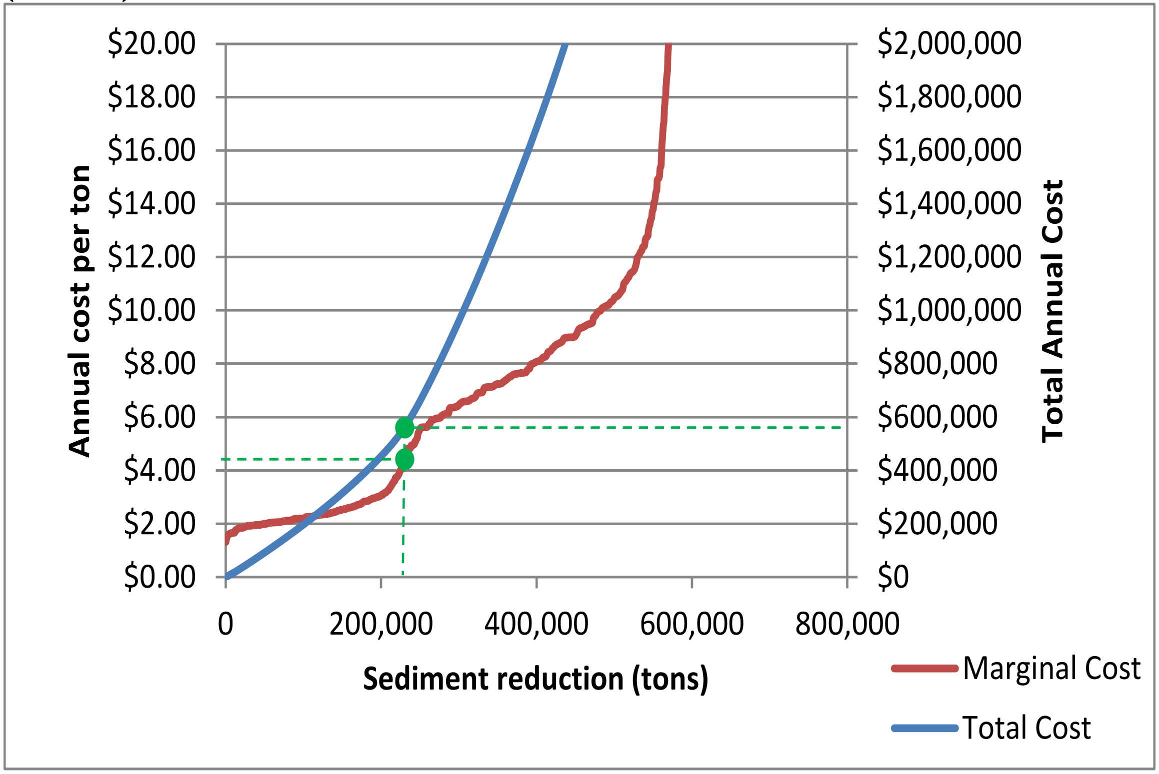
Figure 2.66 Marginal cost curve for sediment reduction for Rand_S_$$$_Y (Case 1a)



Case 1b: Implement BMPs and/or dredge beginning in year 1 (i.e., year 2009) assuming the most erosive 25 percent of farms have already adopted BMPs

Using the same methods as in Case 1a but under the assumption that the most erosive 25 percent of farms have already adopted BMPs, yields somewhat different results. Figure 2.67 shows that BMP implementation is economically preferred to dredging for the first 226,427 tons of sediment per year or $545,544 annual budget. This is equal to reducing 12.2 percent of the baseline sediment loading into TCL each year (attributable to the Kansas portion of the watershed). In other words, all funds should be directed towards BMP implementation if operating under an annual budget of less than $545,544 per year. While this is significantly lower than the $915,274 value from Case 1a, it is still evident that targeted BMP implementation is economically preferred to dredging under "realistically feasible" budget scenarios.[20]

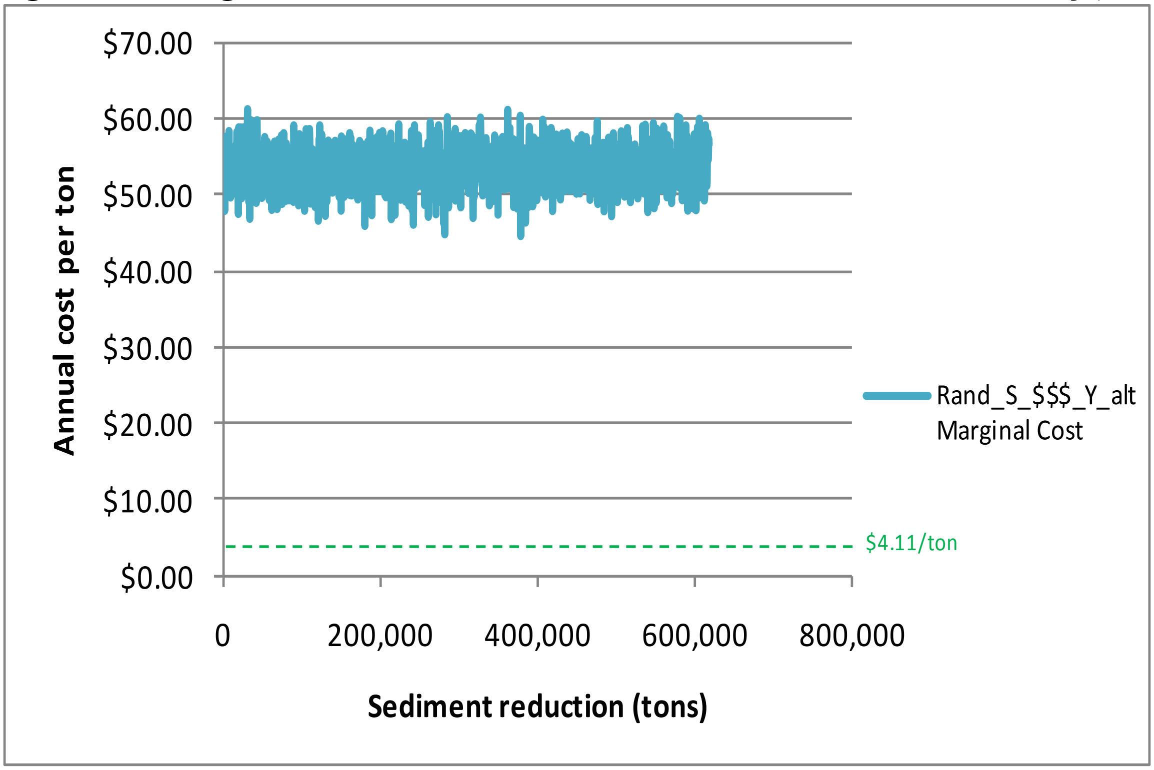
Figure 2.67 Marginal and total cost curves for sediment reduction for Targ_S_$$$_Y_adj (Case 1b)



If targeting of BMPs is not an option, then the prescription here, again, would be to immediately spend the funds dredging. This is based on Figure 2.68, which shows the Rand_S_$$$_Y_adj scenario along with a line equal to the constant marginal cost curve of dredging at $4.11 per ton. The average cost of reducing sediment via BMPs without any targeting is $53.63 per ton, which is nearly 13 times higher than the cost of dredging. Thus, if we assume that BMPs have already been adopted on highly erosive fields throughout TCL watershed, the more important targeting of BMPs becomes.

[20] The term "realistically feasible" is based on a previous assertion that $450,000 annual budget is in all likelihood a maximum based on relevant agency budgets.

Figure 2.68 Marginal cost curve for sediment reduction for Rand_S_$$$_Y_adj (Case 1b)



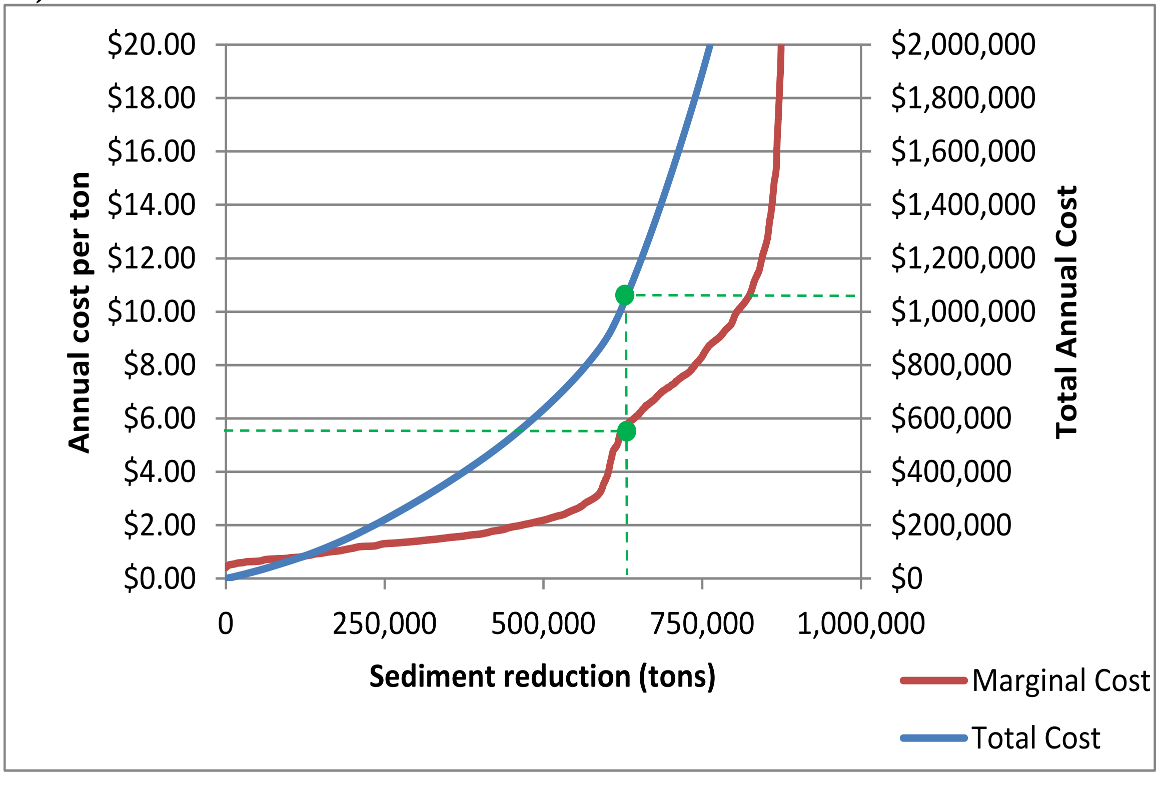
Case2a: Implement BMPs in year 1and dredge beginning in year 16 assuming a random 25% of farms have already adopted BMPs

The second case describes a situation in which BMPs are implemented in years 1 through 15. Then, beginning in year 16, dredging will occur. The question is: What are the savings in dredging costs realized in year 16 due to the implementation of BMPs in years 1 through 15?

This calculation is essentially calculating the present value of the cost of dredging in 15 years. Beginning with a current cost of dredging of $4.11 per ton, a 6.94 percent inflation rate, and a 15 year analysis period, the future value of dredging (at the beginning of year 16) is calculated to be $11.25 per ton. Converting this to present value terms using a discount rate of 4.625 percent (NRCS 2009) yields a present value of $5.71 per ton. The higher inflation rate relative to a lower discount rate results in a present value of dredging in 15 years value that is higher than current dredging costs. From an economic perspective, if dredging is to be delayed 15 years or more, more money can be justifiably spent on BMP implementation.

As Figure 2.69 depicts, up to $1,047,959 should now be spent on targeted BMP implementation. This is an increase of $132,685 per year due to the decision to delay dredging until year 16. This amounts to 629,488 tons of annual sediment reduction or 33.8 percent of the total sediment loading into TCL from the Kansas portion of the watershed. Coincidentally, this also happens to approximately be the point at which the marginal cost curve becomes effectively vertical.

Figure 2.69 Marginal and total cost curves for sediment reduction for Targ_S_$$$_Y (Case 2a)



As stated earlier, this finding is simply a function of the inflation to discount rate difference. If the two rates were set equal, then the prescription from Case 2 would essentially be no different from the prescription from Case 1. In other words, the point at which funding should taken away from BMP implementation is the same. Conversely, if the discount rate was higher than the rate of inflation, less money should be directed towards BMP implementation because dredging is going to relatively cheaper in the future.

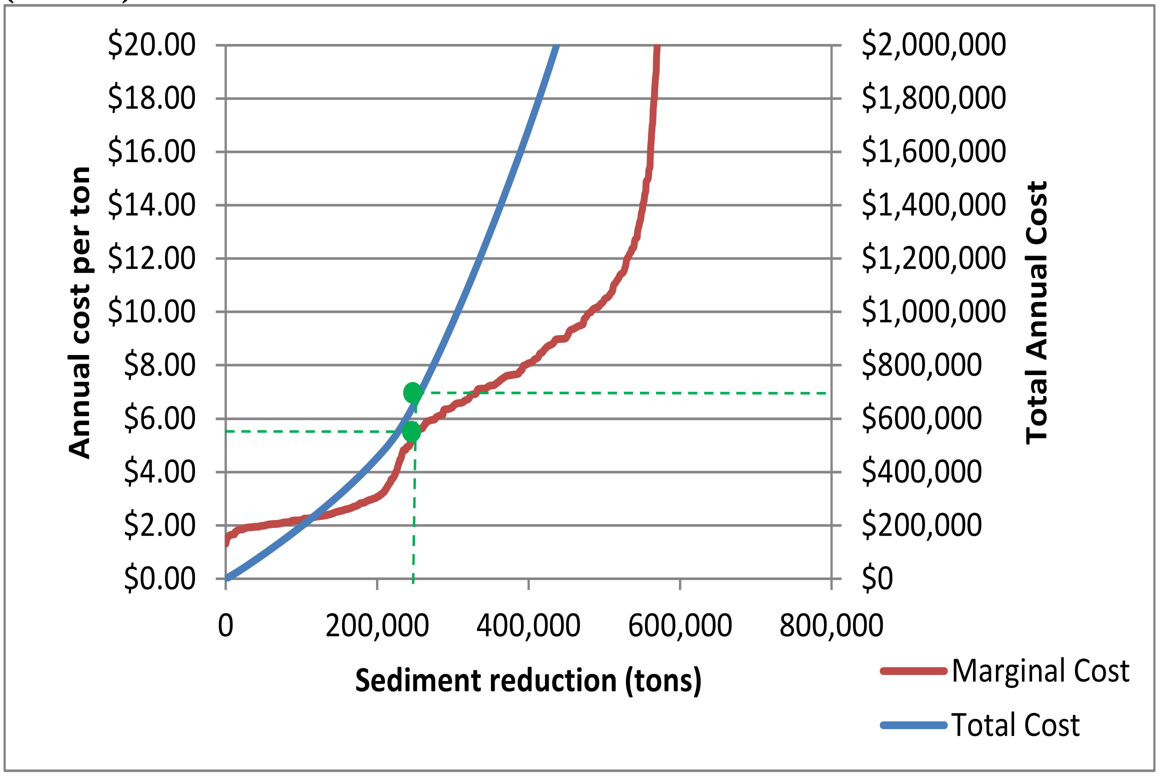
In all cases and scenarios, if BMPs can only be implemented in a random fashion, the prescription would be to forego all BMP implementation in favor of dredging now or in the future. This is because random BMP implementation is between 5 to 8 times more costly than current or delayed dredging costs.

Case 2b: Implement BMPs in year 1 and dredge beginning in year 16 assuming the most erosive 25 percent of farms have already adopted BMPs

Using the same methods as in Case 2a but under the assumption that the most erosive 25 percent of farms have already adopted BMPs, yields somewhat different results. Applying this assumption results in less funding that could be spent on targeted BMP implementation. That is, when Case 2a is compared to Case 2b, nearly $325,000 less could now be spent on targeted BMP adoption. This is displayed in Figure 2.70 which shows that up to $723,347 could now be spent on targeted BMP implementation compared to $1,047,959 in Case 2a.

Making the decision to delay dredging until year 16 (i.e., comparing to Case 1b) results in an increase of $177,803 per year that could be spent on BMPs. Case 2b suggests that 261,199 (an increase from 226,427 tons in Case 1b) tons of annual sediment reduction could be achieved via BMP implementation or 14.0 percent of the total sediment loading into TCL from the Kansas portion of the watershed.

Figure 2.70 Marginal and total cost curves for sediment reduction for Targ_S_$$$_Y_adj (Case 2b)



Conclusion

This study answered the question: How can physiographical and economic relationships within the watershed be quantified to provide insights into the selection of cost-effective alternative management strategies? This question was addressed by integrating a geographic information system (GIS) based watershed model, reservoir rehabilitation management strategies, statistical analyses of historic watershed and water quality data, with an economic analysis of alternative sedimentation reduction strategies. The following are some of the key findings, which can offer decision-makers better insight into the benefits and cost implications associated with achieving various water quality levels and sedimentation reduction goals within a large watershed.

Both physiographical and economic factors must be considered for cost-effective conservation to occur.

Consideration of only one side (i.e., either physiographic or economic) of a soil and water resource issue will not result in an optimal strategy from a cost-effectiveness standpoint. Targeting areas that produce the most pollution per acre is more cost-effective than a random approach, but may miss the mark if those areas also exhibit high BMP costs (e.g., due to high opportunity costs). Likewise, focusing only on areas where BMP costs are low may produce "better than random" results, but may not achieve cost-effective pollution reduction if the areas do not exhibit high levels of pollutant reduction.

Optimal BMP targeting is from 8 to 23 times more cost-effective than random implementation, but also is likely to be more costly to administer.

Random BMP implementation is not an effective method for funding and placing BMPs. This is somewhat representative of a policy where conservation funds are issued to any interested and willing landowner in a county or watershed. While this approach achieves equity, conservation dollars are being spent in areas that do not deliver a good "bang for the buck" relative to other areas. Specifically, a targeted approach can reduce 23 times more sediment for a given budget than a random approach. It should be noted, however, that a highly targeted approach can be costly from an administration standpoint.

BMP implementation is more cost-effective than dredging if done in a targeted manner, but not if randomly implemented.

In the case of TCL watershed, if conservation funds cannot be implemented in a highly targeted manner, then it may in fact be more cost-effective to allocated funds for dredging. Annualized dredging costs are around $5 per ton whereas annualized "random" BMP implementation costs average from $30 to $50 per ton. Under a targeted approach, approximately $500,000 to $1,000,000 per year could be spent on BMP implementation before any funds are spent on dredging. It should be noted that if one were to assume that sediment delivery ratios are equal to one for each subwatershed, these dollar figures would increase.

Up to approximately 1 million dollars per year, not considering "intangible" costs of BMP implementation, could be spent on targeted BMP implementation before some selected dredging may be needed.

"Intangible" costs represent all those costs other than pure accounting costs, which a farmer may take into consideration when deciding whether to implement a given BMP. Examples may include: various hassle factors, need for additional training/education, and/or concern of more future government regulation if participating in a conservation program. This study only included the accounting costs of adopting BMPs, and thus, may have underestimated the total costs of BMP implementation.

However, the original BMP costs were adjusted to reflect more current-day economic values. These adjusted "Y" cost scenarios were used in the dredging cost analysis. Based on this, approximately $500,000 to $1,000,000 could be spent on targeted BMP implementation before any funds are spent on dredging.

If "intangible" costs of BMP implementation are significant and/or BMPs cannot be targeted effectively, dredging is likely more cost-effective.

In general, reservoir dredging has been looked upon as a very expensive approach to reducing reservoir sedimentation. However, it may not be entirely cost-prohibitive on an annualized per unit basis. Relatively low "intangible" costs and/or effective targeting are necessary conditions that must exist for BMP implementation to be more cost-effective than dredging. If either one of these conditions does not hold, dredging may in fact be a more cost-effective approach to addressing sedimentation in TCL. Again, random BMP implementation results in average costs of sedimentation reduction of $30 to $50 per ton whereas dredging costs average $5 per ton.

Limitations and future research needs

While this research analyzes and compares the cost-effectiveness of various BMP implementation approaches in the TCL watershed with dredging, the benefits associated with each of these strategies have not been addressed. Other limitations of this study are that only three in-field cropland BMPs are included in the analysis and streambank stabilization strategies were not considered. In addition to these points, only the Kansas portion (~25 percent) of the entire TCL watershed was considered for BMP application. In other words, "business as usual" is assumed to be the case for the Nebraska portion. There may in fact be value related to an interstate cooperative approach to address these issues. To be clear, a comprehensive benefit-cost analysis is not performed in this study. The following discussion highlights some of the limitations of this study and makes recommendations for future areas of research related to BMP implementation, dredging, and reservoir sedimentation in general.

The exact locations and types of BMPs currently in place throughout the TCL watershed are unknown. Because of this reality, assumptions are made in this study regarding previous BMP implementation. Specifically, 25 percent of the farms are removed from the choice set. This is accomplished by either: 1) randomly removing 25 percent of the farms; or 2) removing the most erosive 25 percent of farms from the choice set. In reality, current conditions are likely somewhere in between these two extremes. Thus, the results presented should be interpreted with this in mind. More accurate information regarding past and current BMP adoption is necessary to enhance the realism of studies like this.

While this analysis compares BMP implementation to dredging from a cost standpoint, this is only half of the story. The benefits created or preserved by each activity must be considered to adequately analyze these management alternatives. Consider the following as a foreword to some of the relevant benefits.

The application of BMPs to reduce soil erosion and nutrient runoff can result in benefits to a watershed region that may not be directly linked to the downstream reservoir (i.e., TCL). BMPs can improve soil productivity over time, which is a benefit to landowners. Improved wildlife habitat for hunting and other related recreation benefits in the watershed above the reservoir also may be created or preserved through BMP implementation. Further, benefits related to improved water quality in streams and rivers may be non-additive. That is, a reduction in nitrogen runoff close to a stream located far away from the reservoir may actually be more valuable to society than a reduction of soil erosion in a field bordering the reservoir. Our analysis only considers the costs and pollutant reductions achieved by BMP implementation and does not attempt to quantify any of the other benefits.

To the extent that society values carbon sequestration in the future, BMP implementation could result in benefits that accrue to society at large and not just those in the watershed or reservoir users. It also may be likely that users of water downstream of TCL would benefit from improved water quality attributable to BMPs.

The possibility of changes in climatic conditions and the impacts of those changes are other wild cards in this discussion. Climatic changes may significantly affect water use, water quality, and TCL watershed ecosystem services. Less frequent but more intense rainfall events or even more droughty conditions may increase the use and benefits of BMPs. The possibilities of these additional benefits and the growth of them would need to be considered in a more comprehensive benefit-cost analysis.

There does not exist a current, comprehensive analysis of the benefits generated by all of the resources in and around TCL or any of the conservation practices implemented throughout the watershed. A 2001 Army Corps of Engineers study estimated benefits generated by TCL, but this study focuses solely on the reservoir (USACE 2001). Without much provided detail, it is likely that this study did not include many of the non-market benefits of TCL. A more comprehensive, watershed-wide analysis of costs and benefits (including non-market values) would be necessary to more adequately compare the various alternatives for protecting and/or restoring TCL: BMP implementation to dredging to BMP implementation with dredging to “do-nothing”.

CHAPTER 3 - Incorporating Point Sources into the Watershed Management Discussion

While nonpoint sources are nearly the sole contributors of sediment in many watersheds, contributions of nutrient pollution often comes from both point and nonpoint sources. Wastewater treatment plants, in particular, emit both nitrogen and phosphorus into receiving surface waters. These point sources are regulated through environmental permits which define the amount of nutrients (and other pollutants) that may be discharged into receiving streams and rivers. Nonpoint sources (with the exception of larger confined animal operations) are generally unregulated. Water quality trading is a policy alternative that attempts to capitalize on cooperative arrangements between regulated point sources and unregulated nonpoint sources.

Chapter 4 incorporates a similar agent-based modeling technique as used in the previous chapter, but focuses on the simulation of a point-nonpoint source water quality trading market for nutrient reduction. Whereas Chapter 2 considered the case of a “watershed manager” attempting to allocate conservation funding in a targeted manner, Chapter 4 simulates a market where the participants have the incentive to find the most cost-effective means of reducing nutrient loading to meet water quality limits. Potentially, society as a whole can benefit from such cooperative arrangements.

As one might imagine, the construction and design of these markets will affect the amount of trading that does or does not occur. Chapter 4 attempts to answer the following research question: How can water quality trading markets be designed in ways that take into account different levels of information among buyers and sellers and what are the implications for the determination of “optimal” trading ratios? To examine the ways that these market imperfections may interact to impact the performance of a WQT market, an agent-based model is constructed, which simulates a hypothetical point-nonpoint market.

CHAPTER 4 - A Simulation of Factors Impeding Water Quality Trading

Introduction

Environmental economists have argued that pollution trading programs are an efficient means of improving environmental quality, as they give firms with the lowest pollution control costs the largest incentive to reduce pollution. Such low-cost firms are able to sell pollution credits to firms with higher control costs. Aligning incentives with control costs is the condition needed to ensure minimum-cost control of pollution overall. Such incentives typically do not arise from traditional, uniform regulations.

Following on the highly successful trading programs for air emissions such as sulfur dioxide (NCEE, 2001), many states have recently adopted trading programs to improve water quality. There are at least 47 water quality trading (WQT) programs currently active or under development worldwide with the overwhelming majority in the United States (Selman et al., 2009). In principle, such programs could be applied to any water-borne pollutant and allow trading among point sources, among nonpoint sources, or between point and nonpoint sources (the latter is known as "point-nonpoint trading"). Most of the existing programs are designed with point-nonpoint trading to limit nutrient loading: point sources are allowed to meet their nutrient emission limits by purchasing water quality credits from agricultural producers in the surrounding watershed. These producers are then obligated to implement a best management practice (BMP) that reduces expected nutrient loading by an amount commensurate with the number of credits sold.

Substantial evidence exists that nonpoint sources can reduce nutrient loading at a much lower cost than point source polluters in many watersheds, suggesting substantial scope and gains from point-nonpoint trading (Faeth, 2000). Despite the potential gains, perhaps the most commonly noted feature of existing programs is low trading volume; none of the programs have had extensive trading activity and many have had no trading at all (Hoag and Kughes-Popp, 1997). A widely cited and vivid example is the Fox River program in Wisconsin (Hahn, 1989), which had only one trade after its inception in 1981 even though an early study (O'Neil, 1983) found substantial potential gains from trading among all participating firms.

These outcomes suggest the presence of obstacles to trading that were not recognized in the design of existing programs. While these obstacles have not been studied in a systematic fashion, individual researchers have identified various trading barriers in different contexts. Two of the barriers discussed in the literature are limited trading information and distortionary trading ratios. Limited information among market participants regarding each others' bid prices will introduce inefficiency because there is no assurance that the executed transactions are the most gainful (Atkinson and Teitenberg, 1991; Netusil and Braden, 2001). The trading ratio in point-nonpoint programs is typically defined as the quantity of expected nonpoint loading reduction needed to offset one unit of point source loadings. Many existing programs set trading ratios substantially greater than one, ostensibly to adjust for the greater uncertainty in nonpoint loading reduction (EPA, 1996). However, such ratios operate like a tax to dampen the benefits from trading, hence reducing trading volume and overall gains from trading (Malik et al., 1993; Horan, 2001, Horan and Shortle, 2005; Hennessy and Feng, 2008).

How can WQT markets be designed in ways that take into account different levels of information among buyers and sellers and what are the implications for the determination of “optimal” trading ratios? To examine the ways that these market imperfections may interact to impact the performance of a WQT market, an agent-based model is constructed, which simulates a hypothetical point-nonpoint market. In particular, the market is modeled using a variant of the sequential, bilateral trading algorithm proposed by Atkinson and Tietenberg (1991). This paper first presents an overview of the simulation modeling technique and then analyzes the effects of two prominent market impediments identified in the WQT literature: information levels and trading ratios.

Relevant literature

While WQT has been promoted by economists as a cost-effective means to achieve water quality goals, experience with actual WQT programs has yet to produce these results. Several theoretical studies have investigated the factors impeding trading (e.g., Malik et al, 1993; Horan, 2001; Hennessy and Feng, 2008; Stavins, 1995), but very few articles have simulated an environmental trading market in action and only a small number of these have focused on water quality trading. Two notable exceptions have utilized trading simulations and relate to this research. An often cited article in the environmental markets literature is Atkinson and Tietenberg (1991) who simulated a sulfur dioxide trading market. Netusil and Braden (2001) followed with a simulation of a water quality market with varying transactions costs. There also are several relevant articles that addressed the effects of a trading ratio including Horan (2001) and Horan and Shortle (2005).

Atkinson and Tietenberg examined the bubble policy of the Emissions Trading Program. The data used in this study came from 27 point sources in the St. Louis Air Quality Control Region. They attempted to explain the divergence in costs between the least cost solution and incentive based emissions trading approaches in air quality. More specifically, the article examined the hypothesis that a sequential, bilateral process cannot achieve a cost-effective equilibrium in markets dealing with non-uniformly mixed pollutants.

Simultaneous trading with complete information was the first scenario modeled. This most closely mimicked the least cost solution. The second scenario consisted of sequential trading with complete information. Firms were assumed to have complete knowledge of each other's control costs, so that trades occurred in the order of gains from exchange – i.e., the first trade was between the two traders that had the most to gain from a transaction. The last scenario was sequential and operated under incomplete information in which a firm was randomly selected and then a "best" trading partner was found. This semi-random selection process continued until no feasible trades remained. This algorithm was run 500 times for each air quality standard. In all of the scenarios, the air quality standards had to be met.

