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Evaluation of Best Management Practices to Reduce Nutrients Runoff in Watersheds in Arkansas

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EVALUATION OF BEST MANAGEMENT PRACTICES TO REDUCE NUTRIENTS RUNOFF IN WATERSHEDS IN ARKANSAS

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of the requirements for the degree of
Doctor of Philosophy in Public Policy

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ABSTRACT

There are many non point sources (NPS) of pollution issues across the state of Arkansas. Each region of the state has different concerns. Many watersheds have been included in the Arkansas's 2008 303(d) list for NPS impairments with sediment and nutrients being the primary causes of concern.

This research hypothesized that there are no cost or net returns risks when adopting best management practices (BMPs) to control nutrients runoff and that selection, timing, placement and cost have no impact on the implementation of BMPs. Using two priority watersheds, the L'Anguille River and the Lincoln Lake, as examples, the environmental benefits and the cost-effectiveness of several BMPs were compared to representative systems that producers currently use.

Current systems were rice and soybeans production under various tillage, buffers and nutrient management practices. Also analyzed were alternative pasture management systems, buffers and poultry litter applications for bermudagrass production. For each system, total phosphorous (TP) loss estimates were linked with production costs, BMP costs and risk premiums within a watershed to create an environmental-economic model.

The model was used to analyze the impact of BMPs in reducing nutrient runoff while minimizing the producers' exposure to additional risk. To accomplish this goal, two mathematical techniques were used: stochastic dominance and genetic algorithm.

Findings showed that BMPs have the potential for reducing nutrient pollutant losses from agricultural land areas. However, ranking BMPs solely in terms of their effectiveness to reduce nutrient runoff can lead to cost-prohibited recommendations.

Since producer's risk aversion level matters, for producers to adopt any of the BMPs analyzed in this study, they would have to receive a risk premium. This is true for both row crop and forage producers. Still, there are some BMPs that can reduce nutrient runoff, maintain agricultural production and improve water quality without affecting producers' cost or net returns dramatically. Consequently, decision makers need to weight trade-offs between nutrient runoff reduction and net cost increase when selecting BMPs. Cost-savings from selecting BMPs become evident when critical factors for reducing TP runoff are analyzed using an environmental-economic model.

This dissertation is approved for recommendation to the Graduate Council

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DEDICATION

I dedicate this work in appreciation and thanksgiving to God the Father, the Son, and the Holy Spirit. I also dedicate this accomplishment to my loving wife Erika, my daughter Anna Sofia, my soon-to-be born daughter Emma Isabel, my parents, sisters, brother, relatives and friends who have supported me throughout my doctoral endeavors.

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Trust in the LORD with all your heart
and lean not on your own understanding;
in all your ways acknowledge him,
and he will make your paths straight.

Proverbs 3: 5–6

I can do all things through Christ which strengtheneth me.

Philippians 4:13

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CHAPTER I

Introduction

In Arkansas, the crop and animal production sectors are important to total state cash receipts and labor income. The Arkansas' agricultural cash receipts from all commodities in year 2007 were over $7.1 billion [NASS, 2008]. The crop sector employed over 59,000 people with a value added to the state's economy of $2.84 billion [Popp et al., 2009]. Similarly, animal agriculture supports almost 58,000 jobs with a value added of $2.28 billion. Poultry production alone supports almost 41,000 jobs and accounts for $1.69 billion of value added [Popp et al., 2009].

In terms of cash receipts, rice (*Oryza sativa*) and soybeans (*Glycine max*) are two of the most important crops in Arkansas. For instance, in 2007, Arkansas led the nation in rice cash receipts totaling $1.02 billion. Soybeans represented $0.75 billion of the cash receipts of the state in 2007 and ranked ninth in production in the nation [NASS, 2008]. Although these numbers seem staggering from an economic point of view, fertilizers and chemicals used for crop production may affect the quality of the water used in the production of rice and soybeans.

Row crop agriculture in the Mississippi Delta region is the major source of income and largely depends on irrigation. Total irrigated area has increased almost three folds over the past 20 years to almost 40 percent of total acreage [Scott et al. 1998]. The greater part of this irrigation water comes from ground water. Municipalities and manufacturing industries located in this region also depend on ground water to meet their water needs. Increased rates of withdrawal of ground water in this region have created rapid ground water depletion and conflict between agricultural and urban sectors. Vast acreages of rice and soybeans employ high levels of fertilizers, pesticides, fungicides, herbicides and water for production. Without proper management, use of these inputs could lead to nutrients and biocides movement off the farm and into nearby rivers and streams, further exacerbating water quality issues that exist in the region.

Similarly, confined animal production not only produce revenues but also results in millions of tons of manure each year which contains high levels of nutrients, pathogens and other potential contaminants [Gitau et al., 2007]. In northwest Arkansas, often producers raise poultry and cattle and grow perennial forage crops in their lands to help to diversify and stabilize their income. Animal manure is rich in nutrients especially nitrogen and phosphorus. Bermudagrass (*Cynodon dactylon*) is one of the most common grasses crop in the region. For optimal growth, it requires high levels of nitrogen but low levels of phosphorus [Coblentz et al., 2004; Sandage and Kratz, 1999].

For many years, scientists based manure and litter applications rates on forage nitrogen needs [Gitau et al., 2007; Wilson et al., 2007]. As a result, some nutrients especially phosphorus may be unused by the crop and consequently build-up in soils. Excess nutrients have the potential to leave the field and enter surface waters, where they encourage algae and bacterial growth [Edwards et al., 1996; Edwards et al., 1997]. In the past twenty years, high levels of sediment and nutrient runoff have threatened the water supplies available for recreational and municipal uses [Ekka et al., 2006]. These issues have triggered state and interstate water quality disputes [Soerens et al., 2003].