The results showed that more stringent standards resulted in greater divergence from the least cost benchmark, for all scenarios. The authors also concluded that the amount of information available and the sequencing of trades played a large role in the amount of cost savings realized. They thought that the most realistic scenario should be found somewhere between the complete information, sequential trading scenario and the random partial information scenario (thus achieving anywhere between 7% to 88% of the least cost benchmark). They did admit, however, that their cost savings results may be too optimistic because they did not account for transactions costs. They also suggested that a market for uniformly mixed pollutants may come closer to achieving the least cost benchmark.

Netusil and Braden (2001) built upon Atkinson and Tietenberg (1991) and extended their previous work in the area of transferable discharge permits. This is one of only a few studies that examined markets for water quality. The authors examined the effects of sequential bilateral trading under imperfect information in a hypothetical sediment loading market. Their model allowed market participants to make multiple trades as opposed to a single trade.

Their research also incorporated different levels of transactions costs into each trade. Another unique issue the authors addressed was lumpy abatement technologies. Trading does not always result in perfectly divisible transactions. This effectively simulated how a market would function in the real-world, since the quantity supplied by a given trader does not always equal the quantity demanded by a given trading partner.

The data used in this analysis came from a 1,064-acre watershed area in Macon County, Illinois. Modeling was performed using a gains-ranked (high information) and a random (zero information) contracting scenario. In each scenario, the number of internal and external contracts was computed. Internal contracts were defined as trades between two sites under common ownership and external contracts were trades between two separate entities.

The results showed that under the gains-ranked scenario, the sediment load under all transaction cost levels were lower than the regulatory policy's requirement. Another important finding in this scenario was that the distribution of internal and external contracts changed as the transactions costs levels changed. High transactions costs resulted in a decrease in overall trading and caused a shift towards internal contracting. An interesting finding was that as transactions costs increased, the overall spending on abatement activities (inclusive of transactions costs) can sometimes decrease. The reasoning is that high transactions costs block low value contracts from occurring and allow the higher value trades to happen. Under random contracting (zero information), however, an increase in transactions costs always resulted in an increase in abatement and total costs.

The conclusions drawn were that neither trading scenario matched the least cost solution. This is because the least cost solution allows for simultaneous multilateral reallocations. Nevertheless, it is important to note that both trading scenarios resulted in substantial cost savings relative to the regulatory approach even at the highest transactions costs level and lowest information level.

Horan (2001) and Horan and Shortle (2005) analyzed different levels of trading ratios in the context of water quality trading. Horan (2001) presented trading ratios utilized in several existing, pilot, and planned point- and nonpoint-source trading markets. These ranged from 1.3:1 to 3:1. Horan and Shortle (2005) performed a numerical example of trading in Susquehanna River Basin and arrived at “optimal” trading ratios in the range of 0.89:1 to 3.3:1

Horan (2001) argued that from a welfare efficiency standpoint, the optimal trading ratio would necessarily be less than one when a WQT model is specified to have uniformly mixed pollutant loads, stochastic nonpoint loads, convex damages, and no transactions costs. This is because the variability in nonpoint loadings creates stochastic ambient pollution concentrations and stochastic damages from pollution. This leads to more social risk if damages are convex in ambient pollution and if increases in nonpoint loadings increase the variability of ambient pollution. Social risk is costly, so there are more benefits to reducing the variable nonpoint source pollution. Higher trading ratios work against this objective because they reduce the trading revenue per unit of loading reduction for nonpoint sources, thereby attracting fewer nonpoint traders and a higher overall level of nonpoint pollution. Thus, smaller trading ratios are more economically efficient.

Horan (2001) suggested that it is realistic to assume policies are designed to allocate resources within the context of policy makers’ preferences, not to maximize aggregate economic surplus. Thus, trading ratios are designed to be politically optimal. He further argued that trading ratios in excess of one may be the rational public sector response to the risk associated with stochastic nonpoint pollution because political support groups are likely to focus on expected loading reductions as opposed to overall social risks. Thus, trading ratios must be greater than one for most trading programs to be politically palatable.

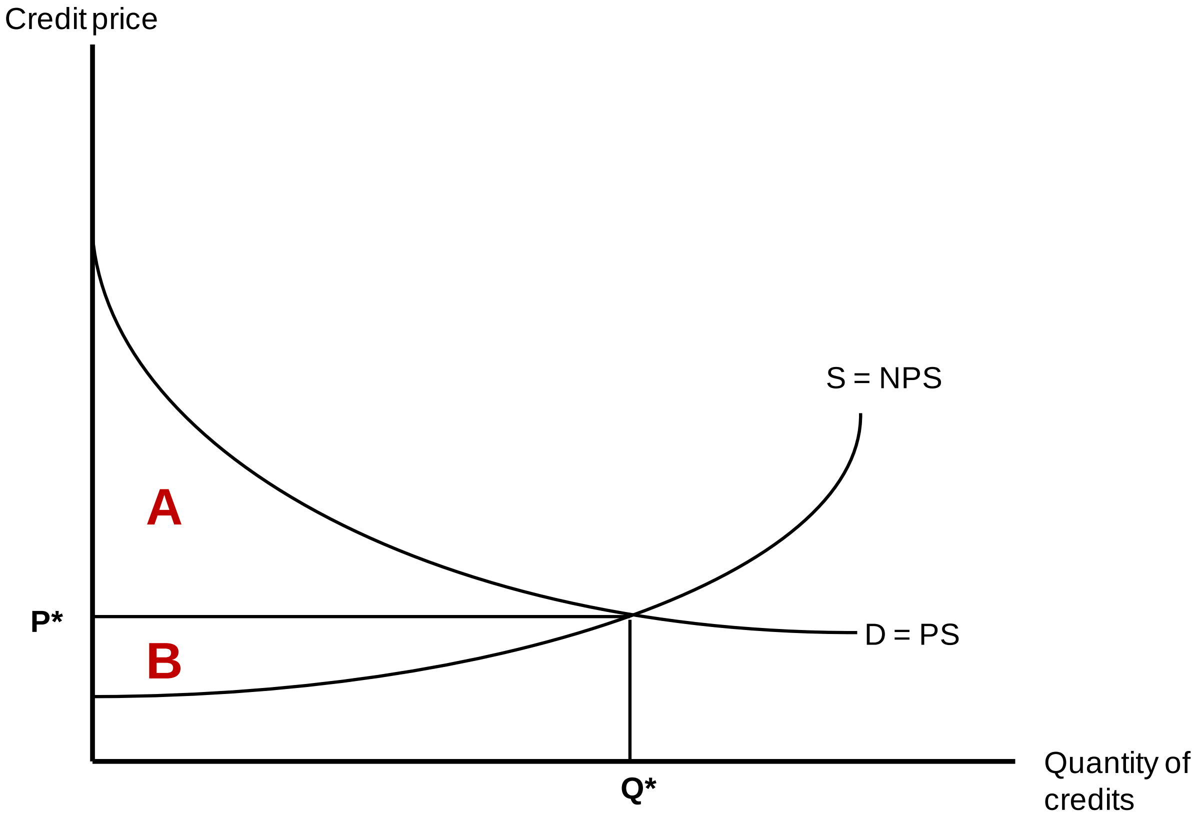
Conceptual Model

As with most markets, WQT markets can suffer from various imperfections and frictions, which tend to hinder trading and/or reduce the overall gains from trading. This section utilizes classic demand a supply diagrams to assess the impact of different market imperfections.

Frictionless market

As a point of comparison, the equilibrium of a frictionless market with no imperfections is discussed first, represented in Figure 4.1. The demand curve in this figure represents treatment plants' willingness to pay (WTP) for purchasing credits, reflecting the cost of controlling pollution through technology upgrades. The supply curve represents farms' cost of pollution control through best management practices, which is their willingness to accept (WTA) to sell credits. When $Q = 0$ credits, treatment plants are meeting their limits by controlling all of their pollution through their own facility upgrades or technological improvements. As Q increases, plants are buying additional credits to allow more of the pollution to be controlled by the nonpoint sources. Thus, at any point on the diagram the total amount of pollution control does not change; however, the sources responsible for the pollution control does change. Stated differently, the quantity of trades has zero effect on expected water quality.

Figure 4.1 Frictionless WQT market



This frictionless market condition assumes there are no intangible or transaction costs, and also that the trading ratio is 1:1. In the equilibrium of this market, point sources purchase $Q*$ credits from nonpoint sources at a price of P^*. Area A represents the market gains to point sources, reflecting the difference between the potential cost of technology upgrades (points along the demand curve) and the actual cost of purchased credits (the price P^*). Area B is the gain to nonpoint sources, or the price received for the credits sold (P^*) less the cost of generating those credits (points along S). The sum of these two areas is equal to total benefits or total cost savings from the program. Cost savings are maximized under these frictionless or "perfect" market conditions.

It is important to note that the areas delineating the gains to point source and nonpoint sources in the figure assume that every contract is traded at the equilibrium price, P^*. This would only occur under a simultaneous trading scenario. However, the way water quality markets are designed, trading must occur in a sequential and bilateral fashion. So, each contract results in a potentially unique price. Acknowledging this would change the individual values of the point- and nonpoint-source gains, but the total cost savings (sum of the two gains) would not vary. This limitation is true for all of the following market scenarios.

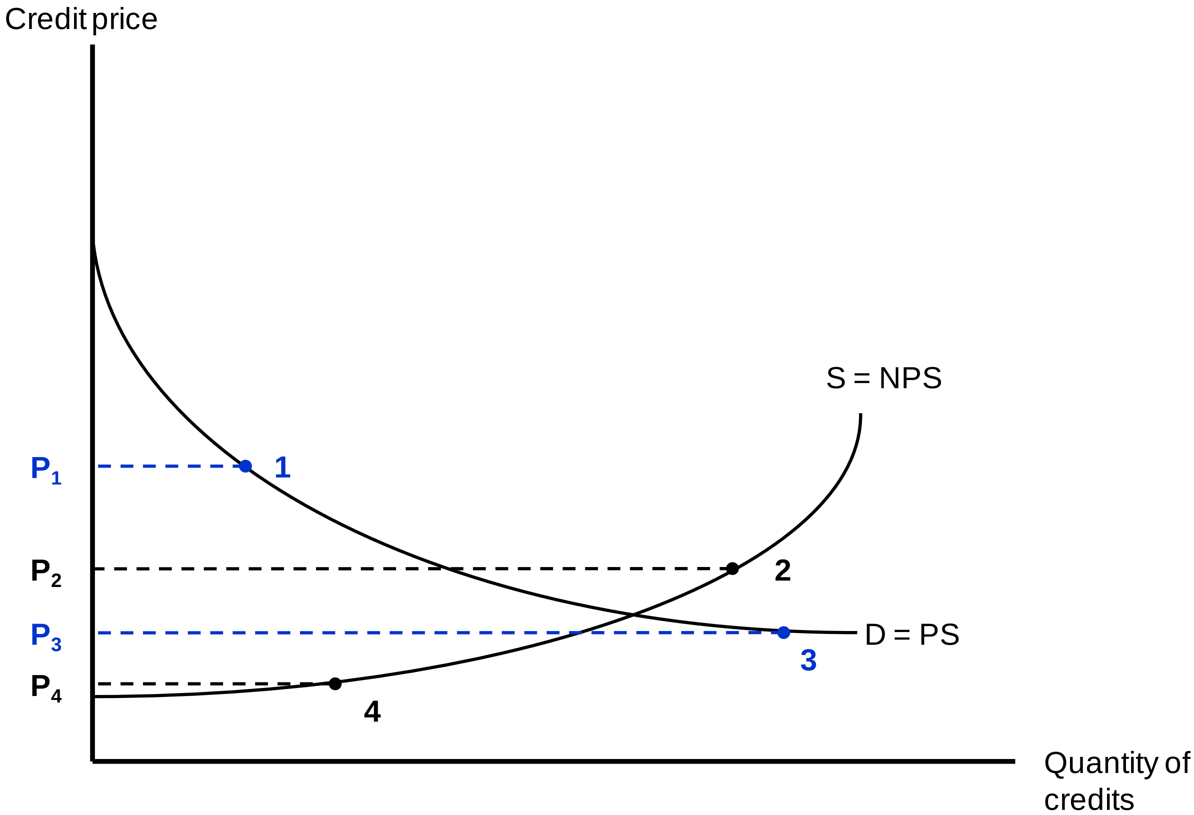
Information levels

The first type of imperfection considered is limited information, which impacts the sequencing of trades. A frictionless market presumes complete information, where every participant in the market knows precisely the willingness-to-pay and willingness-to-accept of all potential traders. In this situation, the trades would be executed in order of their market gains: the first trade would be between the buyer with the highest WTP and the seller with the lowest WTA, with successive trades yielding progressively narrower gaps between WTP and WTA until all gains have been exhausted at the equilibrium point. In a low information scenario, participants have little or zero information on other traders' WTP or WTA values. In this limiting case, buyers and sellers would be traders would be paired together in a random order uncorrelated to the gains from trading.

Ermoliev et al. (2000) actually proved that random-ordered, sequential trading can lead to an efficient outcome ($Q*$ in Figure 4.1). However, this can only occur when every participant has the ability to be a buyer and a seller and there are no transaction costs. That is, traders can back out of earlier trades at no penalty if they find a new trading partner that is more advantageous. This assumption is unlikely to hold for water quality trading programs in practice, where each trade usually involves a binding contract that can only be breached at some financial penalty. All of the models in our paper operate under the assumptions that only point sources are able to buy credits, only nonpoint sources can sell credits, and that the penalties for breaching trade contracts are prohibitively large. Since Ermoliev et al.'s (2000) assumptions are not met in these models, different information levels should result in different levels of cost savings.

Figure 4.2 shows the effects of different information levels in the market. For this example, the focus only will be on the point sources located at points 1 and 3 on the demand curve (hereafter plant 1 and plant 3), and the nonpoint sources located at points 2 and 4 on the supply curve (hereafter farm 2 and farm 4). For simplicity, let us assume that all four of these entities would trade at most one credit. As in any market, the net gain from a given trade is equal to the difference between the price along the demand curve and the price along the supply curve. In a complete information and frictionless market, the first transaction involving any of these traders would be between plant 1 and farm 4. Plant 3 and farm 2 will not engage in trading because there would be a negative net gain from doing so. So, for the four traders combined, the net gain from trading under complete information is $P_1 - P_4$.

Figure 4.2 Effects of information

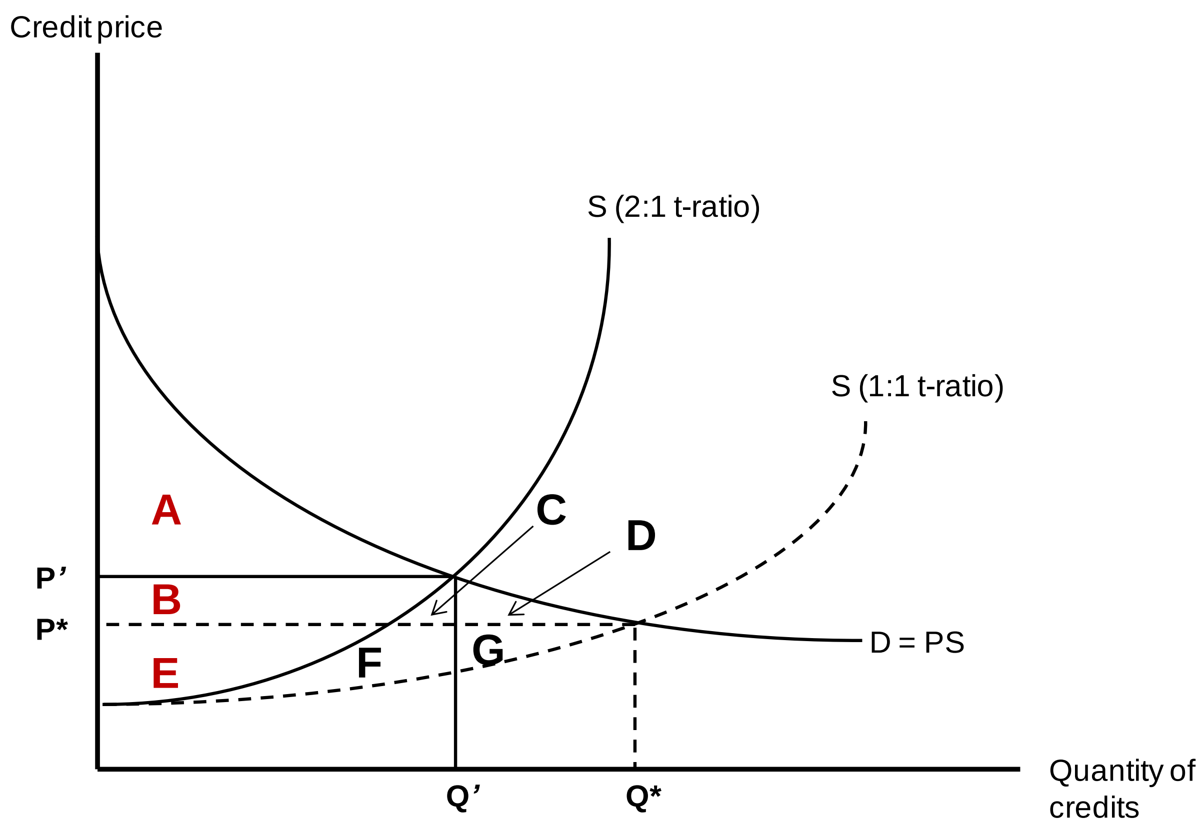


A low information scenario, on the other hand, has the potential to result in different net gains (theoretically, it also has the potential to result in the same net gains). Suppose plant 1 trades with farm 2. The resulting net gain from this transaction is $P_1 - P_2$. Suppose also that plant 3 trades with farm 4 for a net gain of $P_3 - P_4$. The combined net gain from this sequence of trading is $(P_1 - P_2)+(P_3 - P_4) = (P_1 - P_4) - (P_2 - P_3)$. So, assuming that all other traders are paired the same as the complete information scenario, this "ill-ordering" of trades would reduce the overall market gains by $P_2 - P_3$. This suggests that lower information is likely to increase trading volume while reducing the total gains from trading. However, whether point sources or nonpoint sources gain or lose from less information depends on the order of trading that is realized and cannot be unambiguously predicted.

Trading ratios

Figure 4.3 displays the impact of imposing a trading ratio on an otherwise frictionless market. As explained above, maximum efficiency is achieved by a 1:1 trading ratio. Imposing a 2:1 trading ratio affects the nonpoint sources or the suppliers in the market. They must reduce nutrient loading by two pounds in order to receive one tradable credit. This essentially doubles the price of all credits sold, resulting in the steeper supply curve shown in Figure 4.3.

Figure 4.3 Effects of a trading ratio



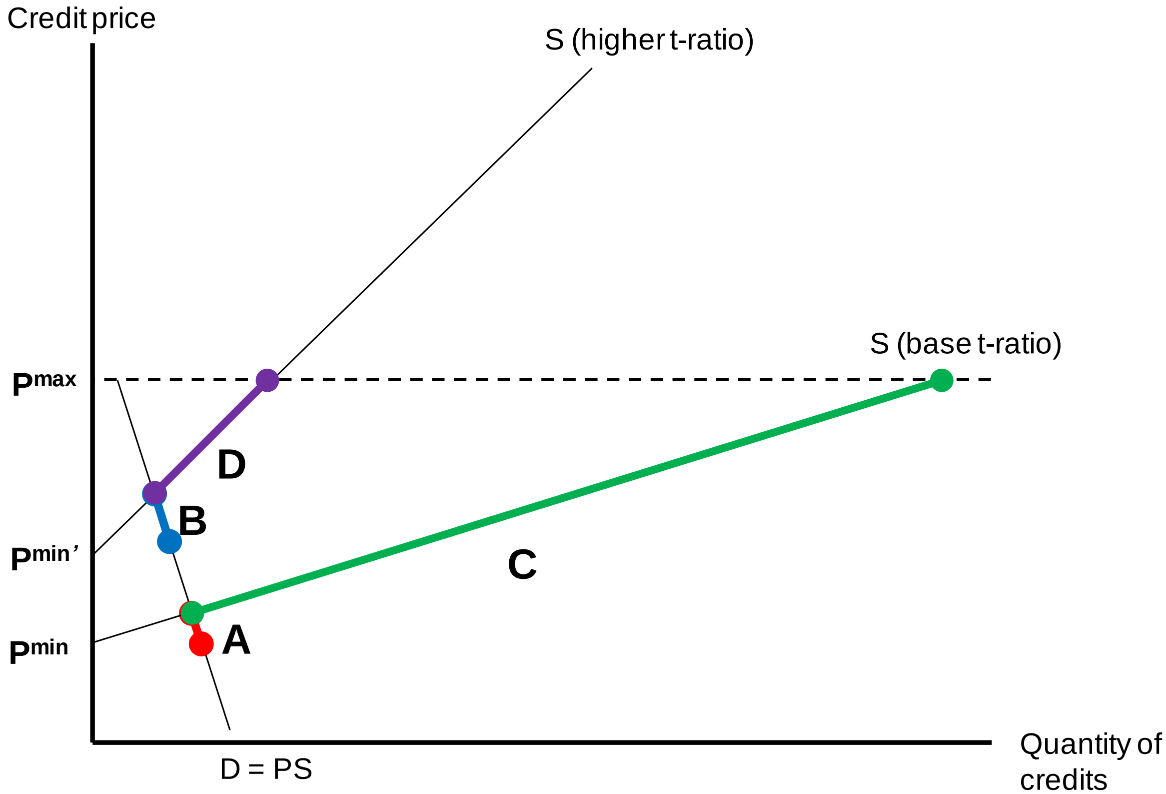
The quantity of credits traded reduces to Q' and the equilibrium price of credits increases to P'. The gains to point sources with the 2:1 trading ratio is area *A*, compared to area *A*+*B*+*C*+*D* in the efficient market. Thus, raising the trading ratio to 2:1 induces a loss to point sources of area *B*+*C*+*D*. The gains to nonpoint sources with a 2:1 trading ratio is area *B*+*E*, compared to area *E*+*F*+*G* in the efficient market. Thus, the net effect of the 2:1 trading ratio to the nonpoint sources is equal to *B*–*F*–*G*. If *B* is bigger than *F*+*G*, then the nonpoint sources benefit from the higher trading ratio. The change in total cost savings from the higher trading ratio is equal to a loss of area *C*+*D*+*F*+*G*.

Unlike the frictionless market, expected loading in this case does respond to changes in the volume of credit trades. Because nonpoint traders must reduce loading by 2 lbs for every 1 pound emitted by point source traders, there will be a net reduction of 1 pound of expected loading for each trade. For the equilibrium depicted in the diagram, point sources increase their expected loading by Q' pounds, while nonpoint sources reduce expected loading by $2Q'$ pounds. This implies a net reduction in expected loading equal to Q' pounds.

Co-effects of information levels and trading ratios

The last type of market imperfection covered in this section of the thesis are the co-effects of trading ratios with low information levels. The combined effects of these two imperfections are illustrated in Figure 4.4. Note, that linear supply and demand curves are used here for clarity.

Figure 4.4 Co-effects of trading ratio and information



First, assume a supply curve under some "base" trading ratio (e.g., 1:1). Next, consider a higher trading ratio case (e.g., 3:1), which as seen before results in an upward shift and pivot of the supply curve. Focusing on the demand side, one can see that the highest price a point source is willing to pay for a credit is equal to P^{max}, which is located at the top of the demand curve. Similarly, the lowest willingness to accept prices are represented where the nonpoint sources' supply curves (under each trading ratio) cross the y-axis and are equal to P^{min} and $P^{min\prime}$.

In previous discussion of information levels, it was found that whenever market participants located to the right of where demand and supply cross trade a less than efficient outcome results. Under a zero information case, these participants, which will be referred to as “poor” traders (high cost sellers and low cost buyers) because they result in “poor” market performance, can and will participate in the market.

Highlighted segments *A*, *B*, *C*, and *D* in Figure 4.4 illustrate the segments of demand and supply that fall to the right of equilibrium. Under the base trading ratio, the potential “poor” traders are equal to line segment *A* on the demand side and segment *C* on the supply side. In the case of a higher trading ratio, the amount of “poor” traders is represented by segment *B* on the demand side and *D* on the supply side. To determine the effects of a higher trading ratio under zero information, these segments must be compared across trading ratio levels.

When segments A and B on the demand side are compared, there is a slight increase. This means that the potential for “poor” point sources to trade in the market increases. On the other hand, when C is compared to D on the supply side, there is a significant decrease, which indicates that the potential for “poor” nonpoint sources trading decreases significantly. Overall, this indicates that increasing the trading ratio can actually improve market efficiency (“ill-ordered” trades decrease) when there is a scarcity of information in the marketplace.

Conceptual model summary

The main predictions of theory are that the lack of information increases the quantity of credits traded and reduces overall cost savings. The trading ratio will also reduce overall cost savings but will reduce the quantity of credits traded. However, several relationships cannot be resolved from theory alone, nor can the magnitude of any of the impacts be assessed. These items will be addressed in the empirical simulation analysis in the following sections.

Simulation Model

An agent-based model (ABM) is created to simulate a hypothetical point-nonpoint source market. ABM's have increasingly been used to study micro-level decisions and the resulting cascade of impacts within complex systems (Tesfatsion, 2006). This simulation is one in which all point sources (hereafter, we also refer to point sources as "plants") are required to meet a lower limit of nutrient concentrations in their discharge stream. Plants can either upgrade their technology to meet this limit, or keep their old technology and buy water quality credits from nonpoint sources (hereafter, also called "farms") to offset their excess discharges. Such a regulatory driver is necessary for the market to function. Farms who sell credits are then obligated to adopt land management practices to reduce expected loadings.

The model relies on pre-specified values of the willingness-to-pay (WTP) for purchasing credits by each plant and the willingness-to-accept (WTA) for selling credits by each farm who is a potential trader. A sequential, bilateral trading algorithm (Atkinson and Tietenberg, 1991) then simulates market outcomes from these base data. As described in the subsections below, the impact of information levels and trading ratios are captured either by varying the input data or by altering the assumptions in the trading algorithm that govern how buyers and sellers are paired together.

ABMs require specification of two types of computational objects: the "agents" themselves and the "environment" in which they operate (Parker et al., 2002).

Agents

The agents in this model are point- and nonpoint-sources of a water contaminant (e.g., nutrients). To create model agents, costs and quantities are generated for each of I = 10 point sources and J = 500 nonpoint sources using random draws from independent lognormal distributions. The lognormal distribution is chosen to allow for the well-documented skewness in the distribution of costs and environmental impacts across the population of polluters (Nowak, et al., 2006). The parameter values of the lognormal distributions for both buyers and sellers are shown in Table 4.1. The distributional parameters and the population sizes are chosen to approximately reflect the data used by Smith (2004) to model phosphorus trading in the Middle Kansas River subwatershed. To ensure that the final results are not sensitive to a particular set of random draws, all scenarios are repeated 10,000 times in Monte Carlo fashion, with a new set of prices and quantities assigned to all agents each time. The results reported are the means of the 10,000 iterations.

Table 4.1 Lognormal distribution parameters for buyers and sellers

Item	Mean	Standard deviation
Buyer quantities (lbs)	5,000	1,250
Buyer WTP ($/lbs)	20	15
Seller quantities (lbs)	200	50
Seller WTA ($/lbs)	12	8

Environment

The “environment” is the trading mechanism that determines how buyers and sellers are paired together in the water quality trading market.

The marginal gains matrix and the trading ratio

In each replication of the model, the WTP and WTA data were randomly generated from the distributions presented in Table 4.1. These data are used to form the core element of the simulation model, the marginal gains matrix. This matrix contains the potential gains from each possible pairing of the farms and plants. The rows of this matrix correspond to plants while its columns correspond to farms. In scenario s, the cell in row i and column j of this matrix is

$$MarGains_{s,i,j} = WTP_{s,i} - t_s WTA_{s,j}$$

where t_s is the assumed trading ratio in scenario s (expressed as the number of credits a farm must sell to offset one unit of plant discharge) and $MarGains$ is the mutual gain if plant i buys one more credit from farm j under the assumptions embedded in scenario s.

A related matrix Q, has the same dimensions and tracks the quantity of credits available for trade between each trading partner. The quantity data are also generated from the distributions in Table 4.1. At the start of trading the (i,j)th element of Q is equal to Q_{ij} = min(q_i, q_j), where q_i and q_j are the randomly generated quantity of credits demanded by plant *i* and quantity of credits to be supplied by farm *j*, respectively. As trading proceeds the values in this matrix are reduced by the quantity transacted by the respective trading partners. A trader is removed from the market when its available quantity reached zero.

The trading algorithm and information levels

The effect of marketplace information is captured by varying the assumptions in the sequential, bilateral trading algorithm that pairs buyers and sellers together in a specific order. Four possible information scenarios are modeled, which are described in turn below.

Complete information or marginal-gains-ranked trading

This scenario assumes that every point source and every nonpoint source in the watershed knows precisely all the WTP and WTA values of all traders. In this situation, the most advantageous trades are executed first. Action begins by the plant with the highest WTP trading with the farm having the lowest WTA. This is determined by the element in the marginal gains matrix with the greatest positive value.

The point source purchases as many credits as it needed or until it buys out the nonpoint source, whichever occurs first. The quantity data and the marginal gains matrix are both updated accordingly when the trade is completed.

The second trade begins by finding the greatest positive number in the updated marginal gains matrix. This determines the next two trading partners. The aforementioned process is then repeated. This marginal gains-ranked process continues until there are no more gains to be made by trading.