Recently proposed federal and state regulations have sought to minimize sediment and nutrient runoff from applications of animal manure. Now producers must follow provisions of Acts 1059, 1060 and 1061[1] by: 1) certifying all those who apply nutrients to crops or pastures land, 2) certifying nutrient management plan writers, 3) registering all cattle and poultry feeding operations and 4) developing and implementing nutrient management plans [Wilson et al., 2007]. The Arkansas Natural Resources Commission (ANRC) imposes penalties on those who fail to comply with the regulations developed under these acts. Additionally, a new water quality based phosphorous index requires that manure and litter be spread based on phosphorous and to minimize its capacity to runoff into lakes, streams and rivers throughout the state [Ekka et al., 2006].

Laws and regulations have played a major role in protecting the country's water resources. A quick review of the history of the federal and states governments' role in regulating water resources will provide a better understanding of current water quality legislation.

National Water Legislation Overview

Federal water legislation started in 1899 with the passage of the River and Harbor Act [Gallagher and Miller, 2003]. The purpose of this act was to protect the nation's waters and promote interstate commerce. In 1948, the Congress enacted the Water Pollution Control Act. The legislation provided federal technical assistance and funds

[1] A more detailed description of these acts can be obtaining by visiting:
http://www.arkleg.state.ar.us/ftproot/acts/2003/public/act1059.pdf
http://www.arkleg.state.ar.us/ftproot/acts/2003/public/act1060.pdf
http://www.arkleg.state.ar.us/ftproot/acts/2003/public/act1061.pdf

to states interested in protecting their water quality [Gallagher and Miller, 2003]. In 1965, Congress passed the Water Quality Act (WQA), which entrusted states with setting water quality standards for interstate navigable waters.

In 1972, the Federal Water Pollution Control Act (FWPCA) reinforced WQA's water quality standards and established a regulatory structure for controlling discharges of pollution into the nation's waters. It made illegal to discharge a polluting substance without a permit. Most importantly, this act encouraged the use of the best available technology for pollution control and directed states to set water quality standards for waters other than those designated as interstate navigable [Gallagher and Miller, 2003]. In 1977, FWPCA was amended by the Clean Water Act (CWA). This act authorized water quality programs, required state water quality standards and permits for discharges of pollutants into navigable waters and authorized funding for wastewater treatment works among others [Gallagher and Miller, 2003].

The CWA recognized two sources of pollution: Point source (PS) and nonpoint source pollution (NPS). When pollution is coming from clearly discernible discharge points such as pipes, wells, containers, concentrated animal-feeding operations, boats, etc is referred as PS. Pollution coming from diffused points of discharge such as runoff from: agricultural fields, lawns, home gardens, construction, parking lots, mining, etc is considered NPS [Callan and Thomas, 2007]. According to the U.S. Environmental Protection Agency (EPA), NSP is the leading cause of impaired water quality among states [U.S. EPA, 2008a].

The EPA, the U.S. Army Corps of Engineers, and the states were entrusted with enforcing various provisions of CWA [Callan and Thomas, 2007]. Under the CWA, states are charged with protecting and restoring the quality of the nation’s waters through assessing the status and condition of a state’s water resources and the progress being made to restore and protect those waters; identification of total maximum daily loads (TMDL) and implementation [Gallagher and Miller, 2003]. Under the CWA states are required to submit assessment reports to EPA. These include but are not limited to sections: 303(d), 305(b) and 319 [U.S. EPA, 2008b].

Section 303(d) requires each state to maintain a list of impaired water bodies and revise the list in even numbered years. In addition, this section ensures that the TMDL (the amount of a pollutant that a water body can receive and still meet water quality standards) program is enforced. Section 305(b) requires comprehensive biennial inventories of the conditions and trends of waters within the state. Section 319 requires information about waters within the state that are threatened by NPS pollution [U.S. EPA, 2008c]. There are several organizations with responsibility for preserving the state’s water quantity, quality and public health. The following section introduces some of them.

Arkansas’ Water Organizations

In Arkansas, there are several organizations with responsibility for preserving the state’s water quantity, quality and public health. The Arkansas Natural Resources Commission (ANRC) is the primary regulatory authority for many of the issues related to water rights, water conservation and water quality. The ANRC is responsible for implementing best management practices (BMPs) to prevent NPS pollution. It also is responsible for developing and implementing the state’s NPS pollution management program. The ANRC is the lead agency for the Arkansas NPS pollution management program. The ANRC also supervises (i.e., location, scope, and progress of projects funded under section 319) over the NPS grant program and funds various 319 projects related to NPS pollution management.

Through grants funded by EPA, the ANRC provides assistance to conservation districts, academic institutions, state government agencies and other organizations to fund projects associated with the reduction of NPS pollutants. Funds are targeted to priority watersheds. The two watersheds analyzed in this study, the L'Anguille River and the Illinois River, are currently priority watersheds.

The Arkansas Department of Environmental Quality (ADEQ) has primary responsibility for permitting and enforcement of CWA provisions in Arkansas. However, the implementation of water quality control activities are distributed across several state agencies, including ADEQ, ANRC, Arkansas Department of Health (ADH), Arkansas Rural Water Association of Arkansas (ARWA), and the Arkansas Agriculture Department (AAD), among others [ADEQ, 2008a]. The ADEQ is entrusted with improving the quality of the state's water bodies. The ADEQ's water quality planning branch is responsible for monitoring water quality, developing water quality standards and allocating ground water and waste loads. The agency ensures that sections 303(d) and 305(b) of the CWA are enforced [ADEQ, 2008a]. The ADEQ, in collaboration with the Pollution Control and Ecology Commission, set pollution limits based on each waterway's designated uses. Different uses require different types and levels of water protection. The designation and protection of specific uses are required by the CWA and the Arkansas General Assembly [ADEQ, 2008a]. The CWA requires each state to develop standards to protect rivers, streams, lakes, etc [Callan and Thomas, 2007].

Arkansas' Water Quality Standards

Water quality standards are essentially numerical limits on pollutants which affect how water is used. The ADEQ determines if current water quality standards are adequate to protect the uses of the waters of the state [ADEQ, 2008a]. The Arkansas Pollution Control and Ecology Commission adopts water quality standards for Arkansas. The ADEQ is obligated to improve water quality in impaired waterways by assigning stricter permit limits for permitted dischargers or by seeking voluntary BMPs to decrease the impact of nonpoint sources of pollution [ADEQ, 2008b]. The federal government requires that each state review its standards every three years [Gallagher and Miller, 2003]. Arkansas as many other states has water quality issues that need constant monitoring.

Arkansas' Water Quality Issues

There are many NPS issues within the State of Arkansas. Each region of the state has different concerns. For instance, the entire length (98.4 miles) of the L'Anguille River has been included in the Arkansas's 2008 303(d) list as impaired for aquatic life [ADEQ, 2008b; EPA, 2009]. Intensive row crop activities, road construction/ditching and stream channel alterations are considered responsible for NPS impairments in the watershed with sediment and nutrients being the primary cause of concern [ADEQ, 2008b]. An excessive sediment loading usually act as a transportation pathway for nutrients. Sediment loads are responsible for clogging of L'Anguille river tributaries.

The EPA had ordered the State of Arkansas to begin work on establishing sediment TMDL for L'Anguille River [ADEQ, 2008a; EPA, 2008c].

In Northwest Arkansas excess nutrients (especially phosphorous) primarily from animal agriculture have been the main concern. Sediment is also an issue due to the accelerated construction (residential, commercial, and industrial). Since many rivers flow from Arkansas into Oklahoma, some suggest that it is the manure from the Arkansas poultry and cattle farms that is contaminating the water as it reaches the Oklahoma border [Edwards et al., 1996; Edwards et al., 1997].

In 1986, the City of Tulsa, Oklahoma sued the City of Fayetteville, Arkansas asking the city to stop discharging pollutants into the Illinois River [Soerens et al., 2003]. In 1992, the dispute reached the U.S. Supreme Court (Oklahoma v. EPA, 962 F.2d 996; 1992). The Supreme Court ruled that the EPA may force upstream states to adhere to downstream states' water quality standards [Soerens et al. 2003].

The Oklahoma Scenic River Commission (OSRC) has recommended that the way to address phosphorous concerns is to impose a limit on the amount of phosphorous that can exist in the waters as they reach the Oklahoma border. In 2002, Oklahoma adopted an in-stream limit of 0.037 milligrams of phosphorous per liter of water in scenic rivers (Title 82. Waters and Water Rights Chapter 21 Scenic Rivers Act 82 Okl. St. § 1452). The EPA approved the standard by July 1, 2003 and it must be met by June 30, 2012 [Soerens et al., 2003]. Nowadays, agricultural producers, the poultry industry, the scientific community among others are concerned that the current phosphorous standard imposed for the Illinois River must be met in all waters across the state.

Objective

Several studies provided evidence of the effectiveness of BMPs in reducing sediment and nutrient runoff. Consequently, the goal of this research is to evaluate how implementation, timing and spatial distribution of agricultural BMPs can be used within two watersheds in Arkansas to reduce nutrient runoff while minimizing the producers' exposure to additional risk. To accomplish this goal, two mathematical techniques were used: stochastic dominance and genetic algorithm.

The first technique ranks BMPs in terms of their effectiveness to reduce total phosphorous runoff based on the relative implementation costs to rice (*Oryza sativa*) and soybean (*Glycine max*) producers and their relative effect on bermudagrass (*Cynodon dactylon*) net returns. The method builds upon the work of Hardaker et al. [2004], Ribera et al. [2004] and Richardson et al. [2006]. The second technique, an optimization process, searches for the combination of BMPs that reduce total phosphorous and total nitrogen runoff and then continues to search the subset of those practices that minimize implementation cost. The method builds upon the work of Gitau et al. [2004], Gitau et al. [2006], Srivastava et al. [2002], Veith et al. [2003] and Veith et al. [2004]. Best management practices were ranked and optimized, respectively, for both cost minimization and water quality improvement.

These methodologies will aid in the identification of BMPs that improve nutrients runoff control. Results from this research will provide producers, natural resource managers, and policymakers with quantitative research on this area that might be used in proposing future water policy changes. Additionally, journal articles describing recommendations resulting from this line of study will become part of the body of literature regarding BMPs and water quality improvement.

Hypotheses

Two primary hypotheses are proposed:

1) There are no cost or net returns risks when adopting BMPs to control nutrients runoff as measured by stochastic dominance ranking techniques; and
2) Selection, timing, placement and cost have no impact on the implementation of BMPs to comply with water quality goals as measured by a genetic algorithm optimization technique.

Dissertation Outline

This dissertation consists of six chapters. Chapter one is an explanation of the current environmental and political situation regarding interactions of agriculture and water resources in Arkansas. Chapter two is a detailed review of literature on relevant BMPs, stochastic dominance and genetic algorithm techniques. Chapters three, four and five are three different articles that examine the current environmental situation in two watersheds in Arkansas and use stochastic dominance and genetic algorithm techniques to rank and to optimize combination of BMPs to reduce nutrient runoff pollution at least cost. Chapter six provides conclusions and discusses results implications for policy and practice.