Zero information trading

The second scenario presumes zero information, in which none of the traders know their own or anyone else's WTP/WTA. Therefore, the trades occur in a completely random order. The single restriction is that only trades resulting in positive gains are allowable. A single element from the marginal gains matrix is chosen at random and this determines the trading partners. The trade is then made and the marginal gains matrix and quantity data are updated. Subsequent trades operate in the same random fashion. Trading continues until no positive gains remain.

Incomplete information trading: WTP Known

The third scenario models the case where the plants' WTP values are known to all traders, but farms' WTA values are unknown. This depicts a situation in which the point sources drive the market. The first trade is between plant with the highest WTP and a randomly selected farm. Plants in remaining trades are selected in descending order of their WTP, paired with a randomly chosen farm each time. Trading data are updated using the same process as the other scenarios.

Incomplete information trading: WTA Known

The fourth scenario is similar to the third but reverses the roles of the plants and farms. Here, the plants' WTP values are unknown, but farms' WTA are common knowledge, implying that farms choices will drive the market. Farms enter the market in ascending order of their WTA, and are paired with randomly chosen plants, following the same previously described updating rules between trades.

The simulation experiments

Table 4.2 lists the assumptions for each of the 24 simulation experiments conducted. Scenarios 1a through 1f assume that all market participants have perfect, complete information regarding others' WTP and WTA values. On the other hand, scenarios 2a through 2f assume that there is zero information known regarding these values. A comparison of scenario sets 1 and 2 will reveal the effect of complete information on market performance. If market performance changes significantly between these two cases, scenarios 3(a through f) and 4(a through f) will illuminate the separate effects of marketplace information on WTP or WTA under the partial information scenarios.

Table 4.2 The simulation experiments

Scenario	Trading Ratio	Information Level
1a	0.5:1	Complete
1b	1:1	Complete
1c	1.5:1	Complete
1d	2:1	Complete
1e	2.5:1	Complete
1f	3:1	Complete
2a	0.5:1	Zero
2b	1:1	Zero
2c	1.5:1	Zero
2d	2:1	Zero
2e	2.5:1	Zero
2f	3:1	Zero
3a	0.5:1	WTP Known
3b	1:1	WTP Known
3c	1.5:1	WTP Known
3d	2:1	WTP Known
3e	2.5:1	WTP Known
3f	3:1	WTP Known
4a	0.5:1	WTA Known
4b	1:1	WTA Known
4c	1.5:1	WTA Known
4d	2:1	WTA Known
4e	2.5:1	WTA Known
4f	3:1	WTA Known

Various levels of the trading ratio also are used. The trading ratio varies from a low of 0.5:1 in the "a" scenarios up to 3:1 in "f" scenarios. The increment between the ratios is 0.5.

Before presenting the simulation results for each scenario, two matters of interpretation should be noted. First, in evaluating the performance of the WQT market, comparisons are made to a baseline situation in which treatment plants would be required to meet the nutrient reduction limit by upgrading technology. Based on the information about the plants' expected costs and quantities in Table 4.1, the limits would require the plants to reduce their annual nutrient load by a combined (expected value of) 10 plants × 5,000 lbs/plant = 50,000 lbs annually. The expected total annual cost of these technology upgrades would be \$20/pound × 50,000 lbs = \$1.0 million. These two values form a baseline for comparing market outcomes. As trades occur in a WQT market, the same loading reduction is achieved but an increasing share of loading reduction is obtained from farms instead of treatment plants. Trading also will reduce the overall cost of achieving the target. Therefore, cost savings can be expressed both in dollar terms and as a percentage of the baseline costs. Likewise, trading volume can be expressed as the number of credits traded (measured in the pounds of loading reduction borne by farms) or as a percentage of the loading reduction target.

Second, the gains from trading are equivalent to the cost savings to *society* from trading. A portion of these cost savings would be a gain to the point sources, to the extent that their credit purchases are less costly than the technology upgrades would have been. The remaining portion would be a benefit to farms, to the extent that credit revenue is larger than their costs of adopting land management practices. However, these simulations make no attempt to partition the total cost savings into the benefits to the two groups. The relative sizes of the gains would depend on the actual credit prices, which would vary across transactions and would depend on the relative negotiating power of the two groups. Lacking any reliable means to estimate the relative bargaining power and contract prices, estimates of the gains to the two groups could only be obtained by making arbitrary assumptions.

Simulation Results

Table 4.3 summarizes the results of the scenarios resulting from the first 50 trades. While all of the scenarios ultimately resulted in more than 50 trades (ranged from 120-300 trades depending on the scenario), real-world evidence has shown that most programs result in very few transactions. Based on this, it was decided to primarily focus on the first 50 trades to provide a more realistic analysis setting. This offers one base of comparison, which would apply if trading is limited. Appendix C displays the scenario results when all possible trades are completed.

Table 4.3 Simulation results

		Volume Traded				Cost Savings		Final Costs	
Scenario	**Trading Ratio**	**Base Loading Reduction by NPS (lbs)**	**Loading Reduction by PS (lbs)**	**Additional Loading Reduction by NPS (lbs)**	**Total Loading Reduction (lbs)**	**Total ($)**	**Percent (%)**	**Total ($)**	**Avg. ($/lb)**
1a	0.5	9,133	31,735	-	40,867	412,685	41.3	587,315	14.37
1b	1.0	9,476	40,524	-	50,000	228,499	22.8	771,501	15.43
1c	1.5	6,351	43,649	3,175	53,175	147,751	14.8	852,249	16.03
1d	2.0	4,816	45,184	4,816	54,816	106,804	10.7	893,196	16.29
1e	2.5	3,888	46,112	5,832	55,832	76,717	7.7	923,283	16.54
1f	3.0	3,239	46,761	6,479	56,479	56,569	5.7	943,431	16.70
2a	0.5	9,139	31,722	-	40,861	226,862	22.7	773,138	18.92
2b	1.0	9,492	40,508	-	50,000	85,333	8.5	914,667	18.29
2c	1.5	6,368	43,632	3,184	53,184	50,567	5.1	949,433	17.85
2d	2.0	4,822	45,178	4,822	54,822	37,452	3.7	962,548	17.56
2e	2.5	3,887	46,113	5,831	55,831	29,546	3.0	970,454	17.38
2f	3.0	3,240	46,760	6,480	56,480	24,331	2.4	975,669	17.27
3a	0.5	9,134	31,733	-	40,866	363,109	36.3	636,891	15.58
3b	1.0	9,476	40,524	-	50,000	177,677	17.8	822,323	16.45
3c	1.5	6,354	43,646	3,177	53,177	101,392	10.1	898,608	16.90
3d	2.0	4,820	45,180	4,820	54,820	66,671	6.7	933,329	17.03
3e	2.5	3,888	46,112	5,832	55,832	43,917	4.4	956,083	17.12
3f	3.0	3,240	46,760	6,480	56,480	31,088	3.1	968,912	17.16
4a	0.5	9,134	31,733	-	40,866	275,477	27.5	724,523	17.73
4b	1.0	9,476	40,524	-	50,000	117,971	11.8	882,029	17.64
4c	1.5	6,351	43,649	3,175	53,175	68,249	6.8	931,751	17.52
4d	2.0	4,816	45,184	4,816	54,816	49,469	4.9	950,531	17.34
4e	2.5	3,888	46,112	5,832	55,832	42,166	4.2	957,834	17.16
4f	3.0	3,240	46,760	6,479	56,479	38,569	3.9	961,431	17.02

NPS = nonpoint source

PS = point source

The first and second columns of Table 4.3 serves as a cross reference for the scenario inputs and assumptions listed in Table 4.2. The third through sixth columns report trading volume; loading reductions by type and source.

The next two columns report the cost savings, in total dollars and as a percentage of the baseline total costs ($1 million). Simulated cost savings varied widely, ranging from about $24,000 to $413,000 or from about 2.4% to 41.3% of baseline costs. Again, the potential cost savings varied substantially under the various simulated market structures.

The last two columns report the final (post-trading) costs. Due to the different trading ratios, some of the scenarios exactly achieved the loading reduction target while others were either below or above the target level. The next-to-last column was computed simply as the baseline (pre-trading) costs less the cost savings from trading (e.g., in scenario 1a, $1,000,000 - $412,685 = $587,315), while the last column expresses the final cost in average terms – i.e., costs per unit of loading reduction achieved (in scenario 1a, $587,315/40,867 lbs = $14.37/lb of loading reduction). The last column provides a useful comparison of the cost-effectiveness across scenarios. With no trading, the cost per unit of loading reduction is $1,000,000/50,000 lbs = $20.00/lb. With trading, this cost ranged from $14.37/lb to $18.92/lb, so as expected, trading will reduce per-unit control costs.

Information levels

The effect of marketplace information on overall cost savings is unambiguously positive. This can be illustrated by comparing scenario 1a (complete information), which resulted in net cost savings of $412,685 to scenario 2a (zero information), which resulted in savings of only $226,862. This relationship between complete and zero information held for every scenario modeled regardless of trading ratios. These results were expected and are similar to the findings of Atkinson and Tietenberg (1991). Intuitively, lower information reduces cost savings because it creates some risk that “high cost” sellers – those with high WTA values – will displace some low cost sellers that could have traded for a larger gain. Similarly, the “low paying” buyers with low WTP values, may displace some of the higher paying buyers. The market transactions that maximize cost savings would include the low cost sellers paired with the high cost buyers, but in the limiting case of zero information, all buyers and sellers are equally likely to participate.

When the gains per trade are depicted graphically, the effects of information levels on market performance become more pronounced. Table 4.5 illustrates the gains per trade under different information levels with a 1:1 trading ratio assuming all trades are completed. Scenario 1b ends at $497,161 of total gains. This level of gains is reached after 227 trades have been completed. Scenario 2b, on the other hand, reaches a maximum of $392,259, but does so after 255 trades; an additional 28 trades. Scenario 1b could have ceased after 118 trades and more gains would have been realized ($393,724) than the total for scenario 2b. If trading were halted after 118 trades in scenario 2b, only $188,623 (48% of its final value) of gains would have been realized.

Figure 4.5 Effects of marketplace information on cost savings with a 1:1 trading ratio

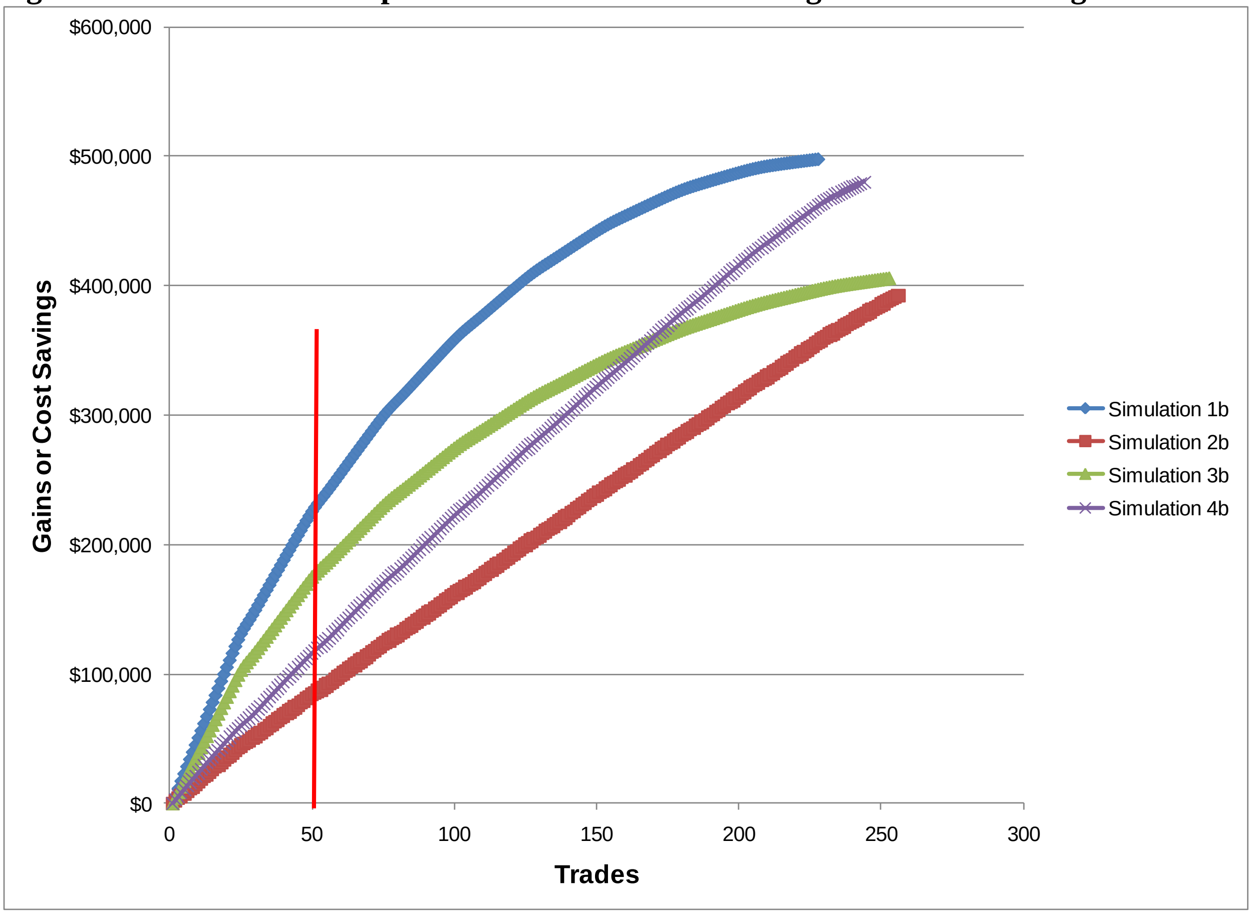
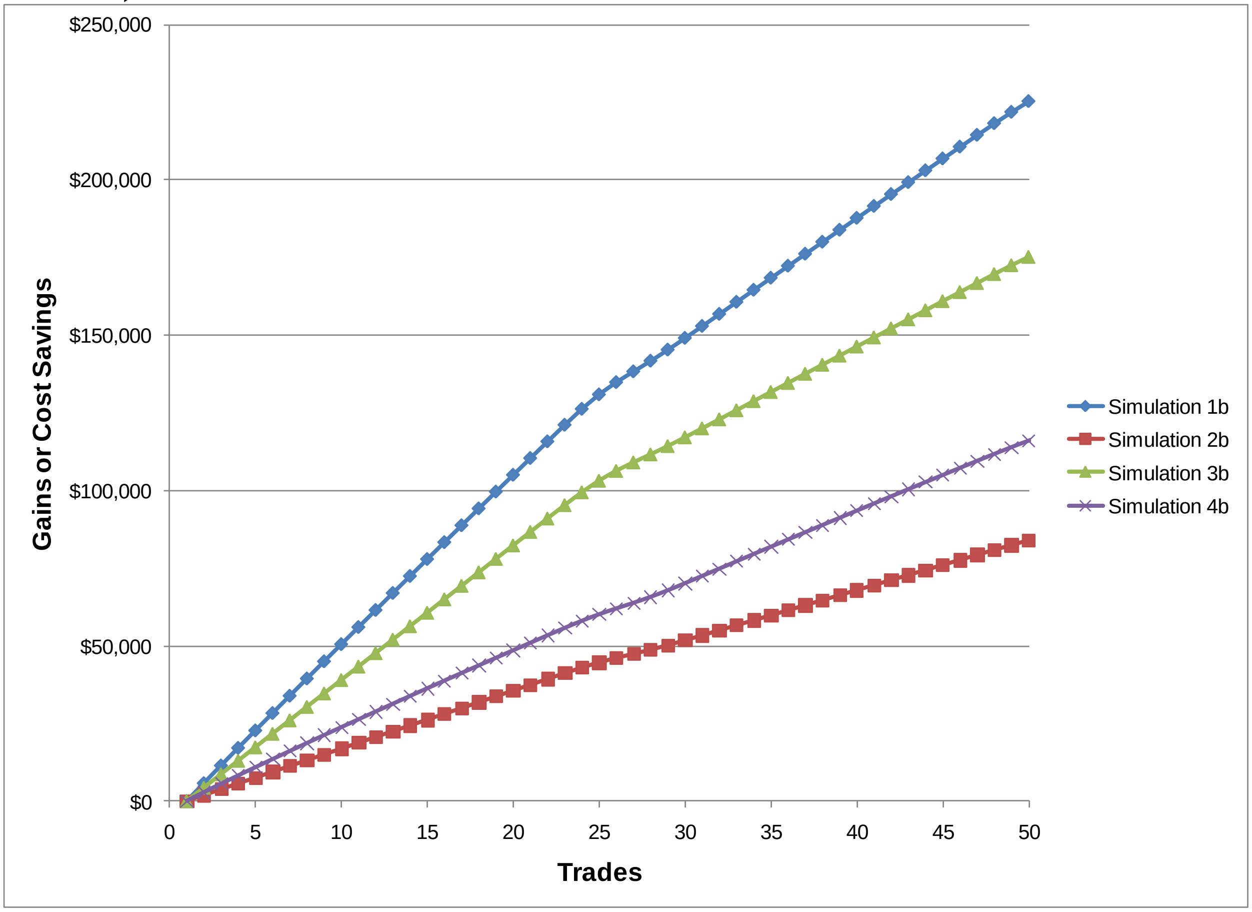


Figure 4.5 also reveals the effects of different types of incomplete information. When traders are informed of buyers' prices (WTP Known - scenario 3b), the cumulative cost savings curve behaves very similarly to the complete information case (scenario 1b) across the early trades while scenario 4 (WTA Known) behaves similarly to the zero information case. Scenario 3b results in more cost savings than scenario 4b across the first 65% of trades. Analyzing only the first 50 trades (Figure 4.6), shows the importance of information regarding buyers' prices relative to sellers' prices when only a limited number of trades occur. These results imply that if market designers feel that only a limited number of trades will be completed, creating an institution that provides accessible information about buyers' prices (3b) is preferred to providing information about sellers' prices (4b). Of course, this still depends on other factors such as the cost of providing this information to market participants.

Figure 4.6 Effects of marketplace information on cost savings with a 1:1 trading ratio (first 50 trades)

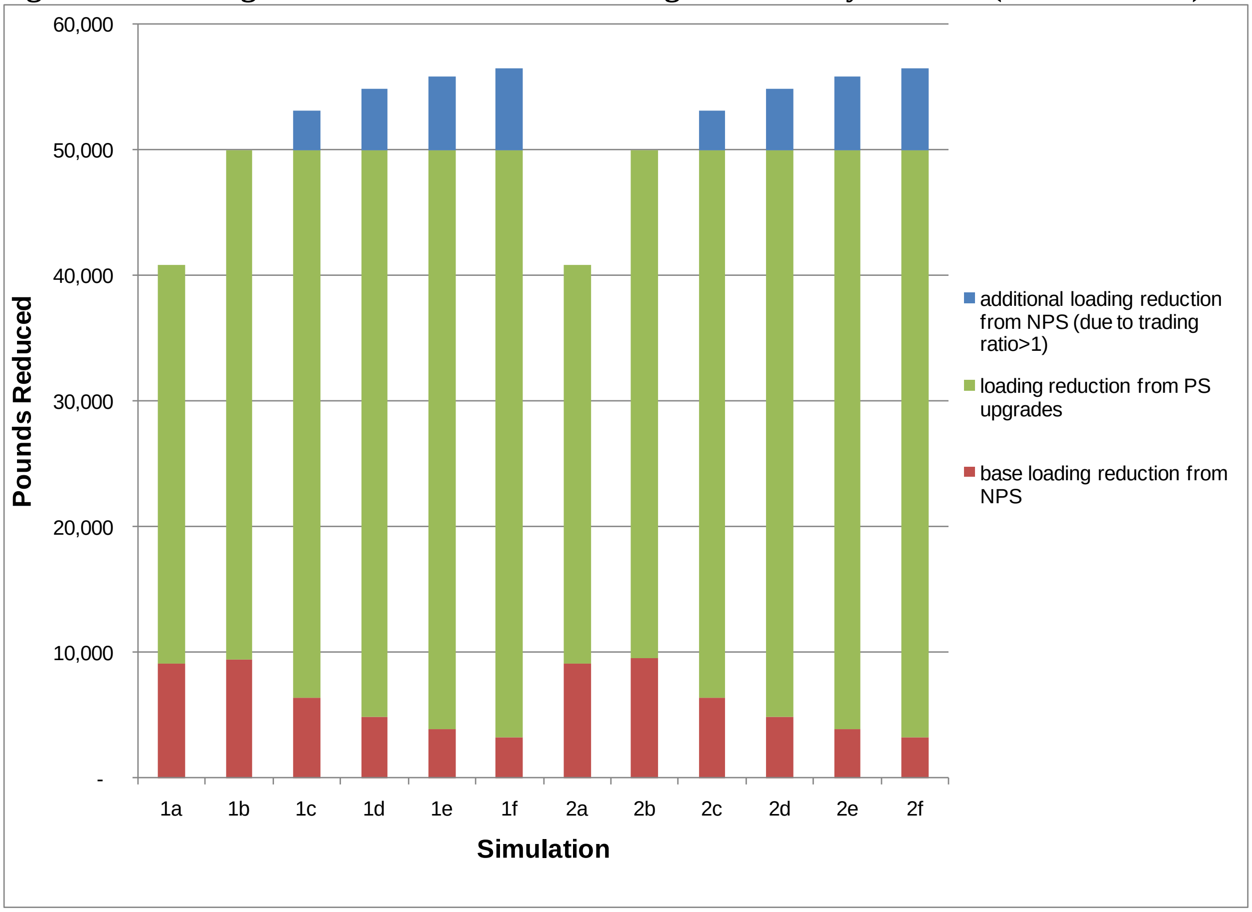


Trading ratio

As expected, there is a negative relationship between the trading ratio and potential gains from trading. Focusing on the “1” scenarios, the cost savings decrease from over $412,000 to $56,000 as the trading ratio increases from 0.5:1 to 3:1. But, this can be somewhat misleading because each of these scenarios results in a different amount of nutrient loading reduction. In the case of a 0.5:1 trading ratio, the nutrient reduction target of 50,000 lbs is not met. And in the case of a 3:1 trading ratio (scenario 1f), there are an additional 6,479 lbs of nutrient reduction beyond the target.

As stated earlier, the purpose of a trading ratio greater than one is to account for nutrient reduction uncertainty and ensure that there is an overall increase in water quality (beyond that which would occur in the absence of WQT and reliance on only technology upgrades). According to the simulation results, this is generally the case. Figure 4.7 illustrates the trading volume and net environmental gains in the different scenarios. The height of the red bars represents the amount of loading reduction transferred from point sources to nonpoint sources through trading. The green bars represent the amount of loading reduction achieved from necessary upgrading of wastewater treatment plants. In cases of a trading ratio greater than 1:1 (i.e., scenarios 1c through 1f and 2c through 2f), there are additional loading reductions achieved beyond the target, represented by the height of the blue bars. With a 2:1 trading ratio for example, each unit of increased plant loadings is offset by a two pound reduction in expected loading by farms, resulting in net environmental gains. Scenario 1d results in 4,816 credits traded. Because of the 2:1 trading ratio, nonpoint sources reduce expected loading by a total of 9,632 lbs (2*4,816), so combining this with the 45,184 lbs of reduction achieved from wastewater treatment plant upgrades the total expected loading reduction amounts to 54,816 lbs. So, the introduction of a trading ratio greater than 1:1 results in an environmental improvement – the 50,000 lbs loading reduction target is exceeded by 4,816 lbs.

Figure 4.7 Trading volume and additional loading reduction by scenario (first 50 trades)



Because of reasons stated earlier, the most useful metric for evaluation and comparison across scenarios may be the average cost of nutrient reductions. The effect of the trading ratio on cost-effectiveness is not independent of the information levels. This is demonstrated graphically by comparing Figure 4.8 and Figure 4.9. Under complete information, an increase in the trading ratio raises average costs throughout the period of trading (Figure 4.8). Increasing the trading ratio from 1:1 to 2:1 (Scenarios 1b and 1d) increases final average costs from \$15.43 to \$16.29, an increase of 5.6%. Increasing the ratio from 1:1 to 3:1 increases final average costs by 8.2%. Further, with complete information, reducing the trading ratio from 1:1 to 0.5:1 results in an increase in final average costs.

Figure 4.8 Effects of a trading ratio under complete information

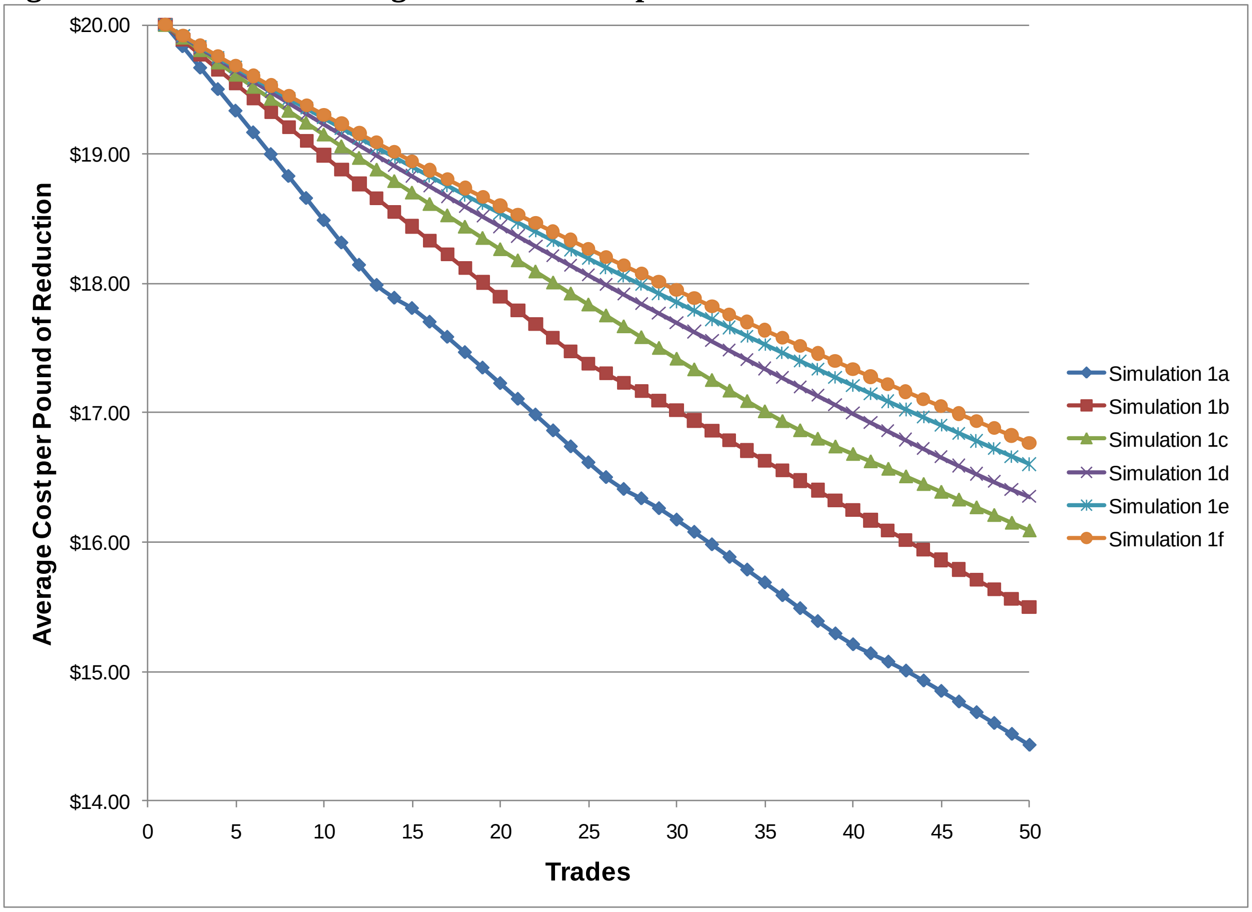
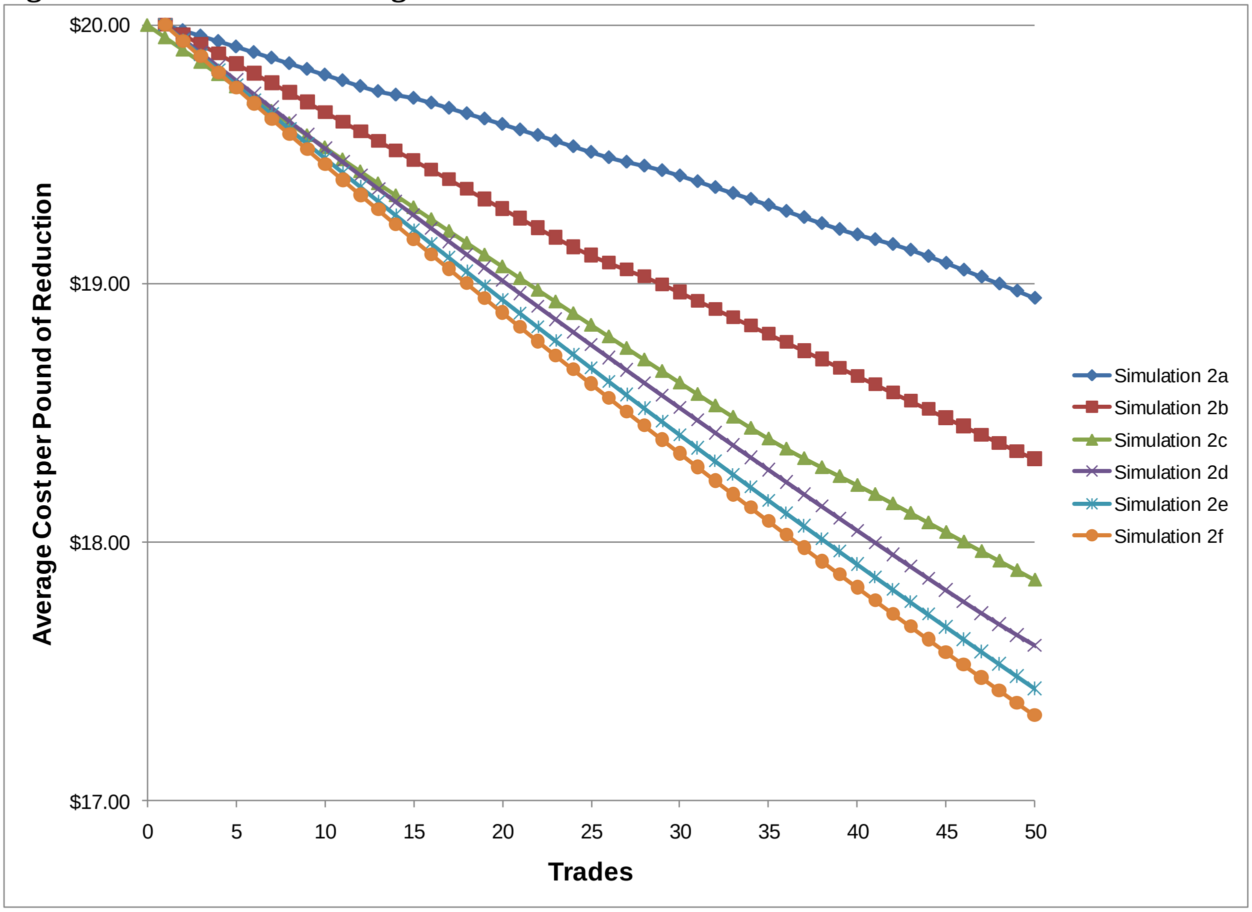


Figure 4.9 Effects of a trading ratio under zero information



The results are different for zero information. Here, the 0.5:1 trading ratio (Scenario 2a) is the least cost-effective (highest average costs) across the first 50 trades (Figure 4.9). Under zero information, we find that the trading ratio has an unambiguously positive effect on cost-effectiveness. One reason this occurs is that high trading ratios help to eliminate the highest-cost sellers by pricing them out of the market. As noted above, zero information creates a risk that high-cost sellers make transactions that displace their low-cost peers. However, this occurs only to the extent that high-cost sellers can find buyers with high enough WTP to generate gainful transactions. An increase in the trading ratio can be interpreted as a proportional increase in each sellers' effective WTA (e.g., a 2:1 trading ratio doubles each sellers' WTA). As such, the sellers with initial WTA's near the maximum WTP will not be able to find a gainful trading partner if the trading ratio is increased.