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CHAPTER II

Introduction

Chapter one outlined the current environmental and political situation regarding interactions of agriculture and water resources in Arkansas. This chapter is a detailed review of literature on relevant best management practices (BMPs), stochastic dominance and genetic algorithm techniques. The chapter starts with definitions used throughout the manuscript and a brief description of the watersheds analyzed in this research. Then, it summaries several articles focusing on BMPs effectiveness, hydrologic modeling using the soil and water assessment tool (SWAT), stochastic dominance using the simulation and econometrics to analyze risk and genetic algorithms. The chapter ends with a conclusion of what is known regarding watershed management including all the components mentioned above.

Point Sources versus Non-Point Sources of Pollution

Water pollution can occur naturally; however, contamination of surface and ground water resources can be divided in two main groups: point source (PS) and nonpoint source (NPS) pollution. Point source pollution is defined as any single identifiable source of pollution from which pollutants are discharged, such as a pipe, ditch or factory smokestack [Callan and Thomas, 2007]. Two common types of PS are factories and sewage treatment plants. Factories can discharge pollutants directly into a water body with or without treatment before they are released. Usually, factories have a single point from which all of the wastewater is discharged. Sewage treatment plants treat human wastes and send the treated effluent to a stream or river.

Concentrated animal feeding operations (CAFOs) such as cows, pigs and chickens are also considered PS pollution. If animals' waste materials are not treated, they can enter nearby water bodies adding to the level of pollution [EPA, 2008a]. To control point source discharges, the Clean Water Act established the National Pollutant Discharge Elimination System (NPDES). Under the NPDES program, factories, sewage treatment plants, and other point sources must obtain a permit from the state and the environmental protection agency (EPA) before they can discharge their waste or effluents into any body of water. Prior to discharge, the point source must use the latest technologies available to treat its effluents and reduce the level of pollutants. If necessary, a second, more stringent set of controls can be placed on a PS to protect a specific water body [EPA, 2007].

Increased control over PS pollution has prompted scientists to focus on how NPS pollution affects the quality of the environment and how it can be controlled. NPS pollution is water pollution affecting a water body from diffuse sources, rather than a PS which discharges to a water body at a single location. NPS may derive from many different sources making it difficult to regulate [EPA, 2008a]. Most NPS pollution occurs as a result of runoff. When rain or melted snow moves over and through the ground, the water absorbs any pollutants it comes into contact with, which eventually empties into a stream or river [EPA, 2008a]. According to the EPA [2008b], NPS pollution is the leading cause of water pollution in the United States, with polluted runoff from agriculture being the primary cause.

The most conventional pollutants found in runoff are sediments, nutrients (i.e., nitrogen and phosphorous) and bacteria [Callan and Thomas, 2007]. Sediment includes silt and suspended solids. Nitrogen and phosphorus are nutrients that in excessive amounts can lead to algae blooms and consequently eutrophication. Bacteria from faulty septic systems, livestock operations and human and pet wastes can be sources of pollution [EPA, 2008c].

Watersheds

Watersheds are areas of land that drain into a single stream or other water resource. It is important to point out that watersheds are defined solely by drainage areas and not by land ownership or political boundaries [EPA 2008a]. This definition of watershed is going to be use throughout this document. Figure 1 displays all the watersheds in Arkansas.

Description of the L'Anguille River Watershed

The L'Anguille River watershed with an area of 2,522 km^2 is located in the Mississippi Delta of eastern Arkansas which drains parts of Craighead, Poinsett, Cross, Woodruff, St. Francis, and Lee Counties (Figure 2). Agriculture is a major economic factor for much of the Mississippi Delta region of Arkansas. The predominant crops in this region are soybeans, rice and wheat [Scott et al., 1998]. Land use in the L'Anguille watershed is predominately agricultural cropland with 26 percent rice, 46 percent soybeans, and 28 percent other uses including forest, pasture, urban and water.

Water quality problem

Row crop agriculture in this region is the major source of income and largely depends on irrigation. Total irrigated area has increased almost three folds over the past 20 years to almost 40% of total acreage [Scott et al., 1998]. The greater part of this irrigation water comes from ground water. Municipalities and manufacturing industries located in this region also depend on ground water to meet their water needs. Increased rates of withdrawal of ground water in this region have created rapid ground water depletion and conflict between agricultural and urban sectors.

The Arkansas Water Quality Inventory Report has listed the entire length of the L'Anguille River as impaired to support aquatic life [ADEQ, 2008]. Excess sediment originating primarily from row crop agriculture was identified as the source of impairment, resulting in the development of a TMDL for total suspended solids (TSS). Also, the drainage of the low-land areas by ditching and the channelization of streams contribute to high turbidity and silt loads carried into the streams from row crop activities [Scott et al., 1998]. Applications of nitrogen and phosphorous to support row crop agriculture may create excess nutrient runoff problems and contribute to water quality degradation in the L'Anguille River.

Description of the Lincoln Lake Watershed

The Lincoln Lake watershed is a sub-watershed within the Illinois River basin located in Northwest Arkansas and Eastern Oklahoma. Moores Creek and Beatty Branch are two major tributaries that flow into Lincoln Lake (Fig. 3). The drainage area of the watershed is 32 km^2. Moores Creek and Beatty Branch drain 21 and 11 km^2, respectively. The impact of agricultural production can be seen from change in land use distribution since 1990. The 1990 forest and agricultural land use in the Lincoln Lake watershed was 43 percent and 45 percent, respectively [Edwards et al., 1997]. During the period of 1992 to 2004, this region has experience a nine percent increase in urban areas and an 11 percent loss of pasture lands which adds to the existing concerns regarding NPS pollution [Gitau et al., 2007].