Co-effects of information levels and trading ratios

Table 4.4 shows the effects of information levels on cost-effectiveness across different trading ratios. Specifically, scenarios 1(a through f) with complete information are compared to scenarios 2(a through f) with zero information. The results show that as the trading ratio increases information levels become less important. At extremely high trading ratios, the difference in average cost-effectiveness between complete- and zero-information approaches zero. It is important to note, however, that this difference will never become positive. In other words, more information is always preferred to less information but it becomes less important as the trading ratio increases.

Table 4.4 Effects of information levels on cost-effectiveness across different trading ratios

Scenarios for Comparison	Trading Ratio	Difference in Average Cost-Effectiveness ($/lb)	More Cost-Effective Scenario?	Conclusions
1a & 2a	0.5:1	-4.55	Complete (1a)	As trading ratio increases, information becomes less important.
1b & 2b	1:1	-2.86	Complete (1b)	
1c & 2c	1.5:1	-1.82	Complete (1c)	
1d & 2d	2:1	-1.26	Complete (1d)	
1e & 2e	2.5:1	-0.85	Complete (1e)	
1f & 2f	3:1	-0.57	Complete (1f)	

Based on these results, the determination of an "optimal" trading ratio should necessarily depend on the amount of information available to market participants. The next section discusses points to consider in the characterization of an "optimal" trading ratio.

Characteristics of an "optimal" trading ratio

Since real-world WQT markets most likely operate somewhere in between complete and zero information, a "partial" information scenario, where there is some information known about both WTP and WTA values, may be more realistic. If the partial information scenario is defined as halfway in between complete and zero information, then averages can be calculated across appropriate scenarios' output data. For example, the output from scenario 1b (complete information, 1:1 trading ratio) and scenario 2b (zero information, 1:1 trading ratio) can be averaged. The averaged data are reported in Table 4.5.

In the process of designing existing programs, potential traders often emphasize cost-effectiveness while environmental groups tend to focus on expected loadings. A possible test of political feasibility is to compare the scenarios based on these two criteria. Based on the information in Table 4.5, the poorest performing scenarios appear to be the cases where there are extremely low or high trading ratios. The "a" (0.5:1 trading ratio) scenario have the lowest average costs of all scenarios at $16.65/lb of reduction. Most importantly, however, is the fact that the "a" scenario result in only 40,864 lbs of loading reduction - 9,136 lbs short of the goal. This is the only scenario that fails to meet the goal of 50,000 lbs of loading reduction. For this reason, the 0.5:1 trading ratio would not be a politically or socially acceptable.

Table 4.5 Partial information scenarios

Scenario	Trading Ratio	Volume Traded: Base Loading Reduction by NPS (lbs)	Volume Traded: Loading Reduction by PS (lbs)	Volume Traded: Additional Loading Reduction by NPS (lbs)	Total Loading Reduction (lbs)	Cost Savings: Total ($)	Cost Savings: Percent (%)	Final Costs: Total ($)	Final Costs: Avg. ($/lb)
a	0.5	9,136	31,728	-	40,864	319,774	32.0	680,226	16.65
b	1.0	9,484	40,516	-	50,000	156,916	15.7	843,084	16.86
c	1.5	6,359	43,641	3,180	53,180	99,159	9.9	900,841	16.94
d	2.0	4,819	45,181	4,819	54,819	72,128	7.2	927,872	16.93
e	2.5	3,888	46,112	5,831	55,831	53,132	5.3	946,868	16.96
f	3.0	3,240	46,760	6,479	56,479	40,450	4.0	959,550	16.99

Disregarding scenario “a”, scenario “b” (1:1 ratio) results in the greatest amount of cost savings (16%) and the lowest average costs at $16.86/lb. However, there is no additional loading reduction achieved beyond the 50,000 lbs target.

The “f” scenario (3:1 trading ratio) exhibits the highest average costs of nutrient reduction at $16.99/lb. The overall cost savings of 4% are minimal. On the positive side, however, is the fact that this scenario does result in 6,479 lbs of additional loading reduction.

It is difficult to definitively rank scenarios b through f as the ordering would be dependent upon normative judgments about the relative weighting of the criteria. There are, however, several definite implications for an “optimal” trading ratio.

If overall information availability is a concern or if the goal is to maximize total loading reduction a higher trading ratio (e.g., 3:1) is recommended. On the other hand, if it is presumed that information will be readily disseminated and understood by market participants, a lower trading ratio may be more economical. The cost of disseminating information to market participants needs to be considered during the decision-making process. If the goal is to simply maximize cost savings while achieving the reduction goal, a 1:1 trading ratio shows the greatest potential. However, if WQT market designers hope to gain additional loading reduction while maintaining high levels of cost savings a 1.5:1 trading ratio may be most appropriate. If overall average cost-effectiveness or additional nutrient reductions is of importance and buyer and seller information is scarce, a higher trading ratio may be in order.

Simulation of real-world WQT markets

While the model developed here utilized constructed data, there is no reason why these same market simulation algorithms could not simulate markets from observed data in particular locations. Because WQT programs, by nature, involve complex interactions between economics and the biophysical world, accurately simulating a WQT market requires detailed cost and watershed modeling data.

There are two types of cost data needed. On the point source side, facility upgrade costs and annual operation maintenance costs of meeting a more stringent nutrient standard are needed for wastewater treatment plants in the study watershed. These data either can be attained from surveys or by using general industry cost functions (e.g., Greenhalgh and Sauer, 2003). In either case, the one-time and annual costs along with the appropriate time horizon should be used to calculate the annualized costs, which considers the time value of money by including a discount rate.

For nonpoint sources, the expected costs for BMPs are needed. These costs can come from surveys or from previous research. University Extension fact sheets can often times provide general estimates for this type of data (e.g., Devlin et al., 2003). One-time and annual costs should be converted to an annualized basis in analogous fashion to the point source data.

Further, traders may perceive “intangible” costs that are weighed against any potential gains. That is, the assumption that only monetary trading gains enter traders’ utility functions may not hold. A growing literature documents that the behavior of participants in an institution is influenced by institutional processes and rules, independent of the participants' fiscal outcomes (Berg, et al., 2005; Johnston and Duke, 2007). Obtaining the information necessary to estimate intangible costs that may exist is crucial for simulating a real-world WQT market. Since these data are subjective by nature, it only can be obtained accurately through interaction with potential market participants via experiments, interviews, or surveys.

Along with the economic data, biophysical watershed data are needed. Watershed models play a central role in the simulation and execution of real-world WQT markets. Watershed models represent a scientific understanding of how land characteristics, BMPs, and other factors relate to pollutant loading into surface waterbodies (Nejadhashemi et al., 2009). There are many types of models ranging from very simple to very advanced (see Nejadhashemi et al., 2009 for guidance in choosing a model). Regardless of the type of model used, the minimum output from the model should be: the baseline nutrient loading from each subwatershed, reduction in loading from each subwatershed after a given BMP(s) is implemented, and relevant delivery ratios.

Combining all of this information will allow the researcher to generate the necessary WTP and WTA curves discussed previously in this paper. The procedures laid out in this paper should be followed to simulate sequential, bilateral trading in the real-world watershed.

Conclusion

While there is substantial evidence that nonpoint sources have lower nutrient reduction costs than point sources, experience with WQT reveals a common theme: little or no trading activity. The success of WQT seems, in part, to depend on the structure of the market created to bring buyers and sellers together to transact exchanges. These outcomes suggest the presence of obstacles to trading that were not recognized in the design of existing programs.

While the complete information scenario serves as a useful benchmark, most existing WQT markets are decentralized in nature, so that limited information causes traders to be matched in a less efficient sequence. A variety of information levels are possible. One side of the market may have more information than the other (incomplete information) or neither side having any knowledge of the other side's bid or offer prices (zero information). Each of these scenarios leads to a different sequencing of trades.

Several notable results are found regarding information levels. The results imply that if market designers feel that only a limited number of trades will be consummated, creating an institution that provides accessible information about buyers' prices is preferred to providing information about sellers' prices. Overall, more information is always better, but it becomes less important with higher trading ratios.

Trading ratios are a common component of many existing WQT programs. A typical trading ratio of 2:1 requires a nonpoint source to reduce two pounds of expected nutrient loading in order to receive one pound of trading credit. These ratios are purported to serve as a "safety factor" and are incorporated to account for the uncertainty in the measurement and monitoring of nonpoint source loading. Because nonpoint traders must reduce loading by two pounds for every one pound emitted by point source traders, there will be a net reduction of one pound of expected loading for each trade. So, while inhibiting some trades from ever occurring, trading ratios also have the potential to improve water quality beyond trading with a 1:1 trading ratio. This paper examines these tradeoffs in terms of effects on market performance and then describes procedures that can be used to characterize an optimal trading ratio if one exists. Based on the findings of this study, an "optimal" trading ratio should depend on the market designers' goals and the amount of information available and the cost of disseminating this information.

Previous studies (Malik et al, 1993; Horan, 2001; Horan and Shortle, 2005) have shown that under plausible conditions a trading ratio greater than 1:1 is likely to increase the risk of environmental damage because it dampens the incentive for nonpoint sources to trade and results in a greater share of overall loading attributed to (risky) nonpoint sources. This result is at odds with the trading ratios chosen in existing programs, nearly all of which are greater than 1:1. Horan (2001) offers one potential explanation for this discrepancy – certain groups of political stakeholders lobby for higher trading ratios because their goal is to raise overall loading reductions. Here, we find that apart from any implications on environmental risk or political-economic factors, there is an economic welfare justification for high trading ratios in certain situations with limited trading information. Limited information introduces a random element to market participation, creating a risk that high-cost sellers (low-cost buyers) will transact to displace low-cost sellers (high-cost buyers) who could have traded for greater gain. To the extent that high trading ratios price the highest-cost sellers and lowest-cost buyers out of the market, it reduces this risk and lowers average costs.

There are several limitations to this study. One is that these simulations did not consider the risk and variability associated with NPS loading. Mean loading values were used. In the real-world, there will most definitely be some years in which the BMPs put in place by farms will over-perform and significantly reduce nutrient runoff and in other years the BMPs may significantly under-perform. Incorporating this stochastic process into the model would illuminate the effect of environmental risk – which previous research has shown will tend to decrease the welfare-maximizing trading ratio – against the information effects considered in the present study. A stochastic model also would be capable of predicting policy-relevant measures such as the percentage of time nutrient reduction targets would be exceeded and by how much.

Two other important market impediments not addressed in this study are transactions costs and intangible costs. These two factors may play a major role in determining the success or failure of a market for water quality.

Based on the findings of this paper and the previous research that helped to mold this study, there appears to be a need for the comprehensive simulation of a WQT market in a real-world watershed to provide a further examination of potential market impediments. The data requirements for a study such as this would be substantial, but necessary for describing the "true" story that has and continues to be played out in past, current, and future WQT markets.

CHAPTER 5 - Concluding Remarks

Nearly a decade of working in the water resource economics research and extension fields has provided an appreciation for the role that economics can play in the management of our water resources as well as the limitations that exist. The following are a few general observations based on my extension experience and research.

Cost-effective conservation is smart economics and is a way of getting the biggest "bang for the buck," but it may not be the most politically or socially palatable approach. In other words, cost-effective policies may fund conservation practices for one farmer, while a neighbor farmer just down the road receives nothing due to not meeting the cost-effective criteria needed to receive any funding in the way of BMP cost-share or incentive payments. A similar case may occur when a farmer who has already been using a suite of conservation practices funded out of his own pocket gets no additional funding, while his neighbor, whose fields have massive gullies after every rain resulting from years of neglecting terraces and moldboard plowing, receives substantial conservation payments.

What is "right" or "wrong" or "fair" in this situation? Or, to whom should conservation payments be issued? These are most definitely challenging questions and certainly hot topics in conservation policy arenas. First, there is likely not a "Pareto-optimal" approach where everyone is made better off (or at least as well off) and no one is made worse off. Many policies seem to attempt to achieve this result often times at the taxpayers' expense. Secondly, it seems reasonable to assert that, from an economic perspective, conservation payments should only be issued for practices where the vast majority of benefits go to those offsite or downstream. In other words, in cases where the external benefits of the BMP are much greater than those received by the farmers themselves.

As stated in Chapter 2, a BMP such as no-till has been adopted by many farmers on their own without outside compensation. This is most likely due to the increased net returns offered from no-till cropping systems for certain farming operations. For this reason, it is questionable as to whether management practices like no-till should be funded through conservation programs. If it makes economic sense to the farmer to adopt no-till, he will adopt. If it doesn't make economic sense, he will not adopt. It is a debatable point as to whether or not a relatively small per acre incentive payment for three years (i.e., EQIP) is going to be enough to convince a farmer to change their entire cropping management strategy. It is economically reasonable to presume that any farmer who has in the past received conservation funding for converting to no-till would have converted to no-till on their own without any outside compensation or returned to their conventional farming methods at the conclusion of the allotted time period. Cases such as these yield a negative return on investment for the conservation funding agencies. Further, these cases have the potential to "harm" neighboring farmers.[21]

A tillage management strategy is a significant and long-term decision and investment by a farmer and a little money for a few years is likely not going to cause any change in behavior that would not have occurred otherwise without the conservation funding. If policy cost-effectiveness is of concern, conservation dollars ought not to be directed towards cropping management strategies such as these that many farmers have already found to be very cost-effective and profitable on their own without outside compensation.

On the other hand, BMPs such as filter strips offer little financial benefit to the farmer. Rather, the overwhelming majority of the benefits go to downstream stakeholders. These represent market failures by way of externalities. In these cases, cost-share and incentive

[21] Farmers who get conservation payments may be able to afford higher bids for cash renting cropland compared to neighboring farmers who did not receive the payments.

payment funding can be economically justified. Most farmers operate a profit-seeking business. Just like any other business they have a goal of remaining in operation and viable in the future. So, a profit must be made. Taking profitable cropland out of production for the benefit of society and wildlife may sound great in theory, but the truth is that it is not feasible for the majority of farmers. Society stands to benefit from BMPs such as filter strips and permanent vegetation establishment, so society should justifiably bear some of the cost. As an aside, it is my experience that most farmers will voluntarily contribute some of their own resources (e.g., time and money) to such projects even if the majority of benefits go downstream. Most farmers are excellent stewards of the land and desire to conserve our soil and water resources for future generations.

Related to all of this, it is not cost-effective to allocate conservation funds to individuals for practices they are already doing (i.e., early versions of the Conservation Security Program). Again, this is paying farmers for something that they obviously thought generated positive net returns or made sense to them in some other way. Throwing more money at existing BMPs depletes budget resources without improving environmental quality.

The idea of "cost-effective conservation" was addressed in this dissertation and every attempt was made to make this research as applicable as possible to real-world policy. It was found that targeting of conservation practices is 8 to 23 (note: not small by any stretch of the imagination) times more cost-effective than an approach where funds are given to any willing farmer/landowner who fills out an application. This really highlights the necessity of targeting. Considering the case of a watershed impacted by reservoir sedimentation, saving or spending funds on dredging would be economically preferred to random or even semi-random BMP implementation. It should be noted that "optimal" targeting is difficult in the real-world and most likely cannot be achieved to the degree modeled in this dissertation. But, one policy alternative that does offer some potential in attaining the most cost-effective environmental improvement is competitive bidding. Specifically, a BMP auction policy approach.[22] BMP auctions are an excellent way of creating the proper incentives to allow the "market" to identify the most cost-effective environmental improvements in a watershed.

Doing much research in the area of WQT and meeting with both farmers and those in the wastewater treatment plant (WWTP) industry helps to provide an understanding and a sense of the potential success/failure for this policy alternative. This chapter concludes with a few concluding remarks related to WQT.

Right now, it does not appear that WQT has great potential - at least in the central part of the United States. The current nutrient discharge limits in place (or those being proposed for the very near future) are achievable by most WWTPs with relatively little effort and/or financial resources.

The WWTP community sees a lot of risk associated with participating in these types of markets relative to "concrete and steel" engineering solutions that can be achieved via plant upgrades. Further, cities desire to have up to date and modern treatment facilities. WWTPs notoriously, whether deservedly or undeservedly, get a bad rap for being dirty, smelly, and pollution causing. A poor, rundown looking facility does not help this cause. A WWTP operator in central Kansas summarized it best by saying, "Look, we work around crap all day long, we don't want a facility that looks like crap." In other words, they want shiny, state-of-the-art facilities. So, why would they want to pay farmers to put conservation practices in at the expense of facility improvements?

[22] BMP auctions were briefly described in Chapter 1.

However, if EPA cranks the nutrient limits down to very low levels in the future (given today's costs of technology), WQT may have more potential. This would be the necessary driver for WQT to work. This would likely create such a huge divergence in point versus nonpoint source control costs to overcome the risk, uncertainty, and overall reluctance by WWTPs to want to participate in WQT markets.

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Appendix A - Field operations and enterprise budgets

The following field operations and cropping budgets were assembled for each crop rotation and tillage system combination in both the Nebraska and Kansas side of the TCL watershed. Note that all cost values are in a dollars per acre basis. The field operations data were used in the SWAT model. The budgets presented here were not used in determining the costs of the BMPs. They are simply included as additional cropping information.

Table A.1 Field operations for continuous corn

	Conventional Tillage		Reduced Tillage		No-Tillage	
CORN	Chisel	5-Nov	Chisel	5-Nov	Herbicide application	10-Oct
	Tandem disk	27-Mar	Knife anhydrous amm.	5-Apr	Knife anhydrous amm.	5-Apr
	Knife anhydrous amm.	5-Apr	Field cultivate	15-Apr	Herbicide application	15-Apr
	Field cultivate	15-Apr	Herbicide application	15-Apr	Plant corn	16-Apr
	Herbicide application	15-Apr	Plant corn	16-Apr	Fertilizer application	16-Apr
	Plant corn	16-Apr	Fertilizer application	16-Apr	Herbicide application	20-May
	Fertilizer application	16-Apr	Herbicide application	20-May	Harvest corn	1-Oct
	Herbicide application	20-May	Harvest corn	1-Oct		
	Harvest corn	1-Oct				

Table A.2 Budget for continuous corn

	CORN		
	Tillage Type		
INCOME PER ACRE	Conv.	Red.	NT
A. Yield per acre	110	110	110
B. Price per bushel	4.21	4.21	4.21
C. Net government payment	13.60	13.60	13.60
D. Indemnity payments	-	-	-
E. Miscellaneous income	-	-	-
F. Returns/acre ((A x B) + C + D + E)	476.70	476.70	476.70
COSTS PER ACRE			
1. Seed	85.86	85.86	85.86
2. Herbicide	23.03	23.03	29.93
3. Insecticide / Fungicide	-	-	-
4. Fertilizer and Lime	134.25	134.25	134.25
5. Crop Consulting	-	-	-
6. Crop Insurance	-	-	-
7. Drying	-	-	-

8. Miscellaneous	8.25	8.25	8.25
9. Custom Hire / Machinery Expense	131.53	119.72	99.03
10. Non-machinery Labor	9.49	9.49	9.49
11. Irrigation			
a. Labor	-	-	-
b. Fuel and Oil	-	-	-
c. Repairs and Maintenance	-	-	-
d. Depreciation on Equipment / Well	-	-	-
e. Interest on Equipment	-	-	-
12. Land Charge / Rent	76.00	76.00	76.00
G. SUB TOTAL	468.41	456.60	442.81
13. Interest on 1/2 Nonland Costs	13.73	13.32	12.84
H. TOTAL COSTS	482.14	469.92	455.64
I. RETURNS OVER COSTS (F - H)	(5.44)	6.78	21.06
J. TOTAL COSTS/BUSHEL (H/A)	4.38	4.27	4.14
K. RETURN TO ANNUAL COST (I+13)/G	1.77%	4.40%	7.65%

Table A.3 Field operations for corn-soybean rotation

	Conventional Tillage		Reduced Tillage		No-Tillage	
CORN	Chisel	5-Nov	Chisel	5-Nov	Herbicide application	10-Oct
	Tandem disk	27-Mar	Knife anhydrous amm.	5-Apr	Knife anhydrous amm.	5-Apr
	Knife anhydrous amm.	5-Apr	Field cultivate	15-Apr	Herbicide application	15-Apr
	Field cultivate	15-Apr	Herbicide application	15-Apr	Plant corn	16-Apr
	Herbicide application	15-Apr	Plant corn	16-Apr	Fertilizer application	16-Apr
	Plant corn	16-Apr	Fertilizer application	16-Apr	Herbicide application	20-May
	Fertilizer application	16-Apr	Herbicide application	20-May	Harvest corn	1-Oct
	Herbicide application	20-May	Harvest corn	1-Oct		
	Harvest corn	1-Oct				
SOYBEANS	Chisel	5-Nov	Field cultivate	15-Apr	Herbicide application	30-Apr
	Tandem disk	27-Mar	Field cultivate	14-May	Plant soybeans	5-May
	Field cultivate	15-Apr	Plant soybeans	16-May	Fertilizer application	5-May
	Field cultivate	14-May	Fertilizer application	16-May	Herbicide application	1-Jun
	Plant soybeans	16-May	Herbicide application	14-Jun	Harvest soybeans	1-Oct
	Fertilizer application	16-May	Harvest soybeans	1-Oct		
	Herbicide application	14-Jun				
	Harvest soybeans	1-Oct				

Table A.4 Budget for corn-soybean rotation

	CORN			SOYBEANS			ROTATION		
	Tillage Type			Tillage Type			Tillage Type		
INCOME PER ACRE	Conv.	Red.	NT	Conv.	Red.	NT	Conv.	Red.	NT
A. Yield per acre	110	110	110	33	33	33			
B. Price per bushel	4.21	4.21	4.21	8.69	8.69	8.69			
C. Net government payment	13.60	13.60	13.60	13.60	13.60	13.60			
D. Indemnity payments	-	-	-	-	-	-			
E. Miscellaneous income	-	-	-	-	-	-			
F. Returns/acre ((A x B) + C + D + E)	476.70	476.70	476.70	300.37	300.37	300.37	388.54	388.54	388.54
COSTS PER ACRE									
1. Seed	85.86	85.86	85.86	35.00	35.00	35.00			
2. Herbicide	23.03	23.03	29.93	11.86	11.86	18.76			
3. Insecticide / Fungicide	-	-	-	-	-	-			
4. Fertilizer and Lime	117.15	117.15	117.15	36.61	36.61	36.61			
5. Crop Consulting	-	-	-	-	-	-			
6. Crop Insurance	-	-	-	-	-	-			
7. Drying	-	-	-	-	-	-			
8. Miscellaneous	8.25	8.25	8.25	8.25	8.25	8.25			
9. Custom Hire / Machinery Expense	131.53	119.72	99.03	101.89	75.21	58.78			
10. Non-machinery Labor	9.49	9.49	9.49	6.37	6.37	6.37			
11. Irrigation									
a. Labor	-	-	-	-	-	-			
b. Fuel and Oil	-	-	-	-	-	-			
c. Repairs and Maintenance	-	-	-	-	-	-			
d. Depreciation on Equipment / Well	-	-	-	-	-	-			
e. Interest on Equipment	-	-	-	-	-	-			
12. Land Charge / Rent	76.00	76.00	76.00	76.00	76.00	76.00			
G. SUB TOTAL	451.31	439.50	425.71	275.98	249.30	239.77	363.64	344.40	332.74
13. Interest on 1/2 Nonland Costs	13.14	12.72	12.24	7.00	6.07	5.73	10.07	9.39	8.99
H. TOTAL COSTS	464.44	452.22	437.95	282.98	255.36	245.50	373.71	353.79	341.72
I. RETURNS OVER COSTS (F - H)	12.26	24.48	38.75	17.39	45.01	54.87	14.83	34.74	46.81
J. TOTAL COSTS/BUSHEL (H/A)	4.22	4.11	3.98	8.58	7.74	7.44			
K. RETURN TO ANNUAL COST	5.63%	8.47%	11.98%	8.84%	20.49%	25.28%			

Table A.5 Field operations for grain sorghum-soybeans-wheat rotation

	Conventional Tillage		Reduced Tillage		No-Tillage	
GRAIN SORGHUM	Chisel	1-Aug	Chisel	15-Aug	Herbicide application	10-Aug
	Tandem disk	1-Sep	Herbicide application	15-Oct	Herbicide application	15-Oct
	Tandem disk	27-Mar	Knife anhydrous amm.	5-May	Knife anhydrous amm.	5-May
	Knife anhydrous amm.	5-May	Field cultivate	15-May	Fertilizer application	25-May
	Field cultivate	15-May	Fertilizer application	25-May	Plant sorghum	25-May
	Fertilizer application	25-May	Plant sorghum	25-May	Herbicide application	25-May
	Plant sorghum	25-May	Herbicide application	25-May	Herbicide application	1-Jul
	Herbicide application	25-May	Herbicide application	1-Jul	Harvest sorghum	25-Sep
	Herbicide application	1-Jul	Harvest sorghum	25-Sep		
	Harvest sorghum	25-Sep				
SOYBEANS	Chisel	5-Nov	Chisel	5-Nov	Herbicide application	30-Apr
	Tandem disk	27-Mar	Field cultivate	15-Apr	Plant soybeans	5-May
	Field cultivate	15-Apr	Field cultivate	14-May	Fertilizer application	5-May
	Field cultivate	14-May	Plant soybeans	16-May	Herbicide application	1-Jun
	Plant soybeans	16-May	Fertilizer application	16-May	Herbicide application	1-Jul
	Fertilizer application	16-May	Herbicide application	14-Jun	Harvest soybeans	1-Oct
	Herbicide application	14-Jun	Harvest soybeans	1-Oct		
	Harvest soybeans	1-Oct				
WHEAT	Field cultivate	10-Oct	Fertilizer appl. (preplant)	15-Oct	Fertilizer appl. (preplant)	15-Oct
	Fertilizer appl. (preplant)	15-Oct	Plant wheat	16-Oct	Plant wheat	16-Oct
	Plant wheat	16-Oct	Harvest wheat	1-Jul	Harvest wheat	1-Jul
	Harvest wheat	1-Jul				

Table A.6 Budget for grain sorghum-soybeans-wheat rotation

	GRAIN SORGHUM			SOYBEANS			WHEAT			ROTATION		
	Tillage Type			Tillage Type			Tillage Type			Tillage Type		
INCOME PER ACRE	Conv.	Red.	NT	Conv.	Red.	NT	Conv.	Red.	NT	Conv.	Red.	NT
A. Yield per acre	76	76	76	33	33	33	50	50	50			
B. Price per bushel	4.33	4.33	4.33	8.69	8.69	8.69	6.24	6.24	6.24			
C. Net government payment	13.60	13.60	13.60	13.60	13.60	13.60	13.60	13.60	13.60			
D. Indemnity payments	-	-	-	-	-	-	-	-	-			
E. Miscellaneous income	-	-	-	-	-	-	-	-	-			
F. Returns/acre ((A x B) + C + D + E)	342.68	342.68	342.68	300.37	300.37	300.37	325.60	325.60	325.60	312.99	312.99	312.99
COSTS PER ACRE												
1. Seed	14.76	14.76	14.76	35.00	35.00	35.00	16.00	16.00	16.00			
2. Herbicide	29.52	36.42	43.32	11.86	11.86	18.76	-	-	-			
3. Insecticide / Fungicide	-	-	-	-	-	-	-	-	-			
4. Fertilizer and Lime	77.92	77.92	77.92	36.61	36.61	36.61	84.82	84.82	84.82			
5. Crop Consulting	-	-	-	-	-	-	-	-	-			
6. Crop Insurance	-	-	-	-	-	-	-	-	-			
7. Drying	-	-	-	-	-	-	-	-	-			
8. Miscellaneous	8.25	8.25	8.25	8.25	8.25	8.25	8.25	8.25	8.25			
9. Custom Hire / Machinery Expense	136.62	108.41	98.66	101.89	75.21	58.78	69.37	58.92	58.92			
10. Non-machinery Labor	8.45	8.45	8.45	6.37	6.37	6.37	7.02	7.02	7.02			
11. Irrigation												
a. Labor	-	-	-	-	-	-	-	-	-			
b. Fuel and Oil	-	-	-	-	-	-	-	-	-			
c. Repairs and Maintenance	-	-	-	-	-	-	-	-	-			
d. Depreciation on Equipment / Well	-	-	-	-	-	-	-	-	-			
e. Interest on Equipment	-	-	-	-	-	-	-	-	-			
12. Land Charge / Rent	76.00	76.00	76.00	76.00	76.00	76.00	76.00	76.00	76.00			
G. SUB TOTAL	351.51	330.20	327.35	275.98	249.30	239.77	261.46	251.01	251.01	268.72	250.16	245.39
13. Interest on 1/2 Nonland Costs	9.64	8.90	8.80	7.00	6.07	5.73	6.49	6.13	6.13	6.75	6.10	5.93
H. TOTAL COSTS	361.16	339.10	336.15	282.98	255.36	245.50	267.95	257.14	257.14	275.47	256.25	251.32
I. RETURNS OVER COSTS (F - H)	(18.48)	3.58	6.53	17.39	45.01	54.87	57.65	68.46	68.46	37.52	56.73	61.67
J. TOTAL COSTS/BUSHEL (H/A)	4.75	4.46	4.42	8.58	7.74	7.44	5.36	5.14	5.14			
K. RETURN TO ANNUAL COST	-2.51%	3.78%	4.68%	8.84%	20.49%	25.28%	24.53%	29.71%	29.71%			

Table A.7 Field operations for continuous soybeans

	Conventional Tillage		Reduced Tillage		No-Tillage	
SOYBEANS	Tandem disk	27-Mar	Field cultivate	15-Apr	Herbicide application	30-Apr
	Field cultivate	15-Apr	Field cultivate	14-May	Plant soybeans	5-May
	Field cultivate	14-May	Plant soybeans	16-May	Fertilizer application	5-May
	Plant soybeans	16-May	Fertilizer application	16-May	Herbicide application	1-Jun
	Fertilizer application	16-May	Herbicide application	14-Jun	Harvest soybeans	1-Oct
	Herbicide application	14-Jun	Harvest soybeans	1-Oct		
	Harvest soybeans	1-Oct				
	Chisel	5-Nov				

Table A.8 Budget for continuous soybeans

	SOYBEANS		
	Tillage Type		
INCOME PER ACRE	Conv.	Red.	NT
A. Yield per acre	33	33	33
B. Price per bushel	8.69	8.69	8.69
C. Net government payment	13.60	13.60	13.60
D. Indemnity payments	-	-	-
E. Miscellaneous income	-	-	-
F. Returns/acre ((A x B) + C + D + E)	300.37	300.37	300.37
COSTS PER ACRE			
1. Seed	35.00	35.00	35.00
2. Herbicide	11.86	11.86	18.76
3. Insecticide / Fungicide	-	-	-
4. Fertilizer and Lime	36.61	36.61	36.61
5. Crop Consulting	-	-	-
6. Crop Insurance	-	-	-
7. Drying	-	-	-
8. Miscellaneous	8.25	8.25	8.25
9. Custom Hire / Machinery Expense	101.89	75.21	58.78
10. Non-machinery Labor	6.37	6.37	6.37
11. Irrigation			
a. Labor	-	-	-
b. Fuel and Oil	-	-	-
c. Repairs and Maintenance	-	-	-
d. Depreciation on Equipment / Well	-	-	-
e. Interest on Equipment	-	-	-
12. Land Charge / Rent	76.00	76.00	76.00
G. SUB TOTAL	275.98	249.30	239.77
13. Interest on 1/2 Nonland Costs	7.00	6.07	5.73
H. TOTAL COSTS	282.98	255.36	245.50
I. RETURNS OVER COSTS (F - H)	17.39	45.01	54.87
J. TOTAL COSTS/BUSHEL (H/A)	8.58	7.74	7.44
K. RETURN TO ANNUAL COST (I+13)/G	8.84%	20.49%	25.28%

Table A.9 Field operations for soybeans-wheat rotation

	Conventional Tillage		Reduced Tillage		No-Tillage	
SOYBEANS	Chisel	1-Aug	Chisel	1-Aug	Herbicide application	1-Aug
	Tandem disk	1-Sep	Herbicide application	1-Sep	Herbicide application	15-Oct
	Tandem disk	27-Mar	Field cultivate	15-Apr	Herbicide application	30-Apr
	Field cultivate	15-Apr	Field cultivate	14-May	Plant soybeans	5-May
	Field cultivate	14-May	Plant soybeans	16-May	Fertilizer application	5-May
	Plant soybeans	16-May	Fertilizer application	16-May	Herbicide application	1-Jun
	Fertilizer application	16-May	Herbicide application	14-Jun	Harvest soybeans	1-Oct
	Herbicide application	14-Jun	Harvest soybeans	1-Oct		
	Harvest soybeans	1-Oct				
WHEAT	Field cultivate	10-Oct	Fertilizer appl. (preplant)	15-Oct	Fertilizer appl. (preplant)	15-Oct
	Fertilizer appl. (preplant)	15-Oct	Plant wheat	16-Oct	Plant wheat	16-Oct
	Plant wheat	16-Oct	Harvest wheat	1-Jul	Harvest wheat	1-Jul
	Harvest wheat	1-Jul				

Table A.10 Budget for soybeans-wheat rotation

	SOYBEANS			WHEAT			ROTATION		
	Tillage Type			Tillage Type			Tillage Type		
INCOME PER ACRE	Conv.	Red.	NT	Conv.	Red.	NT	Conv.	Red.	NT
A. Yield per acre	33	33	33	50	50	50			
B. Price per bushel	8.69	8.69	8.69	6.24	6.24	6.24			
C. Net government payment	13.60	13.60	13.60	13.60	13.60	13.60			
D. Indemnity payments	-	-	-	-	-	-			
E. Miscellaneous income	-	-	-	-	-	-			
F. Returns/acre ((A x B) + C + D + E)	300.37	300.37	300.37	325.60	325.60	325.60	312.99	312.99	312.99
COSTS PER ACRE									
1. Seed	35.00	35.00	35.00	16.00	16.00	16.00			
2. Herbicide	11.86	11.86	18.76	-	-	-			
3. Insecticide / Fungicide	-	-	-	-	-	-			
4. Fertilizer and Lime	36.61	36.61	36.61	84.82	84.82	84.82			

5. Crop Consulting	-	-	-	-	-	-			
6. Crop Insurance	-	-	-	-	-	-			
7. Drying	-	-	-	-	-	-			
8. Miscellaneous	8.25	8.25	8.25	8.25	8.25	8.25			
9. Custom Hire / Machinery Expense	101.89	75.21	58.78	69.37	58.92	58.92			
10. Non-machinery Labor	6.37	6.37	6.37	7.02	7.02	7.02			
11. Irrigation									
a. Labor	-	-	-	-	-	-			
b. Fuel and Oil	-	-	-	-	-	-			
c. Repairs and Maintenance	-	-	-	-	-	-			
d. Depreciation on Equipment / Well	-	-	-	-	-	-			
e. Interest on Equipment	-	-	-	-	-	-			
12. Land Charge / Rent	76.00	76.00	76.00	76.00	76.00	76.00			
G. SUB TOTAL	275.98	249.30	239.77	261.46	251.01	251.01	268.72	250.16	245.39
13. Interest on 1/2 Nonland Costs	7.00	6.07	5.73	6.49	6.13	6.13	6.75	6.10	5.93
H. TOTAL COSTS	282.98	255.36	245.50	267.95	257.14	257.14	275.47	256.25	251.32
I. RETURNS OVER COSTS (F - H)	17.39	45.01	54.87	57.65	68.46	68.46	37.52	56.73	61.67
J. TOTAL COSTS/BUSHEL (H/A)	8.58	7.74	7.44	5.36	5.14	5.14			
K. RETURN TO ANNUAL COST (I+13)/G	8.84%	20.49%	25.28%	24.53%	29.71%	29.71%			

Table A.11 Field operations for continuous wheat

	Conventional Tillage		Reduced Tillage		No-Tillage	
WHEAT	Chisel	1-Aug	Chisel	1-Aug	Herbicide application	1-Aug
	Tandem disk	1-Sep	Herbicide application	1-Sep	Herbicide application	1-Sep
	Tandem disk	1-Oct	Field cultivate	10-Oct	Fertilizer appl. (preplant)	15-Oct
	Field cultivate	10-Oct	Fertilizer appl. (preplant)	15-Oct	Plant wheat	16-Oct
	Fertilizer appl. (preplant)	15-Oct	Plant wheat	16-Oct	Herbicide application	1-Mar
	Plant wheat	16-Oct	Herbicide application	1-Mar	Harvest wheat	1-Jul
	Herbicide application	1-Mar	Harvest wheat	1-Jul		
	Harvest wheat	1-Jul				

Table A.12 Budget for continuous wheat

	WHEAT		
	Tillage Type		
INCOME PER ACRE	Conv.	Red.	NT
A. Yield per acre	50	50	50
B. Price per bushel	6.24	6.24	6.24
C. Net government payment	13.60	13.60	13.60
D. Indemnity payments	-	-	-
E. Miscellaneous income	-	-	-
F. Returns/acre ((A x B) + C + D + E)	325.60	325.60	325.60
COSTS PER ACRE			
1. Seed	16.00	16.00	16.00
2. Herbicide	6.16	13.06	19.96
3. Insecticide / Fungicide	-	-	-
4. Fertilizer and Lime	110.32	110.32	110.32
5. Crop Consulting	-	-	-
6. Crop Insurance	-	-	-
7. Drying	-	-	-
8. Miscellaneous	8.25	8.25	8.25
9. Custom Hire / Machinery Expense	114.44	95.96	75.27
10. Non-machinery Labor	10.79	10.79	10.79
11. Irrigation			
a. Labor	-	-	-
b. Fuel and Oil	-	-	-
c. Repairs and Maintenance	-	-	-
d. Depreciation on Equipment / Well	-	-	-
e. Interest on Equipment	-	-	-
12. Land Charge / Rent	76.00	76.00	76.00
G. SUB TOTAL	341.96	330.38	316.59
13. Interest on 1/2 Nonland Costs	9.31	8.90	8.42
H. TOTAL COSTS	351.27	339.29	325.01
I. RETURNS OVER COSTS (F - H)	(25.67)	(13.69)	0.59
J. TOTAL COSTS/BUSHEL (H/A)	7.03	6.79	6.50
K. RETURN TO ANNUAL COST (I+13)/G	-4.78%	-1.45%	2.85%

Appendix B - Example MATLAB Simulation Code for Chapter 2

In order for the Chapter 2 code to work correctly, several "functions" are relied upon and the associated m.files need to be accessible (i.e., in the current directory in MATLAB). A list of these publicly available m.files are listed below:

- keep3.m
- officedoc.m (Note, this is not a free program. See the following link for more details regarding officedoc - http://undocumentedmatlab.com/OfficeDoc/)
- randswap.m
- unique_no_sort

Example Code for Targeted BMP Implementation focusing on sediment and $50,000 annual budget

```
%Full information BMP implementation, Marginal Gains based implementation
%Sediment Reduction

clear %clears workspace; comment this out if using MasterRunFile
clc %clears command window
delete ('BestS_15yr_50K.xls') %deletes existing Excel spreadsheet output
OutFile = 'C:\Documents and Settings\Craig Smith\My
Documents\Ph.D\Cost_Effective_WS_Management\SimModel_6\BestS_15yr_50K.xls';

warning off MATLAB:divideByZero

%What are the Sediment reduction goals and budget constraint and iterations? comment if
%using MasterRunFile
RedGoal = 100000000;
Budget = 50000;
xpercent = 0.25; %percent of farms to eliminate
iterationsbest = 3000; %number of iterations (e.g., 1000 or more)

%Load Cost and Quantity data
WSdata = xlsread('Tuttle_Model_Data.xls', 'MATinput','A2:O1859');
TotFarms = size(WSdata,1);
SubWS = WSdata(:,2);
num_counties = 10; %number of counties
num_BMPs = 3; %number of BMPs available
seed_value = 31517; %seed value

%Need to eliminate "xpercent" of the farms because we will assume that
%xpercent of the farms have already adopted BMPs or will never adopt BMPs
ineligiblefarms = round(xpercent*TotFarms);

%---------------------------------
SubWS_percent = xlsread('BMPCosts_15yrs.xls','input','D3:AH12');
```

```
%Create a matrix with max(SubWS) columns representing the subwatersheds
%and the data in the rows represents which HRUs belong to each subwatershed
SW = zeros(TotFarms,max(SubWS)); %preallocate a TotFarms by max(SubWS) matrix
for i=1:max(SubWS)
 SW_a = find(SubWS==i);
 SW_b = zeros(TotFarms - size(SW_a,1),1); %need to add a column vector of zeros to make each vector
the same length
 SW_c = cat(1,SW_a,SW_b);
 SW(:,i) = SW_c; %SW is the resulting matrix
end;

%--------------------------------------
%need a 1 by num of SubWS's matrix with number of HRUs in each SubWS
SW_count = zeros(1,max(SubWS)); %preallocate
for i = 1:max(SubWS)
 SW_count(1,i) = max(find(SW(:,i)>0)); %this is # of HRUs in each SubWS
end;

Co_SW_matrix = SubWS_percent(:,1:max(SubWS)); %this is % of SubWS in each county
Co_SW_matrix_1 = zeros(num_counties,max(SubWS)); %preallocate

for i = 1:num_counties
 Co_SW_matrix_1(i,:) = round((Co_SW_matrix(i,:).*SW_count)-.05); %subtract .05 so that we don't get
any negative #'s in
 %the Co_SW_matrix_2 which is calculated next
end;
%---------------------------------------
%Need to make sure each column adds up to the correct number of HRUs
Co_SW_matrix_2 = zeros(1,max(SubWS));

for i = 1:max(SubWS)
 Co_SW_matrix_2(1,i) = SW_count(1,i) - sum(Co_SW_matrix_1(1:9,i));
end;

Co_SW_matrix_1(num_counties,:) = Co_SW_matrix_2;
%---------------------------------------

BMP_ann_costs = SubWS_percent(:,29:31);
BMP_cost_matrix = zeros(TotFarms,num_BMPs); %preallocate a matrix with TotFarms by 3 (# of
BMPs) columns
BMP_matrix1 = zeros(TotFarms,max(SubWS));
BMP_matrix2 = zeros(TotFarms,max(SubWS));
BMP_matrix3 = zeros(TotFarms,max(SubWS));

for j = 1:max(SubWS)
 A = 0;
 for i = 1:num_counties
 if Co_SW_matrix_1(i,j) == 0
 continue
 end
```

```
 BMP_matrix1(A+1:Co_SW_matrix_1(i,j)+A,j) = BMP_ann_costs(i,1);
 BMP_matrix2(A+1:Co_SW_matrix_1(i,j)+A,j) = BMP_ann_costs(i,2);
 BMP_matrix3(A+1:Co_SW_matrix_1(i,j)+A,j) = BMP_ann_costs(i,3);
 A = Co_SW_matrix_1(i,j)+A;
 end;
end;

%---------------------------------------
%Subdivide matrix into column vectors cell arrays

for i = 1:max(SubWS)
 y{i} = zeros(TotFarms,1);%preallocate
 bmp1{i} = zeros(TotFarms,1);
 bmp2{i} = zeros(TotFarms,1);
 bmp3{i} = zeros(TotFarms,1);
end;

for i = 1:max(SubWS)
 y{i} = SW(:,i);
end

for i = 1:max(SubWS)
 bmp1{i} = BMP_matrix1(:,i);
end

for i = 1:max(SubWS)
 bmp2{i} = BMP_matrix2(:,i);
end

for i = 1:max(SubWS)
 bmp3{i} = BMP_matrix3(:,i);
end
%----------------------------------------

%Get rid of zeros in each column vector
for i=1:max(SubWS)
 y_new{i} = y{1,i}(y{1,i}~=0);
end

for i=1:max(SubWS)
 bmp1_new{i} = bmp1{1,i}(bmp1{1,i}~=0);
end

for i=1:max(SubWS)
 bmp2_new{i} = bmp2{1,i}(bmp2{1,i}~=0);
end

for i=1:max(SubWS)
 bmp3_new{i} = bmp3{1,i}(bmp3{1,i}~=0);
end
```

```
%----------------------------------------

%Combine common Subwatershed vectors, so the result will be 3 BMP cost
%column vectors. We can then randomly pair these using the randswap function
for i = 1:max(SubWS)
 combined_bmpcosts{i} = cat(2,bmp1_new{1,i},bmp2_new{1,i},bmp3_new{1,i});
end
rand('seed',seed_value); %set seed value

%----------------------------------------
%Start simulating the BMP implementation scenarios. Note that this is the
%outerloop

for j = 1:iterationsbest
 j
 tic;
 HRU_id = WSdata(:,1);
 FarmArea = WSdata(:,3);
 BaseNLoad = WSdata(:,4);
 BMP1NLoad = WSdata(:,5);
 BMP2NLoad = WSdata(:,6);
 BMP3NLoad = WSdata(:,7);

 BMP1NQuantity = BaseNLoad - BMP1NLoad;
 BMP2NQuantity = BaseNLoad - BMP2NLoad;
 BMP3NQuantity = BaseNLoad - BMP3NLoad;

 BasePLoad = WSdata(:,8);
 BMP1PLoad = WSdata(:,9);
 BMP2PLoad = WSdata(:,10);
 BMP3PLoad = WSdata(:,11);

 BMP1PQuantity = BasePLoad - BMP1PLoad;
 BMP2PQuantity = BasePLoad - BMP2PLoad;
 BMP3PQuantity = BasePLoad - BMP3PLoad;

 BaseSLoad = WSdata(:,12);
 BMP1SLoad = WSdata(:,13);
 BMP2SLoad = WSdata(:,14);
 BMP3SLoad = WSdata(:,15);

 BMP1SQuantity = BaseSLoad - BMP1SLoad;
 BMP2SQuantity = BaseSLoad - BMP2SLoad;
 BMP3SQuantity = BaseSLoad - BMP3SLoad;

 %Now randomly pair the combined BMP costs matrix with an HRU
 for i = 1:max(SubWS)
 rand_bmpcosts = randswap(combined_bmpcosts{1,i});
 SW_bmpcosts{i} = cat(2,y_new{1,i},rand_bmpcosts);
```

```
end

%Reshape and order the bmpcosts matrix in numerical order by the first
%column which is HRU id number
SW_bmpcosts = reshape(SW_bmpcosts,max(SubWS),1);
stacked_bmpcosts = cell2mat(SW_bmpcosts);
ordered_HRU_bmpcosts = sortrows(stacked_bmpcosts,1);

%Determine Total and Average BMP costs for each HRU for N,P, and S

%Nitrogen Costs
BMP1NCost = ordered_HRU_bmpcosts(:,2).*FarmArea;
BMP2NCost = ordered_HRU_bmpcosts(:,3).*FarmArea;
BMP3NCost = ordered_HRU_bmpcosts(:,4).*FarmArea;

AVGBMP1NCost = BMP1NCost./BMP1NQuantity;
AVGBMP2NCost = BMP2NCost./BMP2NQuantity;
AVGBMP3NCost = BMP3NCost./BMP3NQuantity;

%Phosphorus Costs
BMP1PCost = ordered_HRU_bmpcosts(:,2).*FarmArea;
BMP2PCost = ordered_HRU_bmpcosts(:,3).*FarmArea;
BMP3PCost = ordered_HRU_bmpcosts(:,4).*FarmArea;

AVGBMP1PCost = BMP1PCost./BMP1PQuantity;
AVGBMP2PCost = BMP2PCost./BMP2PQuantity;
AVGBMP3PCost = BMP3PCost./BMP3PQuantity;

%Sediment Costs
BMP1SCost = ordered_HRU_bmpcosts(:,2).*FarmArea;
BMP2SCost = ordered_HRU_bmpcosts(:,3).*FarmArea;
BMP3SCost = ordered_HRU_bmpcosts(:,4).*FarmArea;

AVGBMP1SCost = BMP1SCost./BMP1SQuantity;
AVGBMP2SCost = BMP2SCost./BMP2SQuantity;
AVGBMP3SCost = BMP3SCost./BMP3SQuantity;

%Get rid of zeros and negatives in Average BMP cost matricies
BMPsAVGNCosts = cat(2,AVGBMP1NCost,AVGBMP2NCost,AVGBMP3NCost);
findzerosN = find(BMPsAVGNCosts<=0); %finds zeros and negatives in BMPsAVGNCosts matrix
BMPsAVGNCosts(findzerosN) = nan; %replaces zeros and negatives with nan's which is need for this
program

BMPsAVGPCosts = cat(2,AVGBMP1PCost,AVGBMP2PCost,AVGBMP3PCost);
findzerosP = find(BMPsAVGPCosts<=0); %finds zeros and negatives in BMPsAVGPCosts matrix
BMPsAVGPCosts(findzerosP) = nan; %replaces zeros and negatives with nan's which is need for this
program

BMPsAVGSCosts = cat(2,AVGBMP1SCost,AVGBMP2SCost,AVGBMP3SCost);
findzerosS = find(BMPsAVGSCosts<=0); %finds zeros and negatives in BMPsAVGSCosts matrix
```

```
BMPsAVGSCosts(findzerosS) = nan; %replaces zeros and negatives with nan's which is need for this
program

%Get rid of the negatives and zeros
NReductions = cat(2, BMP1NQuantity, BMP2NQuantity, BMP3NQuantity);
PReductions = cat(2, BMP1PQuantity, BMP2PQuantity, BMP3PQuantity);
SReductions = cat(2, BMP1SQuantity, BMP2SQuantity, BMP3SQuantity);

% findreductionsN = find(NReductions<0); %finds negative values in N reductions data
% NReductions(findreductionsN) = 0; %replaces negatives with zeros

% findreductionsP = find(PReductions<0); %finds negative values in P reductions data
% PReductions(findreductionsP) = 0; %replaces negatives with zeros

findreductionsS = find(SReductions<0); %finds negative values in S reductions data
SReductions(findreductionsS) = 0; %replaces negatives with zeros

%Need to eliminate "xpercent" of the farms because we will assume that
%xpercent of the farms have already adopted BMPs or will never adopt
%BMPs. This is done by randomly selecting xpercent of the farms and
%setting the appropriate rows in the BMPsAVGSCosts to zero. Note that
%if we were trading in regards to another pollutant (N or P), then this
%code would need to be changed to the appropriate BMP Avg Cost matrix.
%If there are already more farms with negatives and zeros than
%ineligible farms, then this piece of code has no effect

num_of_zeros = size(find(SReductions(:,1) == 0),1);
while num_of_zeros < ineligiblefarms
eliminate_id = round(rand(1)*TotFarms);
if eliminate_id == 0
continue
end
SReductions(eliminate_id,1:3) = zeros(1,3);
num_of_zeros = size(find(SReductions(:,1) == 0),1);
end;
num_of_zeros = size(find(SReductions(:,1) == 0),1);

findreductionsS_zeros = find(SReductions == 0);
BMPsAVGSCosts(findreductionsS_zeros) = nan;%set corresponding cells in BMPAVG S Cost
%matrix to nan

CummNQuantity = 0;
TotBMPNCost1 = 0;
CummPQuantity = 0;
TotBMPPCost1 = 0;
CummSQuantity = 0;
TotBMPSCost1 = 0;
zeromatrix = zeros(TotFarms,num_BMPs);%zeros matrix of dimension TotFarms x 3 which is # of
BMPs
nanmatrix = nan(TotFarms,num_BMPs);%nan matrix of dimension TotFarms x 3 which is # of BMPs
```

```
%This is the innerloop where the actual BMP implementation occurs
i = 0;
while (CummSQuantity < RedGoal) && (i < TotFarms) %loop while below reduction goal AND while
the number of
%BMP projects implemented is less than or equal to the total number of farms (this is because each
%farm can only implement one BMP)

[FarmID,BMP] = find(min(min(BMPsAVGSCosts)) == BMPsAVGSCosts); %Find minimum avg PCost

if BMPsAVGSCosts(FarmID,BMP) == nan %if there is zero SCost for BMP implementation
%set that Farm-BMP Combo to nan and the corresponding SReductions value to zero
BMPsAVGSCosts(FarmID,BMP) = nan;
SReductions(FarmID,BMP) = 0;
continue; %go back to the start of the while loop
end;

if SReductions == zeromatrix
break; end;

% if BMPsAVGSCosts == nanmatrix %this can be commented out if the
% budget and/or reduction goal are binding
% break; end;

if size ([FarmID,BMP],1) > 1 %If there are BMPs (and/or Farms) with identical SCosts, pick the first one
FarmID = FarmID(1);
BMP = BMP(1);
end;

AVGPracticeSCost = BMPsAVGSCosts(FarmID,BMP);
Area = FarmArea(FarmID,1);
NQuantity = NReductions(FarmID,BMP);
PQuantity = PReductions(FarmID,BMP);
SQuantity = SReductions(FarmID,BMP);
TotPracticeSCost = AVGPracticeSCost*SQuantity;

if (TotPracticeSCost + TotBMPSCost1) > Budget
BMPsAVGSCosts(FarmID,BMP) = nan;
SReductions(FarmID,BMP) = 0;
continue;
end; %if implementing this BMP will exceed the budget, take that Farm-BMP Combo out of the market

SReductions(FarmID,BMP) = SReductions(FarmID,BMP) - SQuantity; %Update SReductions1 Matrix
i = i + 1;

if SReductions(FarmID,BMP) == 0
BMPsAVGSCosts(FarmID,:) = nan; %If the previous BMP was fully implemented, take that farm out of
the market
SReductions(FarmID,:) = 0;
end;
```

```
 if i == 1 %save data
 Simout = [Area, FarmID, BMP, AVGPracticeSCost, SQuantity, TotPracticeSCost];
 OtherSimout = [NQuantity, PQuantity];
 else Simout = [Simout; Area, FarmID, BMP, AVGPracticeSCost, SQuantity, TotPracticeSCost];
 OtherSimout = [OtherSimout; NQuantity, PQuantity];
 end;

 Count = (1:i)'; %this numbers the rows in the first column of output
 TotArea = sum(Simout(:,1));
 CummSQuantity = sum(Simout(:,5));
 TotBMPSCost = sum(Simout(:,6));
 TotBMPSCost1 = TotBMPSCost + 0;
 CummNQuantity = sum(OtherSimout(:,1));
 CummPQuantity = sum(OtherSimout(:,2));
 numofBMP1 = size(find(Simout(:,3)==1),1); %calculates # of BMP1 implemented
 numofBMP2 = size(find(Simout(:,3)==2),1); %calculates # of BMP2 implemented
 numofBMP3 = size(find(Simout(:,3)==3),1); %calculates # of BMP3 implemented
 end;

 a = nan(i-1,1); %nan matrix that is i-1 rows and 1 column
 TotBMPnumOUT = cat(1,i,a); %the scalar value is inserted at top of a matrix to make
 %a i x 1 matrix for output purposes - same procedure for next 5
 %output variables
 TotAreaOUT = cat(1,TotArea,a);
 TotBMPSCostOUT = cat(1,TotBMPSCost,a);
 RedGoalOUT = cat(1,RedGoal,a);
 BudgetOUT = cat(1,Budget,a);
 CummNQuantityOUT = cat(1,CummNQuantity,a);
 CummPQuantityOUT = cat(1,CummPQuantity,a);
 CummSQuantityOUT = cat(1,CummSQuantity,a);
 numofBMP1OUT = cat(1,numofBMP1,a);
 numofBMP2OUT = cat(1,numofBMP2,a);
 numofBMP3OUT = cat(1,numofBMP3,a);

 Output = cat(2,Count, Simout, OtherSimout, TotBMPnumOUT, TotAreaOUT, CummSQuantityOUT,
TotBMPSCostOUT, RedGoalOUT,...
 BudgetOUT, CummNQuantityOUT, CummPQuantityOUT, numofBMP1OUT, numofBMP2OUT,
numofBMP3OUT);
 % numericalOutput = num2cell(Output); %change the numerical array into a cell array

 OUT{j} = {Output};
 toc
 time2{j} = toc;
end;

disp ('Successfully finished the iterations!!')
%------------------------------------------------

%Finds the maximum number of BMP projects implemented(rows) in the output data. Changes all
```

```
%matrices to have the same number of rows. Zeros are put in the rows that
%are added.For more information, go to section 15.3 in the array manipulation
%publication


for j=1:iterationsbest
 b(j) = max(OUT{1,j}{1,1}(:,1)); %finds total # of BMP projects implemented in each iteration
end;

m = mean(b); %finds average # of BMP projects implemented across all iterations
m = round(m); %rounds the average # to nearest whole number
% aa = a(:)'; %creates another matrix aa equal to a
% aa = aa(ones(m,1),:); %transforms aa into an m by iterations matrix
bb = (1:m)'; %creates bb which is a column vector going from 1 to m
% bb = bb(:,ones(length(a), 1)); %transforms bb into a m by iterations matrix
% %with each column going from 1 to m
% b = bb .* (bb <= aa); %the dot indicates array multiplication (not the same
% %as matrix multiplication. Arrays in bb are multiplied by an array of ones
% %and zeros corresponding to the number of BMP projects implemented
% M = mean(b,2); %sums across all rows of the b matrix resulting in a column vector

for i = 1:iterationsbest %this loop equalizes number of rows (equal to mean # of BMP projects
implemented)
 %across all iterations so that the means can be calcualted
 cc{i} = OUT{i}{1}(:,2); %area
 ee{i} = OUT{i}{1}(:,6); %tons of soil reduction
 ff{i} = OUT{i}{1}(:,7); %total BMP cost
 gg{i} = OUT{i}{1}(:,8); %pounds of N reduction
 hh{i} = OUT{i}{1}(:,9); %pounds of P reduction
 ii{i} = OUT{i}{1}(1,10); %num of BMPs
 jj{i} = OUT{i}{1}(1,11); %total area
 kk{i} = OUT{i}{1}(1,12); %cummulative soil reduction
 ll{i} = OUT{i}{1}(1,13); %total BMP costs
 mm{i} = OUT{i}{1}(1,14); %soil reduction goal
 nn{i} = OUT{i}{1}(1,15); %budget
 oo{i} = OUT{i}{1}(1,16); %cummulative N reduction
 pp{i} = OUT{i}{1}(1,17); %cummulative P reduction
 qq{i} = OUT{i}{1}(1,18); %num of BMP1 implemented
 rr{i} = OUT{i}{1}(1,19); %num of BMP2 implemented
 ss{i} = OUT{i}{1}(1,20); %num of BMP3 implemented

 [u,y] = size(cc{i});
 if u >= m
 cc1{i} = cc{i}(1:m,:);
 ee1{i} = ee{i}(1:m,:);
 ff1{i} = ff{i}(1:m,:);
 gg1{i} = gg{i}(1:m,:);
 hh1{i} = hh{i}(1:m,:);
 else v = m-u;
 w = zeros(v,1);
```

```
 cc1{i} = cat(1,cc{i},w);
 ee1{i} = cat(1,ee{i},w);
 ff1{i} = cat(1,ff{i},w);
 gg1{i} = cat(1,gg{i},w);
 hh1{i} = cat(1,hh{i},w);
 end;
end;

%convert cell array of matricies to single matrix
ccc = cell2mat(cc1);
eee = cell2mat(ee1);
fff = cell2mat(ff1);
ggg = cell2mat(gg1);
hhh = cell2mat(hh1);
iii = cell2mat(ii);
jjj = cell2mat(jj);
kkk = cell2mat(kk);
lll = cell2mat(ll);
mmm = cell2mat(mm);
nnn = cell2mat(nn);
ooo = cell2mat(oo);
ppp = cell2mat(pp);
qqq = cell2mat(qq);
rrr = cell2mat(rr);
sss = cell2mat(ss);
ddd = sum(mean(fff,2))/sum(mean(eee,2)); %avg S reduction costs (total)
ttt = sum(mean(fff,2))/sum(mean(ggg,2)); %avg N reduction costs (total)
uuu = sum(mean(fff,2))/sum(mean(hhh,2)); %avg P reduction costs (total)

%finds mean of rows
mccc = mean(ccc,2); %area
meee = mean(eee,2); %tons of soil reduction
mfff = mean(fff,2); %total BMP cost
mvvv = mfff./meee; %avg S reduction incremental costs
mddd = cat(1,mean(ddd,2),nan(m-1,1)); %avg S reduction costs (total)
mggg = mean(ggg,2); %pounds of N reduction
mwww = mfff./mggg; %avg N reduction incremental costs
mttt = cat(1,mean(ttt,2),nan(m-1,1)); %avg N reduction costs (total)
mhhh = mean(hhh,2); %pounds of P reduction
mxxx = mfff./mhhh; %avg P reduction incremental costs
muuu = cat(1,mean(uuu,2),nan(m-1,1)); %avg P reduction costs (total)
miii = cat(1,mean(iii,2),nan(m-1,1)); %num of BMPs
mjjj = cat(1,sum(mccc),nan(m-1,1)); %total area
mkkk = cat(1,sum(meee),nan(m-1,1)); %cummulative soil reduction
mlll = cat(1,sum(mfff),nan(m-1,1)); %total BMP costs
mmmm = cat(1,mean(mmm,2),nan(m-1,1)); %soil reduction goal
mnnn = cat(1,mean(nnn,2),nan(m-1,1)); %budget
mooo = cat(1,sum(mggg),nan(m-1,1)); %cummulative N reduction
mppp = cat(1,sum(mhhh),nan(m-1,1)); %cummulative P reduction
mqqq = cat(1,mean(qqq,2),nan(m-1,1)); %num of BMP1 implemented
```

```
mrrr = cat(1,mean(rrr,2),nan(m-1,1)); %num of BMP2 implemented
msss = cat(1,mean(sss,2),nan(m-1,1)); %num of BMP3 implemented

SumOut =
cat(2,bb,mccc,mfff,meee,mvvv,mddd,mggg,mwww,mttt,mhhh,mxxx,muuu,miii,mjjj,mlll,mmmm,mnnn,
mkkk,mooo,mppp,mqqq,mrrr,msss);
SumOutcell = num2cell(SumOut);
Headings = {'#' 'Area (ac)' 'TotBMPCost' 'S_Quantity (tons)' 'AVGincremCost_S (/ton)' 'AVGred_S_Cost
(/ton)' 'N_Quantity (lbs)' 'AVGincremCost_N (/lb)'...
 'AVGred_N_Cost (/lb)' 'P_Quantity (lbs)' 'AVGincremCost_P (/lb)' 'AVGred_P_Cost (/lb)'
'TotBMPnum' 'Total Area (ac)' 'TotBMPCost'...
 'S_RedGoal (tons)' 'Budget' 'Cumm_S_Quantity (tons)' 'Cumm_N_Quantity (lbs)' 'Cumm_P_Quantity
(lbs)'...
 '# of BMP1' '# of BMP2' '#of BMP3'};

allOutput = [Headings; SumOutcell];
xlswrite('BestS_15yr_50K.xls',allOutput,1,'A1');

%----------------------------------------------------------------

% Run OfficeDoc to format Excel output
% Open document in 'append' mode:
[file,status,errMsg] = officedoc('BestS_15yr_50K.xls', 'open', 'mode','append');

status = officedoc(file, 'format', 'sheet', 1, 'Range', 'A1:W1', 'bold','on','WrapText',1);
status = officedoc(file, 'format', 'sheet', 1, 'Range', 'D:D,E:E,F2,H:H,I2,K:K,L2',
'NumberFormat','$#,##0.00');
status = officedoc(file, 'format', 'sheet', 1, 'Range', 'D:D,G:G,J:J,U2,V2,W2', 'NumberFormat','#,##0.00');
status = officedoc(file, 'format', 'sheet', 1, 'Range', 'C:C,O2,Q2', 'NumberFormat','$#,##0');
status = officedoc(file, 'format', 'sheet', 1, 'Range', 'B:B, M2,N2,P2,R2,S2,T2', 'NumberFormat','#,##0');
status = officedoc(file, 'format', 'sheet', 1, 'Range', 'A:W', 'ColAutoFit',1);

% Close the document, deleting standard sheets and releasing COM server:
status = officedoc(file, 'close', 'release',1,'delStd','off');
toc
% Re-display document; file is no longer valid so we must use file name:
%officedoc('BestS_15yr_50K.xls', 'display');
```