Water quality problem

The Illinois River has long been a subject of political and environmental debate due to nutrient enrichment and accelerated eutrophication. In 1992, the U.S. Supreme Court ruled that EPA may require upstream states to adhere to downstream states' water quality standards. The Illinois River has been listed as a scenic river in Oklahoma and therefore is subject to a total phosphorus (TP) criterion of 0.037 milligram per litter (mg/L) which was established by the Oklahoma Water Resources Board [Smith, 2002]. The average flow weighted TP concentration at the Illinois River near the Arkansas-Oklahoma border was approximately 0.40 mg/L [Green and Haggard, 2001], over ten times greater than the TP criteria suggested by the Oklahoma Water Resources Board. Phosphorus has been recognized as the nutrient of concern in this watershed.

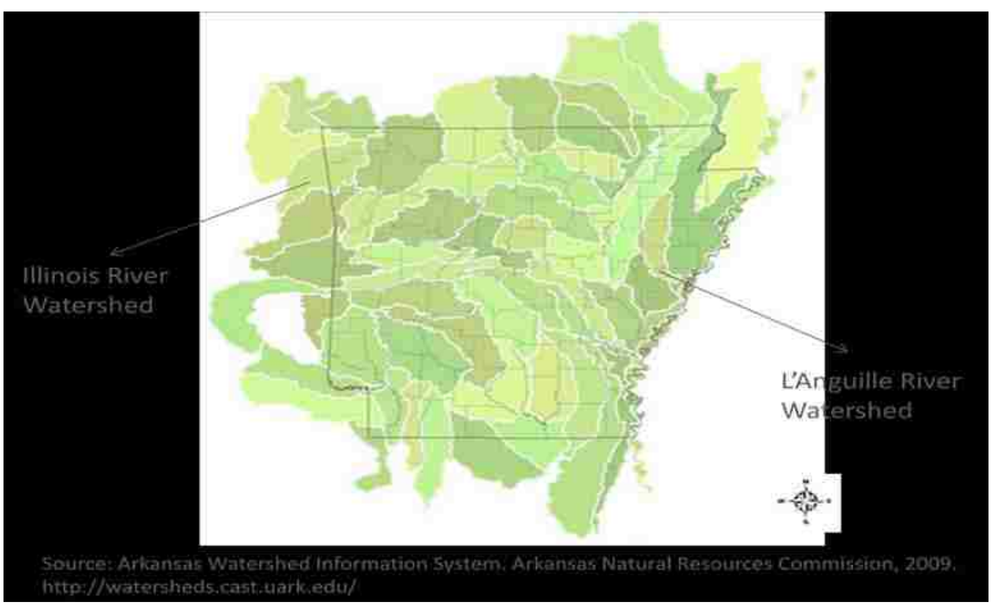

Figure 1. Watersheds in Arkansas

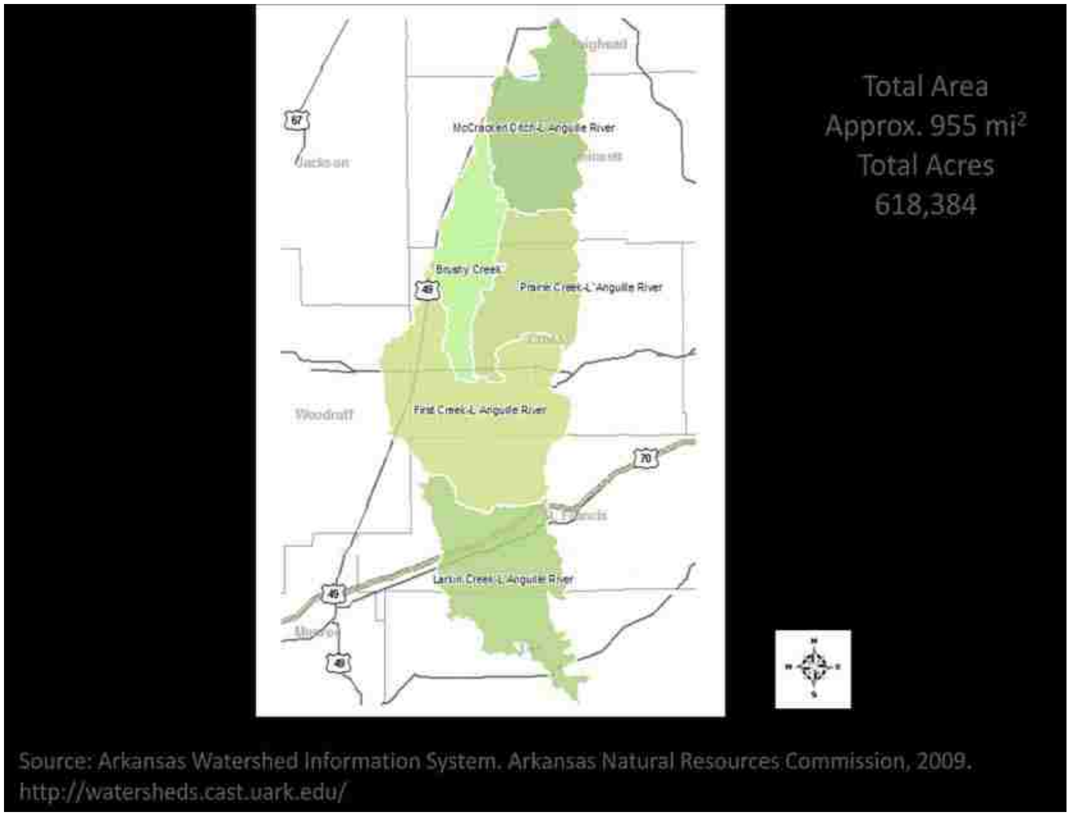

Figure 2. L'Anguille River Watershed

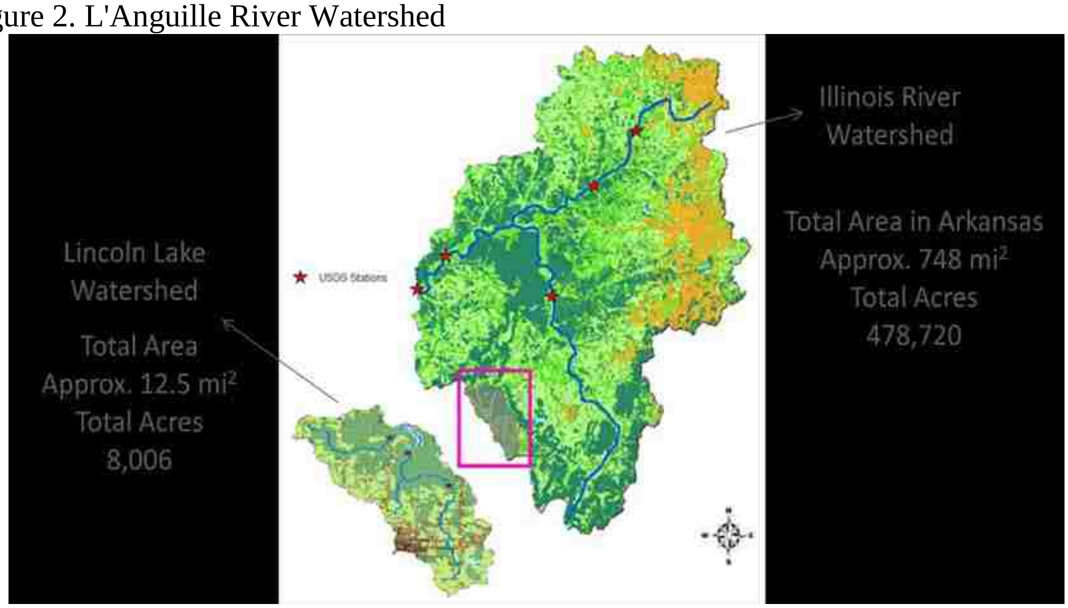

Figure 3. Lincoln Lake Watershed

Best Management Practices

Introduction

Public concerns about human health impacts due to eutrophication of surface waters have emerged in the past two decades. Eutrophication can occur naturally; however, recently, it is believed to be a consequence of nutrient pollution release from domestic sewage and runoff from urban lawns, golf courses and agricultural lands [Corell, 1998; Daniel et al., 1994; Sharpley et al., 2007; Sims et al., 2000; Srivastava et al., 1996]. Eutrophication promotes excessive algae growth which alters the normal equilibrium of the ecosystem, causing a lack of oxygen in the water which jeopardizes aquatic life [Daniel et al., 1994; Daniels et al. 2004; Sharpley et al., 2007]. Phosphorus generally is the limiting nutrient in rest water systems [Corell, 1998; Daniels et al., 2004; Moore and Edwards, 2005; Perry, 1998; Sims and Sharpley, 2005].

Commonly, farmers in Arkansas fertilize based on soil testing results. However, studies have shown unbalanced nitrogen to phosphorous ratios, particularly in manure producing areas. This suggests the potential for soil phosphorous levels to be excessive relative to crop requirements [Slaton et al., 2004].

A set of best management practices (BMPs) has been studied by several researchers in Arkansas to limit and/or control NPS pollution. Among the BMPs studied are protective vegetative filter strips, litter/manure treated with chemical amendments and the combination of both. Several studies conducted in Arkansas suggested that these BMPs are effective in controlling phosphorous runoff. For instance several authors have reported that litter treated with alum could reduce phosphorous concentrations in runoff water by 87 percent [Shreve et al., 1995; Moore et al., 1999]. Likewise, Chaubey et al., [1995] observed mass transport reductions of total phosphorous (TP) and ortho-phosphorus (PO_4-P) by averages of 40 percent and 39 percent respectively when using vegetative filter strips of 3.1 meters in length. Although, BMPs seem to be one of the possible solutions to water degradation, the effectiveness of BMPs should be rated in terms of their impact on pollutant loads, acceptability by farmers, cost-effectiveness and ease of implementation and maintenance as suggested by Logan [1990]. Studies describing these BMPs are presented below.

Treated Litter/Manure with Chemical Amendments

Past research has shown that chemical amendments reduced phosphorous concentrations in runoff by reducing the solubility of manure phosphorous through precipitation and/or adsorption reactions [Shreve et al., 1995]. Generally speaking, crops need more amounts of nitrogen and potassium than phosphorous. Field applications of poultry litter at rates to meet forage nitrogen requirements normally result in an over application of phosphorous [Daniel et al., 1994; Moore et al., 1999; 2005; Shreve et al., 1995; Sims and Sharpley, 2005; VanDevender et al., 2003].

Adding chemical amendments to poultry litter has been suggested as a BMP to help reduce the potential environmental effects of poultry production. Shreve et al. [1995] evaluated the effects of two chemical amendments, alum (Al_2SO_4-$14H_2O$) and ferrous sulfate ($FeSO_4$-$7H_2O$), on phosphorous runoff from field applied poultry litter and on total forage yield from fields receiving amended litter. Alum reduced phosphorous concentrations in runoff by 87 percent and 63 percent of that from litter alone for the first and second runoff events, respectively. On the other hand, ferrous sulfate decreased phosphorous concentration by 77 percent and 48 percent, respectively. No differences in soluble phosphorous and TP loads were observed between treatments for the second and third runoff events. However, amending litter with ferrous sulfate significantly increased total nitrogen (TN) concentrations in the first and second events compared with the other treatments [Shreve et al., 1995]. The authors concluded that in combination with proper timing and rate of litter applications, treating litter with alum may be used as an environmental and economic management tool in the poultry industry.