Example Code for Random BMP Implementation focusing on sediment and $50,000 annual budget

```
%Random BMP implementation
%Sediment Reduction

clear %clears workspace; comment this out if using MasterRunFile
clc %clears command window
delete ('RandS_15yr_50K.xls') %deletes existing Excel spreadsheet output
OutFile = 'C:\Documents and Settings\Craig Smith\My
Documents\Ph.D\Cost_Effective_WS_Management\SimModel_6\RandS_15yr_50K.xls';

warning off MATLAB:divideByZero

%What are the Sediment reduction goals and budget constraint and iterations? comment if
%using MasterRunFile
RedGoal = 100000000;
Budget = 50000;
xpercent = .25; %percent of farms to eliminate
iterations = 3150; %number of iterations (e.g., 1000 or more ** note: increase by roughly 5%)

%Load Cost and Quantity data
WSdata = xlsread('Tuttle_Model_Data.xls', 'MATinput','A2:O1859');
TotFarms = size(WSdata,1);
SubWS = WSdata(:,2);
num_counties = 10; %number of counties
num_BMPs = 3; %number of BMPs available
seed_value = 31517; %seed value

%Need to eliminate "xpercent" of the farms because we will assume that
%xpercent of the farms have already adopted BMPs or will never adopt BMPs
ineligiblefarms = round(xpercent*TotFarms);

%---------------------------------
SubWS_percent = xlsread('BMPCosts_15yrs.xls','input','D3:AH12');

%Create a matrix with max(SubWS) columns representing the subwatersheds
%and the data in the rows represents which HRUs belong to each subwatershed
SW = zeros(TotFarms,max(SubWS)); %preallocate a TotFarms by max(SubWS) matrix
for i=1:max(SubWS)
 SW_a = find(SubWS==i);
 SW_b = zeros(TotFarms - size(SW_a,1),1); %need to add a column vector of zeros to make each vector
the same length
 SW_c = cat(1,SW_a,SW_b);
 SW(:,i) = SW_c; %SW is the resulting matrix
end;

%--------------------------------------
%need a 1 by num of SubWS's matrix with number of HRUs in each SubWS
SW_count = zeros(1,max(SubWS)); %preallocate
```

```
for i = 1:max(SubWS)
 SW_count(1,i) = max(find(SW(:,i)>0)); %this is # of HRUs in each SubWS
end;

Co_SW_matrix = SubWS_percent(:,1:max(SubWS)); %this is % of SubWS in each county
Co_SW_matrix_1 = zeros(num_counties,max(SubWS)); %preallocate

for i = 1:num_counties
 Co_SW_matrix_1(i,:) = round((Co_SW_matrix(i,:).*SW_count)-.05); %subtract .05 so that we don't get
any negative #'s in
 %the Co_SW_matrix_2 which is calculated next
end;
%---------------------------------------
%Need to make sure each column adds up to the correct number of HRUs
Co_SW_matrix_2 = zeros(1,max(SubWS));

for i = 1:max(SubWS)
 Co_SW_matrix_2(1,i) = SW_count(1,i) - sum(Co_SW_matrix_1(1:9,i));
end;

Co_SW_matrix_1(num_counties,:) = Co_SW_matrix_2;
%---------------------------------------

BMP_ann_costs = SubWS_percent(:,29:31);
BMP_cost_matrix = zeros(TotFarms,num_BMPs); %preallocate a matrix with TotFarms by 3 (# of
BMPs) columns
BMP_matrix1 = zeros(TotFarms,max(SubWS));
BMP_matrix2 = zeros(TotFarms,max(SubWS));
BMP_matrix3 = zeros(TotFarms,max(SubWS));

for j = 1:max(SubWS)
 A = 0;
 for i = 1:num_counties
 if Co_SW_matrix_1(i,j) == 0
 continue
 end
 BMP_matrix1(A+1:Co_SW_matrix_1(i,j)+A,j) = BMP_ann_costs(i,1);
 BMP_matrix2(A+1:Co_SW_matrix_1(i,j)+A,j) = BMP_ann_costs(i,2);
 BMP_matrix3(A+1:Co_SW_matrix_1(i,j)+A,j) = BMP_ann_costs(i,3);
 A = Co_SW_matrix_1(i,j)+A;
 end;
end;

%---------------------------------------
%Subdivide matrix into column vectors cell arrays

for i = 1:max(SubWS)
 y{i} = zeros(TotFarms,1);%preallocate
 bmp1{i} = zeros(TotFarms,1);
 bmp2{i} = zeros(TotFarms,1);
```

```
 bmp3{i} = zeros(TotFarms,1);
end;

for i = 1:max(SubWS)
 y{i} = SW(:,i);
end

for i = 1:max(SubWS)
 bmp1{i} = BMP_matrix1(:,i);
end

for i = 1:max(SubWS)
 bmp2{i} = BMP_matrix2(:,i);
end

for i = 1:max(SubWS)
 bmp3{i} = BMP_matrix3(:,i);
end
%-----------------------------------------

%Get rid of zeros in each column vector
for i=1:max(SubWS)
 y_new{i} = y{1,i}(y{1,i}~=0);
end

for i=1:max(SubWS)
 bmp1_new{i} = bmp1{1,i}(bmp1{1,i}~=0);
end

for i=1:max(SubWS)
 bmp2_new{i} = bmp2{1,i}(bmp2{1,i}~=0);
end

for i=1:max(SubWS)
 bmp3_new{i} = bmp3{1,i}(bmp3{1,i}~=0);
end

%----------------------------------------

%Combine common Subwatershed vectors, so the result will be 3 BMP cost
%column vectors. We can then randomly pair these using the randswap function
for i = 1:max(SubWS)
 combined_bmpcosts{i} = cat(2,bmp1_new{1,i},bmp2_new{1,i},bmp3_new{1,i});
end

%-----------------------------------------
%Outer loop for testing purposes
% for k=1:1
%keep3 function is a complement to the clear fcn. in that it clears all
%variables except the ones listed
```

```
keep3 combined_bmpcosts RedGoal Budget xpercent iterations WSdata TotFarms SubWS num_counties
num_BMPs ineligiblefarms OutFile y_new seed_value
rand('seed',seed_value);%set seed value
OUT = cell(1,iterations);
%----------------------------------------
%Start simulating the BMP implementation scenarios. Note that this is the
%outerloop
for j = 1:iterations
 j
 tic;
 HRU_id = WSdata(:,1);
 FarmArea = WSdata(:,3);
 BaseNLoad = WSdata(:,4);
 BMP1NLoad = WSdata(:,5);
 BMP2NLoad = WSdata(:,6);
 BMP3NLoad = WSdata(:,7);

 BMP1NQuantity = BaseNLoad - BMP1NLoad;
 BMP2NQuantity = BaseNLoad - BMP2NLoad;
 BMP3NQuantity = BaseNLoad - BMP3NLoad;

 BasePLoad = WSdata(:,8);
 BMP1PLoad = WSdata(:,9);
 BMP2PLoad = WSdata(:,10);
 BMP3PLoad = WSdata(:,11);

 BMP1PQuantity = BasePLoad - BMP1PLoad;
 BMP2PQuantity = BasePLoad - BMP2PLoad;
 BMP3PQuantity = BasePLoad - BMP3PLoad;

 BaseSLoad = WSdata(:,12);
 BMP1SLoad = WSdata(:,13);
 BMP2SLoad = WSdata(:,14);
 BMP3SLoad = WSdata(:,15);

 BMP1SQuantity = BaseSLoad - BMP1SLoad;
 BMP2SQuantity = BaseSLoad - BMP2SLoad;
 BMP3SQuantity = BaseSLoad - BMP3SLoad;

 %Now randomly pair the combined BMP costs matrix with an HRU
 for i = 1:max(SubWS)
 rand_bmpcosts = randswap(combined_bmpcosts{1,i});
 SW_bmpcosts{i} = cat(2,y_new{1,i},rand_bmpcosts);
 end

 %Reshape and order the bmpcosts matrix in numerical order by the first
 %column which is HRU id number
 SW_bmpcosts = reshape(SW_bmpcosts,max(SubWS),1);
 stacked_bmpcosts = cell2mat(SW_bmpcosts);
 ordered_HRU_bmpcosts = sortrows(stacked_bmpcosts,1);
```

```
%Determine Total and Average BMP costs for each HRU for N,P, and S

%Nitrogen Costs
BMP1NCost = ordered_HRU_bmpcosts(:,2).*FarmArea;
BMP2NCost = ordered_HRU_bmpcosts(:,3).*FarmArea;
BMP3NCost = ordered_HRU_bmpcosts(:,4).*FarmArea;

AVGBMP1NCost = BMP1NCost./BMP1NQuantity;
AVGBMP2NCost = BMP2NCost./BMP2NQuantity;
AVGBMP3NCost = BMP3NCost./BMP3NQuantity;

AVGBMP1NCost(isinf(AVGBMP1NCost)) = 0; %replace infinity values with zeros
AVGBMP2NCost(isinf(AVGBMP2NCost)) = 0; %replace infinity values with zeros
AVGBMP3NCost(isinf(AVGBMP3NCost)) = 0; %replace infinity values with zeros

%Phosphorus Costs
BMP1PCost = ordered_HRU_bmpcosts(:,2).*FarmArea;
BMP2PCost = ordered_HRU_bmpcosts(:,3).*FarmArea;
BMP3PCost = ordered_HRU_bmpcosts(:,4).*FarmArea;

AVGBMP1PCost = BMP1PCost./BMP1PQuantity;
AVGBMP2PCost = BMP2PCost./BMP2PQuantity;
AVGBMP3PCost = BMP3PCost./BMP3PQuantity;

AVGBMP1PCost(isinf(AVGBMP1PCost)) = 0; %replace infinity values with zeros
AVGBMP2PCost(isinf(AVGBMP2PCost)) = 0; %replace infinity values with zeros
AVGBMP3PCost(isinf(AVGBMP3PCost)) = 0; %replace infinity values with zeros

%Sediment Costs
BMP1SCost = ordered_HRU_bmpcosts(:,2).*FarmArea;
BMP2SCost = ordered_HRU_bmpcosts(:,3).*FarmArea;
BMP3SCost = ordered_HRU_bmpcosts(:,4).*FarmArea;

AVGBMP1SCost = BMP1SCost./BMP1SQuantity;
AVGBMP2SCost = BMP2SCost./BMP2SQuantity;
AVGBMP3SCost = BMP3SCost./BMP3SQuantity;

AVGBMP1SCost(isinf(AVGBMP1SCost)) = 0; %replace infinity values with zeros
AVGBMP2SCost(isinf(AVGBMP2SCost)) = 0; %replace infinity values with zeros
AVGBMP3SCost(isinf(AVGBMP3SCost)) = 0; %replace infinity values with zeros

%Get rid of zeros and negatives in Average BMP cost matricies
BMPsAVGNCosts = cat(2,AVGBMP1NCost,AVGBMP2NCost,AVGBMP3NCost);
findzerosN = find(BMPsAVGNCosts<=0); %finds zeros and negatives in BMPsAVGNCosts matrix
BMPsAVGNCosts(findzerosN) = 0; %replaces zeros and negatives with 0's which is need for this
program

BMPsAVGPCosts = cat(2,AVGBMP1PCost,AVGBMP2PCost,AVGBMP3PCost);
findzerosP = find(BMPsAVGPCosts<=0); %finds zeros and negatives in BMPsAVGPCosts matrix
```

```
BMPsAVGPCosts(findzerosP) = 0; %replaces zeros and negatives with 0's which is need for this
program

BMPsAVGSCosts = cat(2,AVGBMP1SCost,AVGBMP2SCost,AVGBMP3SCost);
findzerosS = find(BMPsAVGSCosts<=0); %finds zeros and negatives in BMPsAVGSCosts matrix
BMPsAVGSCosts(findzerosS) = 0; %replaces zeros and negatives with 0's which is need for this
program

%Need to eliminate "xpercent" of the farms because we will assume that
%xpercent of the farms have already adopted BMPs or will never adopt
%BMPs. This is done by randomly selecting xpercent of the farms and
%setting the appropriate rows in the BMPsAVGSCosts to zero. Note that
%if we were addressing another pollutant (N or P), then this
%code would need to be changed to the appropriate BMP Avg Cost matrix.
%If there are already more farms with negatives and zeros than
%ineligible farms, then this piece of code has no effect

num_of_zeros = size(find(BMPsAVGSCosts(:,1) == 0),1);
while num_of_zeros < ineligiblefarms
eliminate_id = round(rand(1)*TotFarms);
if eliminate_id == 0
continue
end
BMPsAVGSCosts(eliminate_id,1:3) = zeros(1,3);
num_of_zeros = size(find(BMPsAVGSCosts(:,1) == 0),1);
end;
num_of_zeros = size(find(BMPsAVGSCosts(:,1) == 0),1);

%Get rid of the negatives and zeros
NReductions = cat(2, BMP1NQuantity, BMP2NQuantity, BMP3NQuantity);
PReductions = cat(2, BMP1PQuantity, BMP2PQuantity, BMP3PQuantity);
SReductions = cat(2, BMP1SQuantity, BMP2SQuantity, BMP3SQuantity);

% findreductionsN = find(NReductions<0); %finds negative values in N reductions data
% NReductions(findreductionsN) = 0; %replaces negatives with zeros

% findreductionsP = find(PReductions<0); %finds negative values in P reductions data
% PReductions(findreductionsP) = 0; %replaces negatives with zeros

findreductionsS = find(SReductions<0); %finds negative values in S reductions data
SReductions(findreductionsS) = 0; %replaces negatives with zeros

CummNQuantity = 0;
TotBMPNCost1 = 0;
CummPQuantity = 0;
TotBMPPCost1 = 0;
CummSQuantity = 0;
TotBMPSCost1 = 0;
zeromatrix = zeros(TotFarms,num_BMPs);%zeros matrix of dimension TotFarms x 3 which is # of
BMPs
```

```
%This is the innerloop where the actual BMP implementation occurs
i = 1;
S = [1:TotFarms.*num_BMPs]';
findzerocosts = find(BMPsAVGSCosts == 0);
S([findzerocosts]) = [0]; % Replace some of the elements of S with zero if they have already been ruled
ineligble
S_rand = S(randperm(size(S,1)),:); %randomize the S matrix

%This piece of code moves all zeros to the bottom of the column vector
S_randsort=[];
[m,n]=size(S_rand);
for col=1:n,
a=zeros(m,1);
a(1:sum(S_rand(:,col)>0))=S_rand(find(S_rand(:,col)>0),col);
S_randsort=[S_randsort a];
end

mat_size = [TotFarms,num_BMPs];
[FarmID_1,BMP_1] = ind2sub(mat_size,S_randsort); %The ind2sub command determines the equivalent
subscript values corresponding
%to a single index into an array

%need to eliminate duplicates from FarmID_1 and the
%corresponding elements in BMP_1 vector. This is because only one
%BMP can be implemented on a farm
[FarmID_2,BMP_position] = unique_no_sort(FarmID_1); %this is a specially made function which is
similar to "unique"
%function except that it does not sort
FarmID_2 = (FarmID_2(1:length(FarmID_2)-1))';
BMP_position = (BMP_position(1:length(BMP_position)-1))';

%This loop creates the corresponding BMP_2 matrix to match the FARMID_2
%vector created earlier
for i = 1:length(BMP_position)
BMP_2(i,1) = BMP_1(BMP_position(i,1),1);
end;

i=0;
while (CummSQuantity < RedGoal) && (sum(sum(single(SReductions)))>0) %loop while below
reduction goal AND
%while there are still BMPs available
i = i+1;

if i > length(BMP_position)
break; end;

FarmID = FarmID_2(i);
BMP = BMP_2(i);
```

```
if FarmID == 0
break; end;

if BMPsAVGSCosts(FarmID,BMP)>0 && SReductions(FarmID,BMP)>0
AVGPracticeSCost = BMPsAVGSCosts(FarmID,BMP);
Area = FarmArea(FarmID,1);
NQuantity = NReductions(FarmID,BMP);
PQuantity = PReductions(FarmID,BMP);
SQuantity = SReductions(FarmID,BMP);
TotPracticeSCost = AVGPracticeSCost*SQuantity;
else
continue;
end;

if (TotPracticeSCost + TotBMPSCost1) > Budget
continue;
end;

%SReductions(FarmID,BMP) = SReductions(FarmID,BMP) - SQuantity; %Update Reductions Matrix
SReductions(FarmID,:) = zeros(1,num_BMPs); %after a BMP is implemented, zero out the row so that
farm is eliminated
%from further consideration

if i == 1 %save data
Simout = [Area, FarmID, BMP, AVGPracticeSCost, SQuantity, TotPracticeSCost];
OtherSimout = [NQuantity, PQuantity];
else Simout = [Simout; Area, FarmID, BMP, AVGPracticeSCost, SQuantity, TotPracticeSCost];
OtherSimout = [OtherSimout; NQuantity, PQuantity];
end;

TotArea = sum(Simout(:,1));
CummSQuantity = sum(Simout(:,5));
TotBMPSCost = sum(Simout(:,6));
TotBMPSCost1 = TotBMPSCost + 0;
CummNQuantity = sum(OtherSimout(:,1));
CummPQuantity = sum(OtherSimout(:,2));
numofBMP1 = size(find(Simout(:,3)==1),1); %calculates # of BMP1 implemented
numofBMP2 = size(find(Simout(:,3)==2),1); %calculates # of BMP2 implemented
numofBMP3 = size(find(Simout(:,3)==3),1); %calculates # of BMP3 implemented
end;

num_of_BMPs = size(Simout,1);
Count = (1:num_of_BMPs)'; %this numbers the rows in the first column of output
a = nan(num_of_BMPs-1,1); %nan matrix that is # of BMPs rows and 1 column
TotBMPnumOUT = cat(1,num_of_BMPs,a); %the scalar value is inserted at top of a matrix to make
%a # of BMPs x 1 matrix for output purposes - same procedure for next 5
%output variables
TotAreaOUT = cat(1,TotArea,a);
TotBMPSCostOUT = cat(1,TotBMPSCost,a);
RedGoalOUT = cat(1,RedGoal,a);
```

```
 BudgetOUT = cat(1,Budget,a);
 CummNQuantityOUT = cat(1,CummNQuantity,a);
 CummPQuantityOUT = cat(1,CummPQuantity,a);
 CummSQuantityOUT = cat(1,CummSQuantity,a);
 numofBMP1OUT = cat(1,numofBMP1,a);
 numofBMP2OUT = cat(1,numofBMP2,a);
 numofBMP3OUT = cat(1,numofBMP3,a);

 Output = cat(2,Count, Simout, OtherSimout, TotBMPnumOUT, TotAreaOUT, CummSQuantityOUT,
TotBMPSCostOUT, RedGoalOUT,...
 BudgetOUT, CummNQuantityOUT, CummPQuantityOUT, numofBMP1OUT, numofBMP2OUT,
numofBMP3OUT);
 % numericalOutput = num2cell(Output); %change the numerical array into a cell array

 OUT{j} = {Output};
 toc
 time2{j} = toc;
end;

disp ('Successfully finished the iterations!!')
%-----------------------------------------------

%The rest of the code is for organizing and summarizing all of the output and
%reporting it in a neat formatted fashion

%Delete the cases where the budget constraint was exceeded (this somehow
%occurs in approximately 4% of the cases). So, increase the number of
%iterations by 4%. i.e., if you want 1000 good simulations, run 1040

for j=1:iterations
 costs(j,1) = OUT{1,j}{1,1}(1,13); %finds the TotBMPCost for each iteration
end;

delete_bad = find(costs > Budget)
size_delete = length(delete_bad)

for j=delete_bad
 OUT(j) = [];
end;

%Finds the maximum number of BMP projects implemented(rows) in the output data. Changes all
%matrices to have the same number of rows. Zeros are put in the rows that
%are added.For more information, go to section 15.3 in the array manipulation
%publication

iterations = iterations - size_delete;

for j=1:iterations
 b(j) = max(OUT{1,j}{1,1}(:,1)); %finds total # of BMP projects implemented in each iteration
end;
```

```
m = mean(b); %finds average # of BMP projects implemented across all iterations
m = round(m); %rounds the average # to nearest whole number
% aa = a(:)'; %creates another matrix aa equal to a
% aa = aa(ones(m,1),:); %transforms aa into an m by iterations matrix
bb = (1:m)'; %creates bb which is a column vector going from 1 to m
% bb = bb(:,ones(length(a), 1)); %transforms bb into a m by iterations matrix
% %with each column going from 1 to m
% b = bb .* (bb <= aa); %the dot indicates array multiplication (not the same
% %as matrix multiplication. Arrays in bb are multiplied by an array of ones
% %and zeros corresponding to the number of BMP projects implemented
% M = mean(b,2); %sums across all rows of the b matrix resulting in a column vector

for i = 1:iterations %this loop equalizes number of rows (equal to mean # of BMP projects implemented)
 %across all iterations so that the means can be calcualted
 cc{i} = OUT{i}{1}(:,2); %area
 ee{i} = OUT{i}{1}(:,6); %tons of soil reduction
 ff{i} = OUT{i}{1}(:,7); %total BMP cost
 gg{i} = OUT{i}{1}(:,8); %pounds of N reduction
 hh{i} = OUT{i}{1}(:,9); %pounds of P reduction
 ii{i} = OUT{i}{1}(1,10); %num of BMPs
 jj{i} = OUT{i}{1}(1,11); %total area
 kk{i} = OUT{i}{1}(1,12); %cummulative soil reduction
 ll{i} = OUT{i}{1}(1,13); %total BMP costs
 mm{i} = OUT{i}{1}(1,14); %soil reduction goal
 nn{i} = OUT{i}{1}(1,15); %budget
 oo{i} = OUT{i}{1}(1,16); %cummulative N reduction
 pp{i} = OUT{i}{1}(1,17); %cummulative P reduction
 qq{i} = OUT{i}{1}(1,18); %num of BMP1 implemented
 rr{i} = OUT{i}{1}(1,19); %num of BMP2 implemented
 ss{i} = OUT{i}{1}(1,20); %num of BMP3 implemented

 [u,y] = size(cc{i});
 if u >= m
 cc1{i} = cc{i}(1:m,:);
 ee1{i} = ee{i}(1:m,:);
 ff1{i} = ff{i}(1:m,:);
 gg1{i} = gg{i}(1:m,:);
 hh1{i} = hh{i}(1:m,:);
 else v = m-u;
 w = zeros(v,1);
 cc1{i} = cat(1,cc{i},w);
 ee1{i} = cat(1,ee{i},w);
 ff1{i} = cat(1,ff{i},w);
 gg1{i} = cat(1,gg{i},w);
 hh1{i} = cat(1,hh{i},w);
 end;
end;

%convert cell array of matricies to single matrix
```

```
ccc = cell2mat(cc1);
eee = cell2mat(ee1);
fff = cell2mat(ff1);
ggg = cell2mat(gg1);
hhh = cell2mat(hh1);
iii = cell2mat(ii);
jjj = cell2mat(jj);
kkk = cell2mat(kk);
lll = cell2mat(ll);
mmm = cell2mat(mm);
nnn = cell2mat(nn);
ooo = cell2mat(oo);
ppp = cell2mat(pp);
qqq = cell2mat(qq);
rrr = cell2mat(rr);
sss = cell2mat(ss);
ddd = sum(mean(fff,2))/sum(mean(eee,2)); %avg S reduction costs (total)
ttt = sum(mean(fff,2))/sum(mean(ggg,2)); %avg N reduction costs (total)
uuu = sum(mean(fff,2))/sum(mean(hhh,2)); %avg P reduction costs (total)

%finds mean of rows
mccc = mean(ccc,2); %area
meee = mean(eee,2); %tons of soil reduction
mfff = mean(fff,2); %total BMP cost
mvvv = mfff./meee; %avg S reduction incremental costs
mddd = cat(1,mean(ddd,2),nan(m-1,1)); %avg S reduction costs (total)
mggg = mean(ggg,2); %pounds of N reduction
mwww = mfff./mggg; %avg N reduction incremental costs
mttt = cat(1,mean(ttt,2),nan(m-1,1)); %avg N reduction costs (total)
mhhh = mean(hhh,2); %pounds of P reduction
mxxx = mfff./mhhh; %avg P reduction incremental costs
muuu = cat(1,mean(uuu,2),nan(m-1,1)); %avg P reduction costs (total)
miii = cat(1,mean(iii,2),nan(m-1,1)); %num of BMPs
mjjj = cat(1,sum(mccc),nan(m-1,1)); %total area
mkkk = cat(1,sum(meee),nan(m-1,1)); %cummulative soil reduction
mlll = cat(1,sum(mfff),nan(m-1,1)); %total BMP costs
mmmm = cat(1,mean(mmm,2),nan(m-1,1)); %soil reduction goal
mnnn = cat(1,mean(nnn,2),nan(m-1,1)); %budget
mooo = cat(1,sum(mggg),nan(m-1,1)); %cummulative N reduction
mppp = cat(1,sum(mhhh),nan(m-1,1)); %cummulative P reduction
mqqq = cat(1,mean(qqq,2),nan(m-1,1)); %num of BMP1 implemented
mrrr = cat(1,mean(rrr,2),nan(m-1,1)); %num of BMP2 implemented
msss = cat(1,mean(sss,2),nan(m-1,1)); %num of BMP3 implemented

SumOut =
cat(2,bb,mccc,mfff,meee,mvvv,mddd,mggg,mwww,mttt,mhhh,mxxx,muuu,miii,mjjj,mlll,mmmm,mnnn,
mkkk,mooo,mppp,mqqq,mrrr,msss);
SumOutcell = num2cell(SumOut);
Headings = {'#' 'Area (ac)' 'TotBMPCost' 'S_Quantity (tons)' 'AVGincremCost_S (/ton)' 'AVGred_S_Cost
(/ton)' 'N_Quantity (lbs)' 'AVGincremCost_N (/lb)'...
```

```
 'AVGred_N_Cost (/lb)' 'P_Quantity (lbs)' 'AVGincremCost_P (/lb)' 'AVGred_P_Cost (/lb)'
'TotBMPnum' 'Total Area (ac)' 'TotBMPCost'...
 'S_RedGoal (tons)' 'Budget' 'Cumm_S_Quantity (tons)' 'Cumm_N_Quantity (lbs)' 'Cumm_P_Quantity
(lbs)'...
 '# of BMP1' '# of BMP2' '#of BMP3'};

allOutput = [Headings; SumOutcell];
xlswrite('RandS_15yr_50K.xls',allOutput,1,'A1');
%end;

%-----------------------------------------------------------------

%------------------------------
%This code erases any empty sheets in an excel workbook
%Open the output xls file

excelObj = actxserver('Excel.Application');
%opens up an excel object
excelWorkbook = excelObj.workbooks.Open(OutFile);
worksheets = excelObj.sheets;
%total number of sheets in workbook
numSheets = worksheets.count;

count=1;
for j=1:numSheets
 %stores the current number of sheets in the workbook
 %this number will change if sheets are deleted
 temp = worksheets.count;

 %if there's only one sheet left, we must leave it or else
 %there will be an error.
 if (temp == 1)
 break;
 end

 %this command will only delete the sheet if it is empty
 worksheets.Item(count).Delete;

 %if a sheet was not deleted, we move on to the next one
 %by incrementing the count variable
 if (temp == worksheets.count)
 count = count + 1;
 end
end
excelWorkbook.Save;
excelWorkbook.Close(false);
excelObj.Quit;
delete(excelObj);

% Run OfficeDoc to format Excel output
```

```
% Open document in 'append' mode:
[file,status,errMsg] = officedoc('RandS_15yr_50K.xls', 'open', 'mode','append');

for z=1:1
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'A1:W1', 'bold','on','WrapText',1);
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'D:D,E:E,F2,H:H,I2,K:K,L2',
'NumberFormat','$#,##0.00');
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'D:D,G:G,J:J,U2,V2,W2', 'NumberFormat','#,##0.00');
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'C:C,O2,Q2', 'NumberFormat','$#,##0');
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'B:B, M2,N2,P2,R2,S2,T2', 'NumberFormat','#,##0');
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'A:W', 'ColAutoFit',1);
end

% Close the document, deleting standard sheets and releasing COM server:
status = officedoc(file, 'close', 'release',1,'delStd','off');

% Re-display document; file is no longer valid so we must use file name:
%officedoc('RandS_15yr_50K.xls', 'display');

toc
```