Moore et al. [1999] studied the effects of aluminum sulfate (alum) on ammonia volatilization and phosphorous runoff from poultry litter. Their study showed that phosphorous solubility could be reduced in poultry litter with alum, calcium (Ca) and iron (Fe) amendments.

Moore et al. [1999] stated that alum reduces the solubility of phosphorous in litter, thus, reducing phosphorous runoff. Phosphorus concentrations in runoff water were, on average, 75 percent lower from pastures fertilized with alum-treated litter than from those fertilized with normal litter in small watersheds.

Long-term studies show that whereas normal litter results in a buildup in soil test phosphorous levels (water-soluble phosphorous in soils), particularly at high litter rates, this does not occur with alum-treated litter. The addition of alum has no effect on poultry litter decomposition in soils, except for the possible increased release of nitrogen during mineralization [Moore et al., 2005], which would benefit crop production. Moore et al. [2005] validated several researchers that concluded that treating poultry litter with alum is a cost-effective management practice that significantly reduces NPS phosphorous runoff [Moore et al., 1999; 2005; Shreve et al., 1995].

Phytase is an enzyme which degrades phytate to release phosphorus and other nutrients, making them more available to the animals. VanDevender et al., [2003] demonstrated that the use of Phytase in swine feed can reduce the TP concentration by almost 25 percent in the manure. However, it seems that the proportion of the soluble phosphorous in the manure increases. Phytase manure resulted in lower phosphorous losses than normal manure when applied to demonstration runoff plots. The authors concluded that grazing cattle was effective in consuming significant amounts of phosphorous; however, as most of this consumed phosphorus is re-deposited in their manure, grazing is not an effective way of removing phosphorous from the soil. Therefore, the most logical practice to remove or utilize excess phosphorous and nitrogen from a field or farm would be to harvest the forage and feed it in a location with lower phosphorous and nitrogen concentrations [VanDevender et al., 2003].

Vegetative Filter Strips

Vegetative filter strips have been identified as a BMP that has the potential to remove substantial amounts of sediment and some nutrients and pesticides from cropland. Srivastava et al., [1996] analyzed the influences of litter-treated length and vegetative filter strips (VFS) length on performance of VFS with regard to removing pollutants from runoff originating from grassed areas treated with poultry litter.

Runoff was produced from simulated rainfall applied to both the litter-treated and VFS areas. The authors concluded that runoff mass transport of ammonia-nitrogen (NH_3-N), total Kjeldahl nitrogen (TKN), ortho-phosphorus (PO_4-P), TP, and total organic carbon (TOC) increased with increasing litter-treated length (due to increased runoff) and decreased (approximately first-order exponential decline) with increasing VFS length when affected by VFS length.

Srivastava et al. [1996] concluded that NO_3-N, TKN and TOC, concentrations in runoff did not decrease significantly beyond VFS lengths of 3.1 meters. For NH_3-N, PO_4-P and TP, runoff concentrations decreased up to a VFS length of 6.1 meters, beyond which no significant reductions occurred. Pollutant concentrations decreased with increasing VFS length for all pollutants studied, but mass transport was not affected by VFS length. This result suggests that the concentration reductions were due merely to dilution. In addition, the lack of a significant VFS effect on mass removal effectiveness at the 6.1 meters litter-treated length indicates that a relatively large proportion of mass removal had occurred prior to a VFS length of 3.1 meters.

Chaubey et al. [1995] tested the effectiveness of VFS for the removal of sediment, nutrients, and organic matter from land areas amended with poultry litter. The authors concluded that VFS of 3.1 meters reduced mass transport of TKN, NH_3-N, TP, and PO_4-P by averages of 39, 47, 40, and 39 percent respectively. In contrast, VFS of 21.4 meters reduced mass transport of TKN, NH_3-N, TP, and PO_4-P by averages of 81, 98, 91, and 90 percent respectively. In addition, mass transport of TKN, NH_3-N, and PO_4-P significantly decreased up to a VFS length of approximately 9.2 meters. Mass transport of TP decreased up to a VFS length of 6.1 meters while mass transport of COD and TSS decreased only up to a VFS length of 3.1 meters. Infiltration appeared to be the mechanism most responsible for mass removal of P [Chaubey et al., 1995].

Conclusion

Although the studies analyzed in this review of literature showed that BMPs are effective in reducing sediment and nutrient runoff, there is not an extensive record of publications specific to Arkansas. Poultry litter treated with alum and vegetative filter strips have proven to be efficient in reduction sediment and nutrient runoff. Nevertheless, the ranges of those reductions are quite large and results are highly variable.

Several studies in northwest Arkansas have proved that alum is effective in reducing phosphorous runoff. However, producers find it cost-prohibitive. On the other hand, vegetative filter strips have been used for many decades due to their ability of reducing sediment and nutrient runoff. Still, the proper application of a vegetative filter strip should consider the type and quantity of the potential pollutant (sediment, nutrient, pesticide, etc.), soil characteristics (clay, infiltration rate, permeability, etc.), slope and area of the field draining into the filter. Also important considerations are the type of vegetation applicable to the climatic conditions in a specific area and time of year to properly establish that vegetation. In brief, research that estimates the effectiveness of vegetative filter strips during a long periods of time (i.e., 10, 15, 20 years, etc) or the impact of reducing sediment and nutrient runoff when a combination of BMPs are used are needed.