Appendix C - Additional targeting maps for the original cost scenarios based on Table 2.18

Figure C.1 Spatial average sediment reduction costs under original costs with filter strips

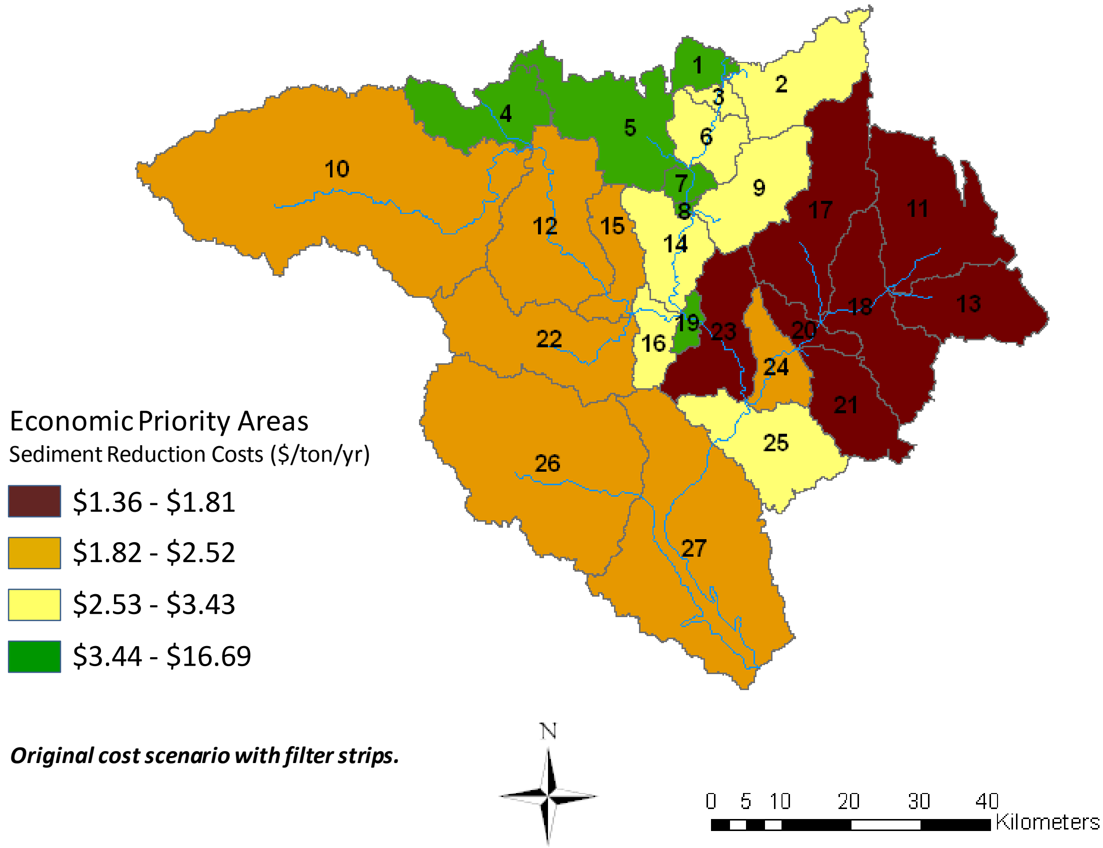


Figure C.2 Spatial average nitrogen reduction costs under original costs with filter strips

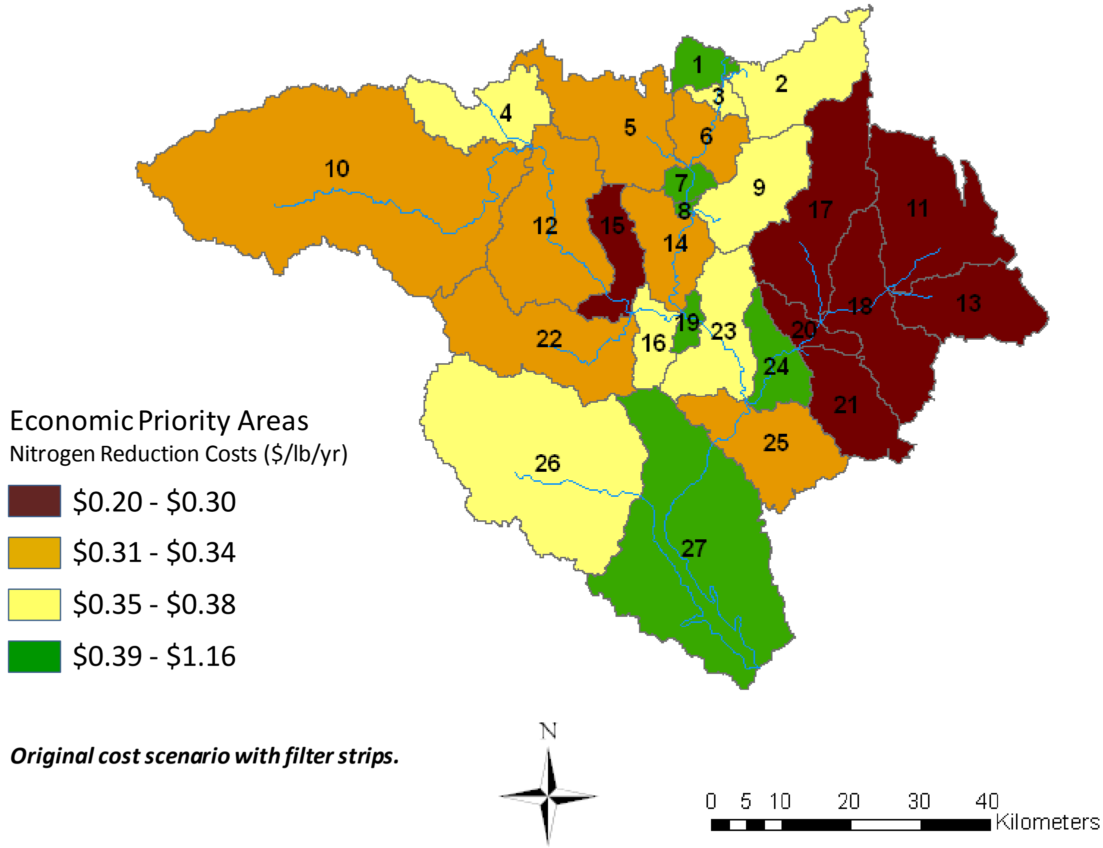


Figure C.3 Spatial average phosphorus reduction costs under original costs with filter strips

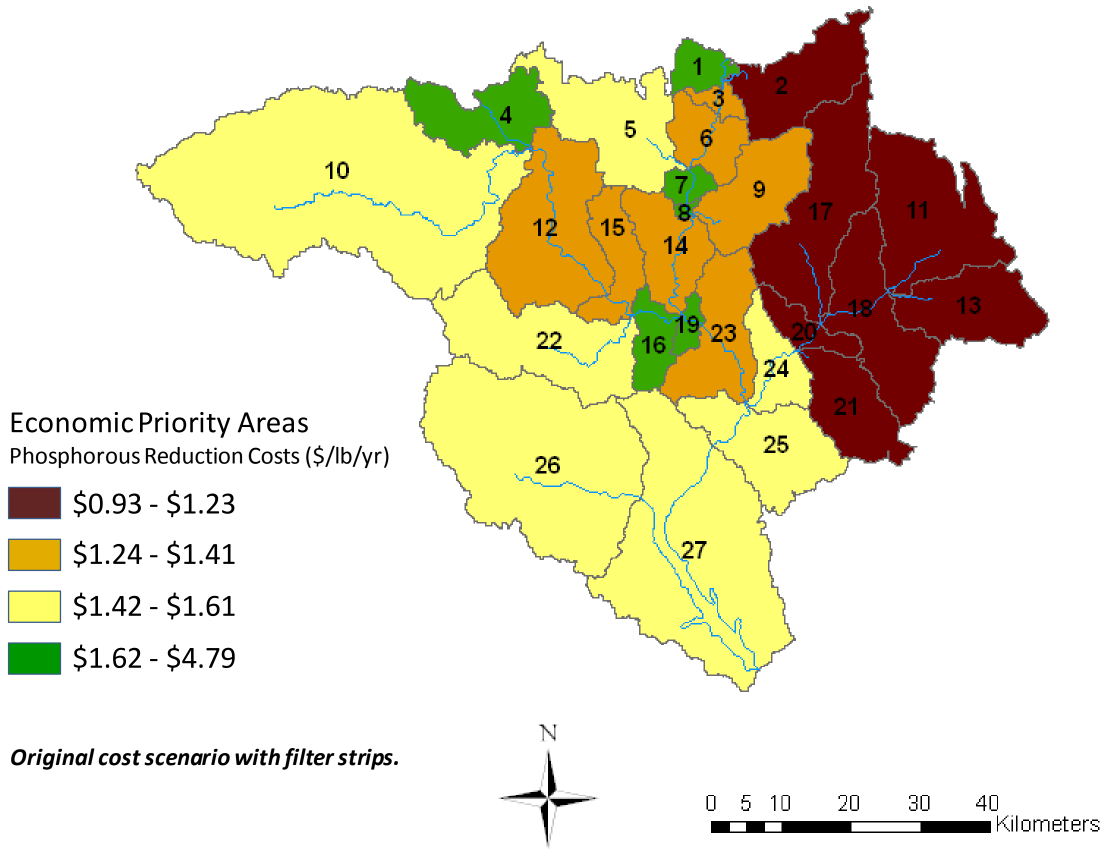


Figure C.4 Spatial average sediment reduction costs under original costs with no-till

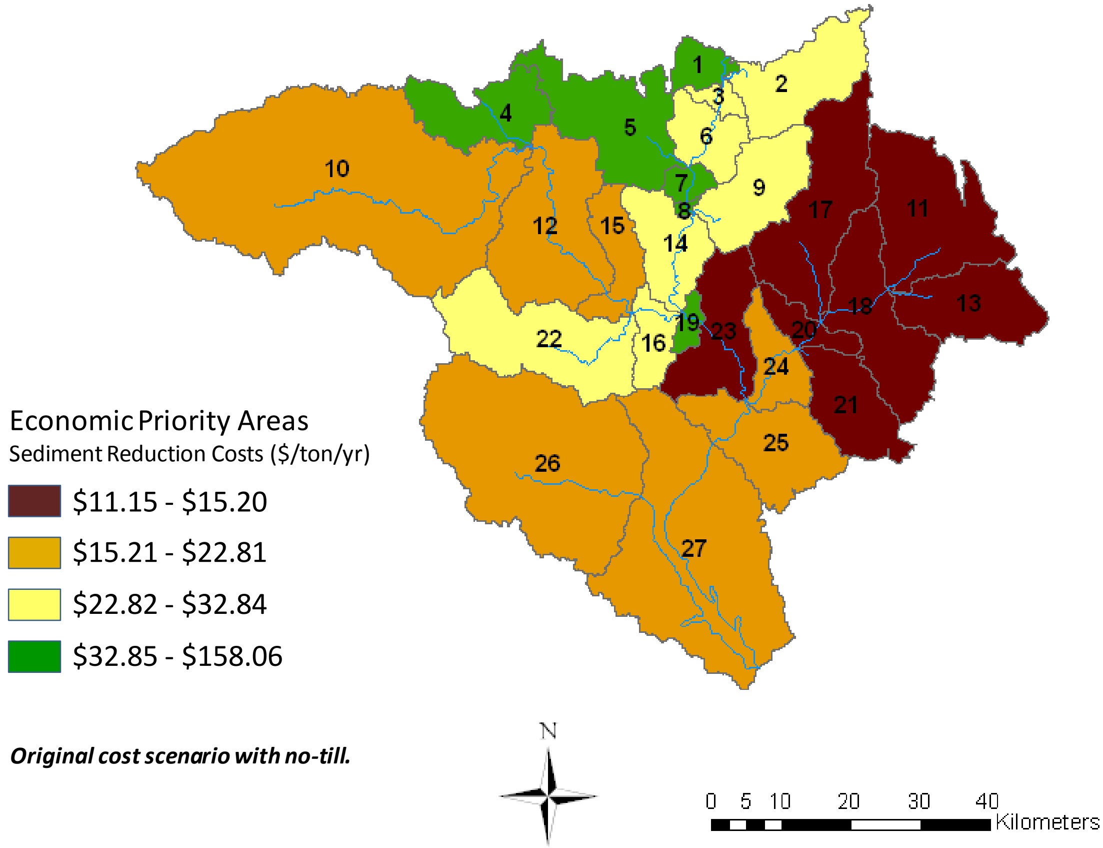


Figure C.5 Spatial average nitrogen reduction costs under original costs with no-till

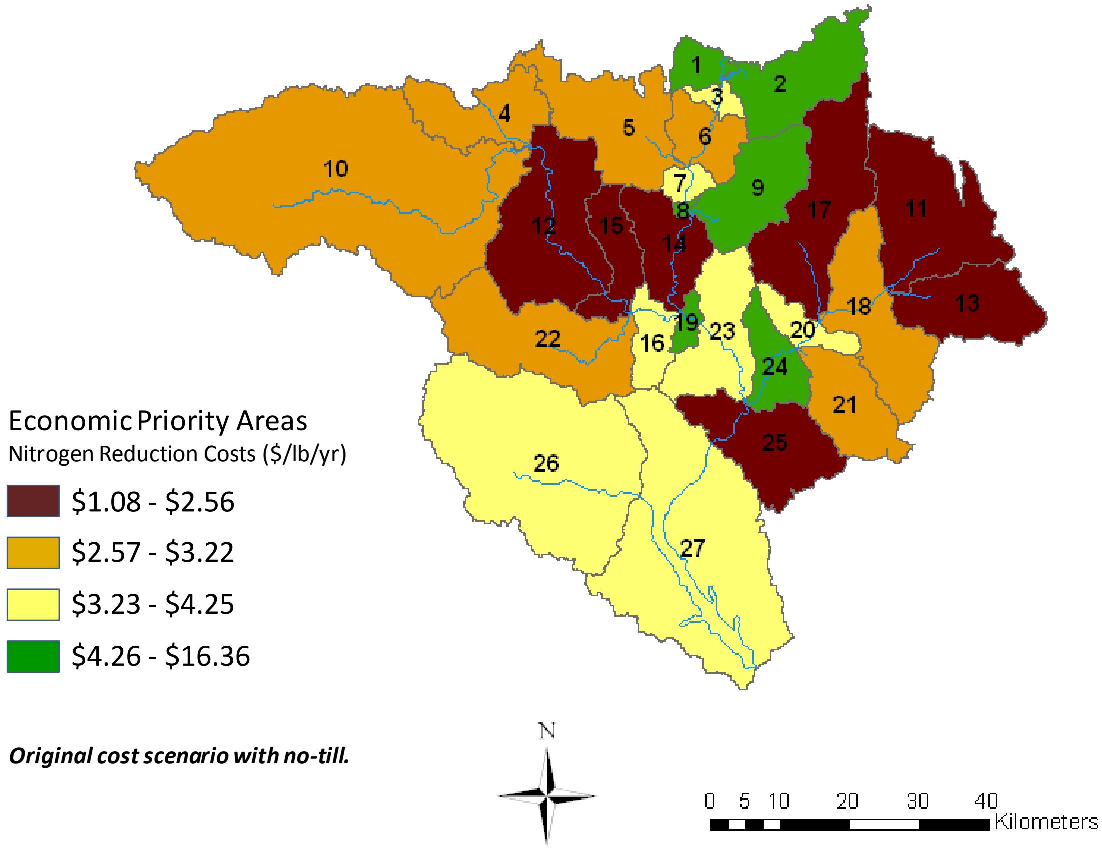


Figure C.6 Spatial average phosphorus reduction costs under original costs with no-till

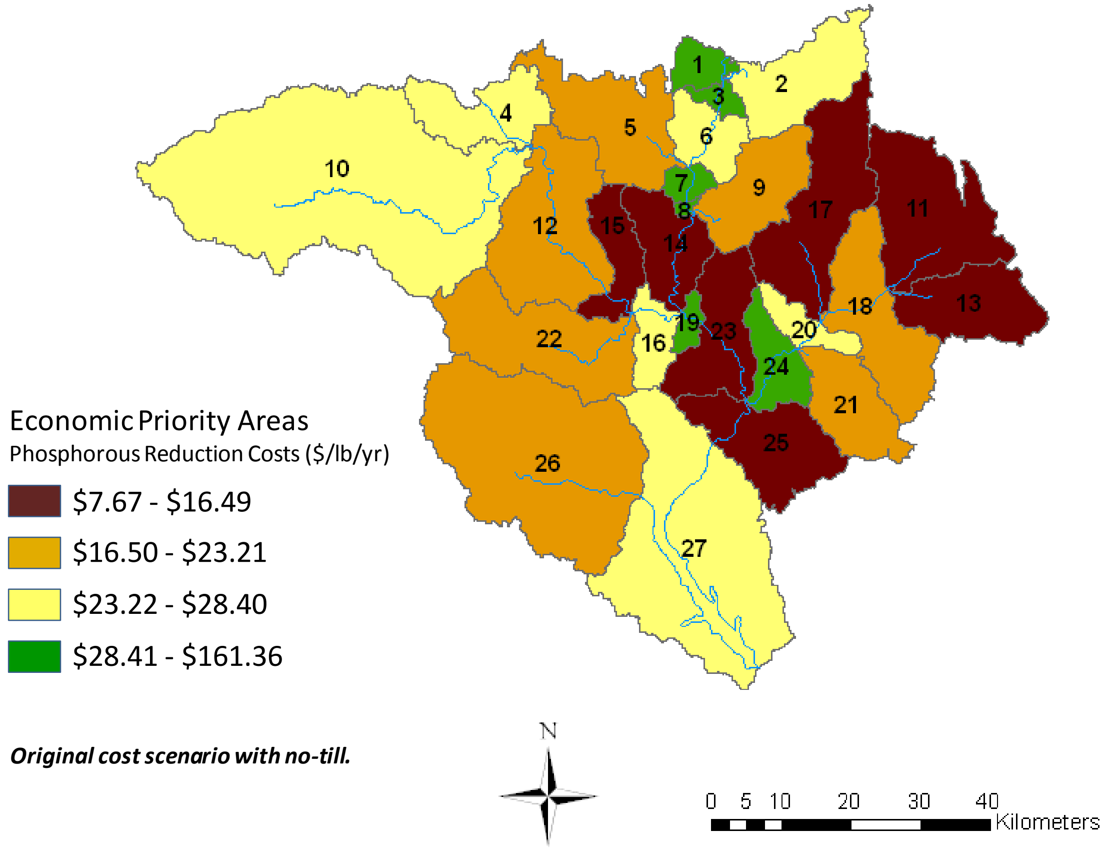


Figure C.7 Spatial average sediment reduction costs under original costs with permanent vegetation

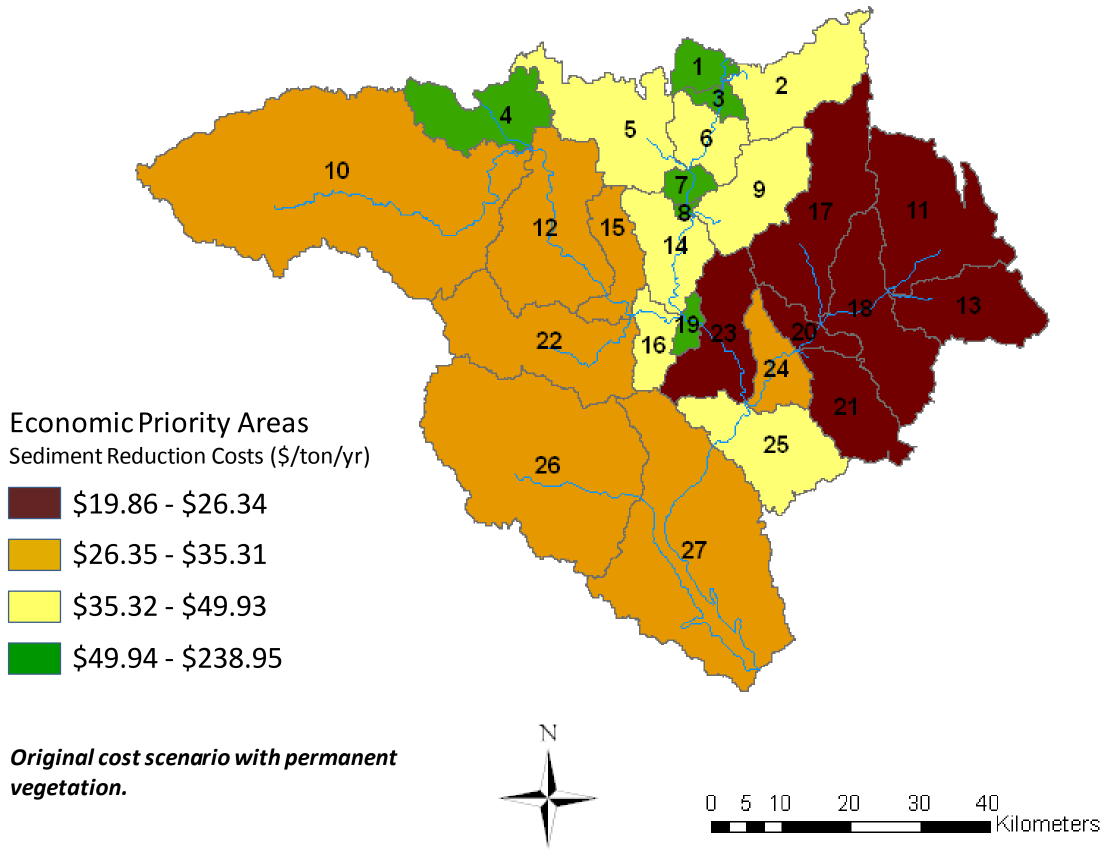


Figure C.8 Spatial average sediment reduction costs under original costs with permanent vegetation

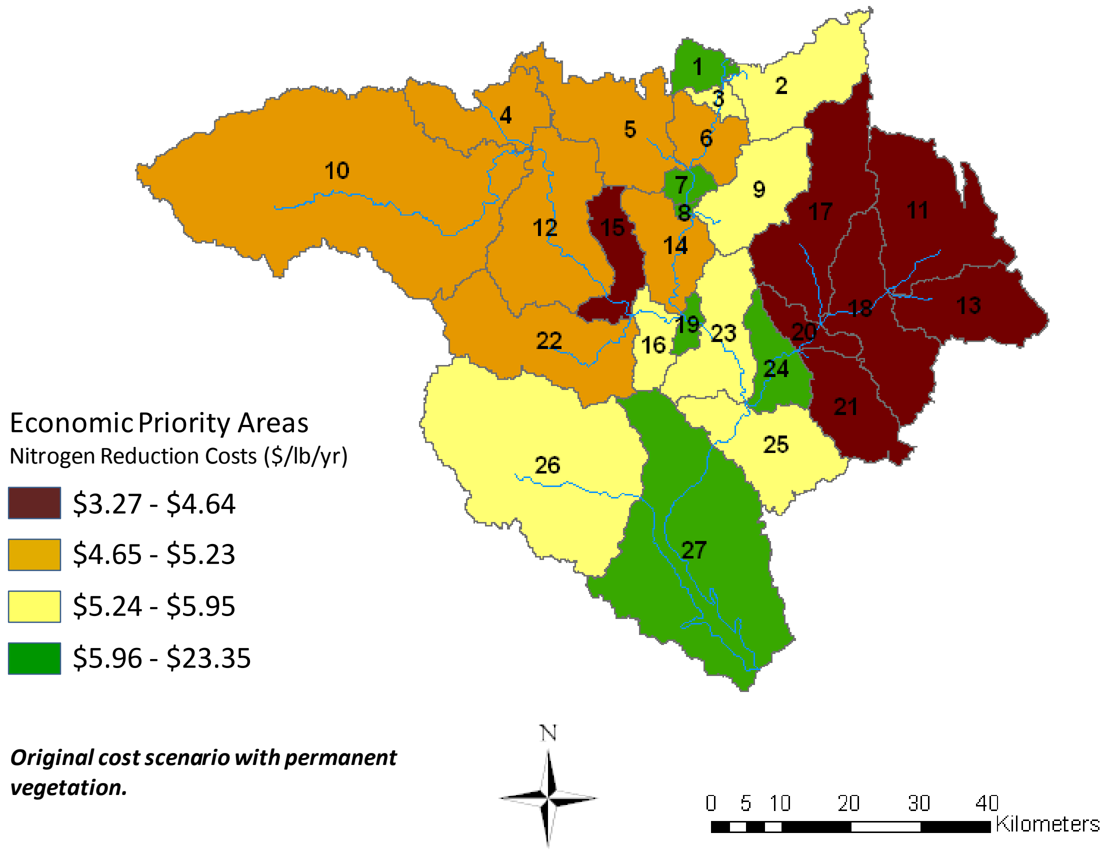
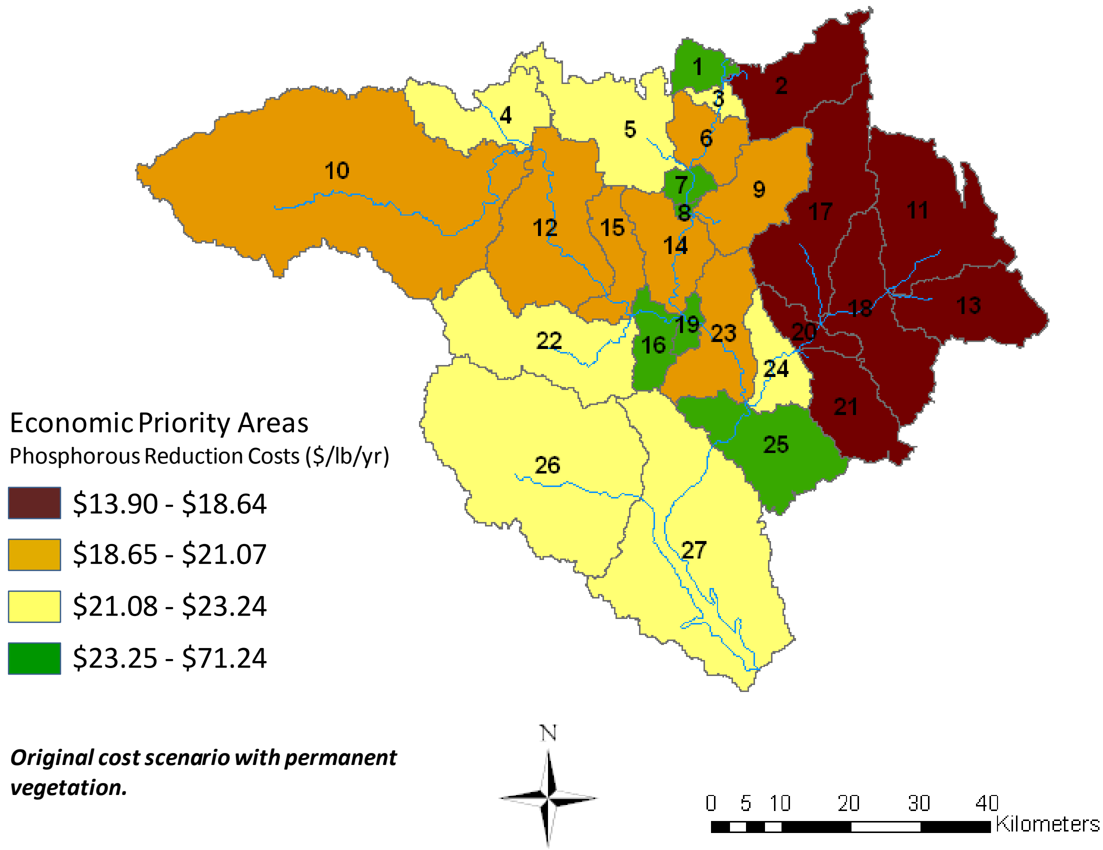


Figure C.9 Spatial average phosphorus reduction costs under original costs with permanent vegetation



Appendix D - Example MATLAB Simulation Code for Chapter 3

Example Code for Targeted for WQT trading under Full Information

```
%Simulation 1: Full information trading
%Full information: highest Marginal Gains element is picked first

clear
clc
tic

outFile = 'C:\Documents and Settings\Craig Smith\My
Documents\Ph.D\WQT_Simulation\Simulations\WQT_1.xls';
delete(outFile) %deletes existing Excel spreadsheet output


%Parameters
tratio = 3; %starting value for trading ratio
trloops = 0; %this should be set to 0 - it counts the number of times through the tratio loop
trcosts = 0;
PSintcost = 0;
NPSintcost = 0;
iterations = 100;
%loops = 1; %should should be set to 1 in most cases, this was initially used to test for appropriate
number of simulations to get stable statistics

p = 10; %number of PS's
n = 500; %number of farms

%trading ratio parameters
trmax = 3; %max trading ratio to consider
trstep = 0.5; %step length for trading ratio

while tratio <= trmax
 tratio
 trloops;

 %keep3 function is a complement to the clear fcn. in that it clears all
 %variables except the ones listed

 keep3 tratio trloops trcosts PSintcost NPSintcost iterations outFile p n trmax trstep

 for j=1:iterations
 j

 %Code to generate a lognormal distribution of PS's. Particularly, log
 %normal distributions of reductions and cost/lb values. This serves as
 %NPS input into the simulations. The logn_rnd function must be in current
```

```
%directory

PSmeanred = 5000; %mean of reductions
PSvarred = 1562500; %variance of reductions
PSmeancost = 20; %mean of costs
PSvarcost = 225; %variance of costs

a = log(PSmeanred)-.5*log(1+(PSvarred/PSmeanred^2));
b = log(1+(PSvarred/PSmeanred^2));

PSlognTotPred = logn_rnd(a,b,p,1);

c = log(PSmeancost)-.5*log(1+(PSvarcost/PSmeancost^2));
d = log(1+(PSvarcost/PSmeancost^2));

PSlognTotPcost = logn_rnd(c,d,p,1);

PSdata = cat(2,PSlognTotPred, PSlognTotPcost);
PSnum = size(PSdata,1);
PSwtp = PSdata(:,2) - PSintcost*ones(PSnum,1);
PSqbuy = PSdata(:,1);

%Code to generate a lognormal distribution of farms. Particularly, log
%normal distributions of reductions and cost/lb values. This serves as
%NPS input into the simulations. The logn_rnd function must be in current
%directory

meanred = 200; %mean of reductions
varred = 2500; %variance of reductions
meancost = 12; %mean of costs
varcost = 64; %variance of costs

a = log(meanred)-.5*log(1+(varred/meanred^2));
b = log(1+(varred/meanred^2));

lognTotPred = logn_rnd(a,b,n,1);

c = log(meancost)-.5*log(1+(varcost/meancost^2));
d = log(1+(varcost/meancost^2));

lognTotPcost = logn_rnd(c,d,n,1);

NPSdata = cat(2,lognTotPred, lognTotPcost);
NPSnum = size(NPSdata,1);
NPSqsold = NPSdata(:,1)/tratio;
NPSwta = tratio*(NPSdata(:,2) + NPSintcost*ones(NPSnum,1));
PSwtp1 = PSwtp;
PSqbuy1 = PSqbuy;
NPSqsold1 = NPSqsold;
```

```
%Marginal Gains matrix
mar.gains = PSwtp*ones(1,NPSnum) - ones(PSnum,1)*NPSwta' - trcosts*ones(PSnum,NPSnum);

i = 0;
while max(max(mar.gains)) > 0
i = i + 1;
[PSid, NPSid] = find(max(max(mar.gains)) == mar.gains); %Find max mar.gains element
if size([PSid, NPSid], 1) > 1 %If PS (NPS) have identical wtp (wta), pick the first one
PSid = PSid(1);
NPSid = NPSid(1);
end;

%Make sure current PS is a feasible trader: it must have sufficient
%supply to meet its demand and have credits left to buy. If either
%of these conditions is not met, a new PS is found that meets both.
PSok = 0;
while PSok == 0
Sellers = (mar.gains(PSid,:) > 0);
Supply = Sellers*NPSqsold1;
if Supply >= PSqbuy1(PSid) && PSqbuy1(PSid) > 0, PSok=1; break; end;
mar.gains(PSid,:) = 0;
PSwtp1(PSid) = 0;
if max(max(mar.gains)) <= 0, PSok=-1; break; end;
PSid = find(max(PSwtp1) == PSwtp1); %find PS with maximum WTP
if size(PSid,1)>1 %If PS have identical wtp, pick the first one
PSid = PSid(1);
end;
end;

%if no PS is a feasbile trading partner, then exit the trading loop
if PSok == -1
%disp('Trading stopped because no feasible PS traders exist.');
break;
end;

PSprice = (NPSwta(NPSid) + PSwtp1(PSid))/2 + trcosts/2;
NPSprice = (NPSwta(NPSid) + PSwtp1(PSid))/2 - trcosts/2;
Quantity = min(PSqbuy1(PSid), NPSqsold1(NPSid));

if i == 1 %save data
Simout = [i, tratio, PSid, NPSid, PSprice, PSwtp1(PSid), NPSwta(NPSid), Quantity, ...
mar.gains(PSid,NPSid), mar.gains(PSid,NPSid)*Quantity];
else Simout = [Simout; i, tratio, PSid, NPSid, PSprice, PSwtp1(PSid), NPSwta(NPSid), ...
Quantity, mar.gains(PSid,NPSid), mar.gains(PSid,NPSid)*Quantity];
end;

PSqbuy1(PSid) = PSqbuy1(PSid) - Quantity;

NPSqsold1(NPSid) = NPSqsold1(NPSid) - Quantity;
if NPSqsold1(NPSid) == 0
```

```
mar.gains(:,NPSid) = 0;
end;
end;
%This writes trades to a cell array
OUT{j} = {Simout}; %store output from each iteration in a cell array
end;

disp ('successfully finished the trading iterations!')

%Finds the maximum number of trades(rows) in the output data. Changes all
%matrices to have the same number of rows. Zeros are put in the rows that
%are added.For more information, go to section 15.3 in the array manipulation
%publication

for j=1:iterations
a(j) = max(OUT{1,j}{1,1}(:,1)); %finds total # of trades in each iteration
end;
m = mean(a); %finds average # of trades across all iterations
m = round(m); %rounds the average # to nearest whole number
% aa = a(:)'; %creates another matrix aa equal to a
% aa = aa(ones(m,1),:); %transforms aa into an m by iterations matrix
bb = (1:m)'; %creates bb which is a column vector going from 1 to m
% bb = bb(:,ones(length(a), 1)); %transforms bb into a m by iterations matrix
% %with each column going from 1 to m
% b = bb .* (bb <= aa); %the dot indicates array multiplication (not the same
% %as matrix multiplication. Arrays in bb are multiplied by an array of ones
% %and zeros corresponding to the number of trades
% M = mean(b,2); %sums across all rows of the b matrix resulting in a column vector

for i = 1:iterations %this loop equalizes number of rows (equal to mean # of trades)
%across all iterations so that the means can be calcualted
cc{i} = OUT{i}{1}(:,6);
dd{i} = OUT{i}{1}(:,7);
ee{i} = OUT{i}{1}(:,8);
ff{i} = OUT{i}{1}(:,9);
gg{i} = OUT{i}{1}(:,10);
[u,y] = size(cc{i});
if u >= m
cc1{i} = cc{i}(1:m,:);
dd1{i} = dd{i}(1:m,:);
ee1{i} = ee{i}(1:m,:);
ff1{i} = ff{i}(1:m,:);
gg1{i} = gg{i}(1:m,:);
else v = m-u;
w = zeros(v,1);
cc1{i} = cat(1,cc{i},w);
dd1{i} = cat(1,dd{i},w);
ee1{i} = cat(1,ee{i},w);
ff1{i} = cat(1,ff{i},w);
gg1{i} = cat(1,gg{i},w);
```

```
 end;
 end;

 ccc = cell2mat(cc1); %converts cell array of matricies to single matrix
 ddd = cell2mat(dd1);
 eee = cell2mat(ee1);
 fff = cell2mat(ff1);
 ggg = cell2mat(gg1);
 mccc = mean(ccc,2); %finds mean of rows
 mddd = mean(ddd,2);
 meee = mean(eee,2);
 mfff = mean(fff,2);
 mggg = mean(ggg,2);
 mhhh = cumsum(mggg);%calculates running total of gains
 SumOut = cat(2,bb,mccc,mddd,meee,mfff,mggg,mhhh);

 % This writes the Cummulative Output to an Excel Spreadsheet (all in a single sheet)
 Headings1 = {'Trade#' 'PSwtp' 'NPSwta' 'Quantity' 'Mar. Gains' 'Gains' 'Cum. Gains'};
 numericalOutput1 = num2cell(SumOut);%converts back into cell array
 allOutput1 = [Headings1; numericalOutput1];
 xlswrite(outFile,allOutput1,int2str(trloops+1),'A1');

 tratio = tratio + trstep; %assign the next tratio to simulate
 trloops = trloops+1;
end;

%------------------------------
%This code erases any empty sheets in an excel workbook
%Open the output xls file

excelObj = actxserver('Excel.Application');
%opens up an excel object
excelWorkbook = excelObj.workbooks.Open(outFile);
worksheets = excelObj.sheets;
%total number of sheets in workbook
numSheets = worksheets.Count;

count=1;
for j=1:numSheets
 %stores the current number of sheets in the workbook
 %this number will change if sheets are deleted
 temp = worksheets.count;

 %if there's only one sheet left, we must leave it or else
 %there will be an error.
 if (temp == 1)
 break;
 end

 %this command will only delete the sheet if it is empty
```

```
 worksheets.Item(count).Delete;

 %if a sheet was not deleted, we move on to the next one
 %by incrementing the count variable
 if (temp == worksheets.count)
 count = count + 1;
 end
end
excelWorkbook.Save;
excelWorkbook.Close(false);
excelObj.Quit;
delete(excelObj);

%---------------------------------
% Run OfficeDoc to format Excel output
% Open document in 'append' mode:
[file,status,errMsg] = officedoc(outFile, 'open', 'mode','append');
disp('Formatting Excel Output...')

for z = 1:trloops
 % Format Output in Excel:
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'A1:G1', 'bold','on','WrapText',1);
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'A:A, D:D', 'NumberFormat','#,##0');
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'B:B, C:C, E:E', 'NumberFormat','$#,##0.00');
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'F:F, G:G', 'NumberFormat','$#,##0');
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'A1:G1050', 'ColAutoFit',1);
end

% Close the document, deleting standard sheets and releasing COM server:
status = officedoc(file, 'close', 'release',1,'delStd','off');
toc
```

Example Code for Targeted for WQT trading under Zero Information

```
%Simulation 2: No information trading
%Low information: PS and NPS picked at random

clear
clc
tic

outFile = 'C:\Documents and Settings\Craig Smith\My
Documents\Ph.D\WQT_Simulation\Simulations\WQT_2.xls';
delete(outFile) %deletes existing Excel spreadsheet output


%Parameters
tratio = 3; %starting value for trading ratio
trloops = 0; %this should be set to 0 - it counts the number of times through the tratio loop
trcosts = 0;
PSintcost = 0;
NPSintcost = 0;
iterations = 100;
%loops = 1; %should should be set to 1 in most cases, this was initially used to test for appropriate
number of simulations to get stable statistics

p = 10; %number of PS's
n = 500; %number of farms

%trading ratio parameters
trmax = 3; %max trading ratio to consider
trstep = 0.5; %step length for trading ratio

while tratio <= trmax
 tratio
 trloops;

 %keep3 function is a complement to the clear fcn. in that it clears all
 %variables except the ones listed

 keep3 tratio trloops trcosts PSintcost NPSintcost iterations outFile p n trmax trstep

 for j=1:iterations
 j

 %Code to generate a lognormal distribution of PS's. Particularly, log
 %normal distributions of reductions and cost/lb values. This serves as
 %NPS input into the simulations. The logn_rnd function must be in current
 %directory

 PSmeanred = 5000; %mean of reductions
 PSvarred = 1562500; %variance of reductions
```

```
PSmeancost = 20; %mean of costs
PSvarcost = 225; %variance of costs

a = log(PSmeanred)-.5*log(1+(PSvarred/PSmeanred^2));
b = log(1+(PSvarred/PSmeanred^2));

PSlognTotPred = logn_rnd(a,b,p,1);

c = log(PSmeancost)-.5*log(1+(PSvarcost/PSmeancost^2));
d = log(1+(PSvarcost/PSmeancost^2));

PSlognTotPcost = logn_rnd(c,d,p,1);

PSdata = cat(2,PSlognTotPred, PSlognTotPcost);
PSnum = size(PSdata,1);
PSwtp = PSdata(:,2) - PSintcost*ones(PSnum,1);
PSqbuy = PSdata(:,1);

%Code to generate a lognormal distribution of farms. Particularly, log
%normal distributions of reductions and cost/lb values. This serves as
%NPS input into the simulations. The logn_rnd function must be in current
%directory

meanred = 200; %mean of reductions
varred = 2500; %variance of reductions
meancost = 12; %mean of costs
varcost = 64; %variance of costs

a = log(meanred)-.5*log(1+(varred/meanred^2));
b = log(1+(varred/meanred^2));

lognTotPred = logn_rnd(a,b,n,1);

c = log(meancost)-.5*log(1+(varcost/meancost^2));
d = log(1+(varcost/meancost^2));

lognTotPcost = logn_rnd(c,d,n,1);

NPSdata = cat(2,lognTotPred, lognTotPcost);
NPSnum = size(NPSdata,1);
NPSqsold = NPSdata(:,1)/tratio;
NPSwta = tratio*(NPSdata(:,2) + NPSintcost*ones(NPSnum,1));
PSwtp1 = PSwtp;
PSqbuy1 = PSqbuy;
NPSqsold1 = NPSqsold;

%Marginal Gains matrix
mar.gains = PSwtp*ones(1,NPSnum) - ones(PSnum,1)*NPSwta' - trcosts*ones(PSnum,NPSnum);

i=0;
```

```
while max(max(mar.gains)) > 0

%Pick trial PS and NPS for first iteration
if i == 0
PSid = double(int16((PSnum-0.01)*rand+0.5));
NPSid = double(int16((NPSnum-0.01)*rand+0.5));
end;

%Make sure current PS is a feasible trader: it must have sufficient
%supply to meet its demand and have credits left to buy. If either
%of these conditions is not met, a new PS is found that meets both.
PSok = 0;
while PSok == 0
Sellers = (mar.gains(PSid,:) > 0);
Supply = Sellers*NPSqsold1;
if Supply >= PSqbuy1(PSid) && PSqbuy1(PSid) > 0, PSok=1; break; end;
mar.gains(PSid,:) = 0;
if max(max(mar.gains)) <= 0, PSok=-1; break; end;
PSid = double(int16((PSnum-0.01)*rand+0.5));
end;

%if no PS is a feasbile trading partner, then exit the trading loop
if PSok == -1
%disp('Trading stopped because no feasible PS traders exist.');
break;
end;

%if current NPS is "sold out" or has no gainful trading partners,
%then set its mar.gains to zero pick a new NPS
if (NPSqsold1(NPSid) == 0) || (max(mar.gains(:,NPSid)) <=0)
mar.gains(:,NPSid) = 0;
NPSid=double(int16((NPSnum-0.01)*rand+0.5));
end;

%if mar.gains for current (PS, NPS) pair is nonpositive, pick a new NPS
if mar.gains(PSid, NPSid) <= 0
NPSid=double(int16((NPSnum-0.01)*rand+0.5));

%otherwise (i.e., if mar.gains are positive) execute trade and save data
else
i = i + 1;
PSprice = (NPSwta(NPSid) + PSwtp(PSid))/2 + trcosts/2;
NPSprice = (NPSwta(NPSid) + PSwtp(PSid))/2 - trcosts/2;
Quantity = min(PSqbuy1(PSid), NPSqsold1(NPSid));
PSqbuy1(PSid) = PSqbuy1(PSid) - Quantity;
NPSqsold1(NPSid) = NPSqsold1(NPSid) - Quantity;

if i == 1 %save data
Simout = [i, tratio, PSid, NPSid, PSprice, PSwtp(PSid), NPSwta(NPSid), Quantity, ...
mar.gains(PSid,NPSid), mar.gains(PSid,NPSid)*Quantity];
```

```
else Simout = [Simout; i, tratio, PSid, NPSid, PSprice, PSwtp(PSid), NPSwta(NPSid), ...
Quantity, mar.gains(PSid,NPSid), mar.gains(PSid,NPSid)*Quantity];
end;

end;
end;

%This writes trades to a cell array
OUT{j} = {Simout}; %store output from each iteration in a cell array

end;

% %Close ActiveX Server input
% invoke(Excel.ActiveWorkbook,'Save');
% Excel.Quit
% Excel.delete
% clear Excel

disp ('successfully finished the trading iterations!')

%Finds the maximum number of trades(rows) in the output data. Changes all
%matrices to have the same number of rows. Zeros are put in the rows that
%are added.For more information, go to section 15.3 in the array manipulation
%publication

for j=1:iterations
a(j) = max(OUT{1,j}{1,1}(:,1)); %finds total # of trades in each iteration
end;
m = mean(a); %finds average # of trades across all iterations
m = round(m); %rounds the average # to nearest whole number
% aa = a(:)'; %creates another matrix aa equal to a
% aa = aa(ones(m,1),:); %transforms aa into an m by iterations matrix
bb = (1:m)'; %creates bb which is a column vector going from 1 to m
% bb = bb(:,ones(length(a), 1)); %transforms bb into a m by iterations matrix
% %with each column going from 1 to m
% b = bb .* (bb <= aa); %the dot indicates array multiplication (not the same
% %as matrix multiplication. Arrays in bb are multiplied by an array of ones
% %and zeros corresponding to the number of trades
% M = mean(b,2); %sums across all rows of the b matrix resulting in a column vector

for i = 1:iterations %this loop equalizes number of rows (equal to mean # of trades)
%across all iterations so that the means can be calcualted
cc{i} = OUT{i}{1}(:,6);
dd{i} = OUT{i}{1}(:,7);
ee{i} = OUT{i}{1}(:,8);
ff{i} = OUT{i}{1}(:,9);
gg{i} = OUT{i}{1}(:,10);
[u,y] = size(cc{i});
if u >= m
cc1{i} = cc{i}(1:m,:);
```

```
 dd1{i} = dd{i}(1:m,:);
 ee1{i} = ee{i}(1:m,:);
 ff1{i} = ff{i}(1:m,:);
 gg1{i} = gg{i}(1:m,:);
 else v = m-u;
 w = zeros(v,1);
 cc1{i} = cat(1,cc{i},w);
 dd1{i} = cat(1,dd{i},w);
 ee1{i} = cat(1,ee{i},w);
 ff1{i} = cat(1,ff{i},w);
 gg1{i} = cat(1,gg{i},w);
 end;
 end;

 ccc = cell2mat(cc1); %converts cell array of matricies to single matrix
 ddd = cell2mat(dd1);
 eee = cell2mat(ee1);
 fff = cell2mat(ff1);
 ggg = cell2mat(gg1);
 mccc = mean(ccc,2); %finds mean of rows
 mddd = mean(ddd,2);
 meee = mean(eee,2);
 mfff = mean(fff,2);
 mggg = mean(ggg,2);
 mhhh = cumsum(mggg);%calculates running total of gains
 SumOut = cat(2,bb,mccc,mddd,meee,mfff,mggg,mhhh);

 % This writes the Cummulative Output to an Excel Spreadsheet (all in a single sheet)
 Headings1 = {'Trade#' 'PSwtp' 'NPSwta' 'Quantity' 'Mar. Gains' 'Gains' 'Cum. Gains'};
 numericalOutput1 = num2cell(SumOut);%converts back into cell array
 allOutput1 = [Headings1; numericalOutput1];
 xlswrite(outFile,allOutput1,int2str(trloops+1),'A1');

 tratio = tratio + trstep; %assign the next tratio to simulate
 trloops = trloops+1;
end;

%------------------------------
%This code erases any empty sheets in an excel workbook
%Open the output xls file

excelObj = actxserver('Excel.Application');
%opens up an excel object
excelWorkbook = excelObj.workbooks.Open(outFile);
worksheets = excelObj.sheets;
%total number of sheets in workbook
numSheets = worksheets.count;

count=1;
for j=1:numSheets
```

```
 %stores the current number of sheets in the workbook
 %this number will change if sheets are deleted
 temp = worksheets.count;

 %if there's only one sheet left, we must leave it or else
 %there will be an error.
 if (temp == 1)
 break;
 end

 %this command will only delete the sheet if it is empty
 worksheets.Item(count).Delete;

 %if a sheet was not deleted, we move on to the next one
 %by incrementing the count variable
 if (temp == worksheets.count)
 count = count + 1;
 end
end
excelWorkbook.Save;
excelWorkbook.Close(false);
excelObj.Quit;
delete(excelObj);

%---------------------------------
% Run OfficeDoc to format Excel output
% Open document in 'append' mode:
[file,status,errMsg] = officedoc(outFile, 'open', 'mode','append');
disp('Formatting Excel Output...')

for z = 1:trloops
 % Format Output in Excel:
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'A1:G1', 'bold','on','WrapText',1);
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'A:A, D:D', 'NumberFormat','#,##0');
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'B:B, C:C, E:E', 'NumberFormat','$#,##0.00');
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'F:F, G:G', 'NumberFormat','$#,##0');
 status = officedoc(file, 'format', 'sheet', z, 'Range', 'A1:G1050', 'ColAutoFit',1);
end

% Close the document, deleting standard sheets and releasing COM server:
status = officedoc(file, 'close', 'release',1,'delStd','off');
toc
```

Appendix E - Additional WQT output from Chapter 4

Table E.1 Simulation results considering all trades occur

			Volume Traded				Cost Savings		Final Costs	
Scenario	**Trading Ratio**	**# of Trades**	**Base Loading Reduction by NPS (lbs)**	**Loading Reduction by PS (lbs)**	**Additional Loading Reduction by NPS (lbs)**	**Total Loading Reduction (lbs)**	**Total ($)**	**Percent (%)**	**Total ($)**	**Avg. ($/lb)**
1a	0.5	134	24,088	1,823	-	25,912	701,703	70.2	298,297	11.51
1b	1.0	227	40,816	9,184	-	50,000	497,161	49.7	502,839	10.06
1c	1.5	224	26,396	23,604	13,198	63,198	319,788	32.0	680,212	10.76
1d	2.0	188	16,210	33,790	16,210	66,210	205,138	20.5	794,862	12.01
1e	2.5	151	9,993	40,007	14,990	64,990	134,540	13.5	865,460	13.32
1f	3.0	121	6,386	43,614	12,772	62,772	90,824	9.1	909,176	14.48
2a	0.5	134	24,112	1,777	-	25,888	597,226	59.7	402,774	15.56
2b	1.0	255	47,156	2,844	-	50,000	392,259	39.2	607,741	12.15
2c	1.5	301	36,035	13,965	18,017	68,017	234,861	23.5	765,139	11.25
2d	2.0	258	22,515	27,485	22,515	72,515	142,475	14.2	857,525	11.83
2e	2.5	203	13,613	36,387	20,419	70,419	90,259	9.0	909,741	12.92
2f	3.0	154	8,356	41,644	16,712	66,712	59,869	6.0	940,131	14.09
3a	0.5	134	24,108	1,785	-	25,892	602,482	60.2	397,518	15.35
3b	1.0	252	46,330	3,670	-	50,000	406,054	40.6	593,946	11.88
3c	1.5	273	32,630	17,370	16,315	66,315	262,055	26.2	737,945	11.13
3d	2.0	228	19,860	30,140	19,860	69,860	161,605	16.2	838,395	12.00
3e	2.5	181	12,261	37,739	18,392	68,392	101,590	10.2	898,410	13.14
3f	3.0	141	7,700	42,300	15,401	65,401	65,051	6.5	934,949	14.30
4a	0.5	134	24,098	1,804	-	25,902	699,950	70.0	300,050	11.58
4b	1.0	243	43,916	6,084	-	50,000	479,847	48.0	520,153	10.40
4c	1.5	266	31,444	18,556	15,722	65,722	293,180	29.3	706,820	10.75
4d	2.0	232	19,951	30,049	19,951	69,951	180,392	18.0	819,608	11.72
4e	2.5	185	12,388	37,612	18,581	68,581	116,491	11.6	883,509	12.88
4f	3.0	147	7,988	42,012	15,976	65,976	81,077	8.1	918,923	13.93