Soil and Water Assessment Tool (SWAT) Overview

Introduction

Hydrological models are powerful tools for assessing NPS pollution and evaluating effectiveness of BMPs on large watersheds [Gupta et al., 1998]. The 1972

Clean Water Act mandated that all states and territories develop a list of impaired waters that do not meet quality standards and establish total maximum daily loads (TMDLs) for the pollutants of concern [EPA., 2008d]. According to Borah et al. [2006], several models were employed to support total maximum daily loads (TMDLs) development in the past decade. Among them, the soil water assessment tool (SWAT) is one of the most used models to assess NPS pollution problems, to plan NPS control measures and to develop and implement TMDL analyses in agricultural and forested watersheds [Gassman et al., 2007].

The SWAT is a physically-based distributed- parameter river basin scale model developed by the United States Department of Agriculture (USDA) Agricultural Research Service (ARS) at Temple, TX [Arnold et al., 1998; Arnold and Fohrer, 2005; Borah et al., 2006; Neitsch et al., 2005]. The SWAT has been used worldwide by government agencies and by the water research community [Gassman et al., 2007]. In the United States, SWAT is being applied to support the USDA Conservation Effects Assessment Project (CEAP) which main goal is to quantify the environmental benefits of conservation practices at both the watershed and the national levels [Mausbach and Dedrick, 2004]. The SWAT is incorporated as a modeling tool in EPA's Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) program for use in development of TMDLs as described in section 303(d) of the Clean Water Act [Gassman et al., 2007].

SWAT predicts the impact of land management practices on water, sediment and agricultural chemical yields in river basins with varying soils, land use and management conditions over long periods of time [Borah et al., 2006; Neitsch et al., 2005]. SWAT accounts for weather, surface runoff, return flow, percolation, evapotranspiration, transmission losses, pond and reservoir storage, crop growth and irrigation, ground water flow, reach routing, nutrient and pesticide loading and water transfer [Borah et al., 2006; Neitsch et al., 2005]. SWAT has eight main components: hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, pesticides and agricultural management [Neitsch et al., 2005]. SWAT simulates these processes by dividing watersheds into sub-basins. These sub-basins are further aggregated based on climate, hydrologic response units (HRU), ponds, ground water, and main channels [Neitsch et al., 2005]. HRUs are areas of land that have unique characteristics such as land use, soil or land management practices [Neitsch et al., 2005]. The overall hydrologic balance is simulated for each HRU [Gassman et al., 2007].

Primary input needed to run the SWAT model include digital elevation data, climate data, soils data, land cover data, and land management information. The land management portion of the SWAT model makes the model a powerful tool for evaluating BMPs and for predicting NPS pollutant loads [Gassman et al., 2007; Neitsch et al., 2005]. SWAT allows entering land management information (i.e., BMP information) into the HRU management file. In this input file, modelers can input land management practices such as planting and harvesting dates, nutrient applications, animal waste applications, pesticide applications, tillage operations, grazing practices and irrigation practices [Neitsch et al., 2005]. Specific BMPs that can be simulated in the HRU management file include crop rotations, conservation tillage practices, integrated pest management, irrigation water management, nutrient management, and grazing management [Gassman et al., 2007; Neitsch et al., 2005].

SWAT Applications

Pollutant Assessments

Several SWAT studies report the effects of various BMPs on pollutant losses. For instance, Gitau et al. [2007] quantified the effects of implementation, timing and spatial distribution of nutrient and grazing management practices on sediment and nutrient loss reduction within the Lincoln Lake watershed in Arkansas during the years 1992 to 2004. Using SWAT the authors attempted to distinguish the effects of BMPs and those due to land use changes. Preliminary results showed that total nitrogen losses increased by 11 percent while sediment and TP losses declined by 22 percent and 4 percent, respectively.

Arabi et al. [2006a] studied the effects of BMPs on nitrogen and phosphorus losses in the Dreisbach and Smith-Fry watersheds in northeast Indiana. Four types of structural BMPs, namely grassed waterways, field borders, parallel terraces and grade stabilization structures were installed in these two watersheds in the 1970s. The coefficient of determination (R^2) and the coefficient of efficiency (NSE) were used to evaluate model predictions. The authors found that SWAT could account for the effects of BMPs on nitrogen losses with monthly validation NSE statistics ranging from 0.52 (Dreisbach) to 0.72 (Smith-Fry). The effects of BMPs on phosphorus were more variable from 0.37 (Smith-Fry) to 0.79 (Dreisbach). SWAT tended to under predict both mineral and TP yields for the months with high measured phosphorus losses but over predicted the phosphorus yields for months with low measured losses. The authors argued that utilization of a model without calibration may result in predictions substantially different from observed data.

Bracmort et al. [2006] studied the long-term (20-year) water quality impact of structural BMPs on sediment and phosphorous loads using SWAT within the Dreisbach and Smith-Fry watersheds in northeast Indiana. The authors developed a method, using SWAT, to characterize the ability of four BMPs (grassed waterways, parallel terraces, field borders, and grade stabilization structures), in good condition and in varying condition, to reduce sediment and TP occurring from non-gully erosion. Results showed that BMPs' efficacy varied with their condition. Under good conditions, BMPs in the Dreisbach watershed reduced average annual sediment and TP by 32 percent and 24 percent, respectively. As BMPs deteriorate, BMPs ability to reduce sediment and TP diminished to 10 percent and 17 percent, respectively. Same patterns were evident in the Smith-Fry watershed. Under good conditions, BMPs reduced average annual sediment and TP by 16 percent and 10 percent, respectively. Under varying conditions, BMPs ability to reduce sediment and TP diminished to 7 percent in both cases.

Butler and Srivastava [2007] created a SWAT interface to analyze BMP effectiveness in reducing NPS pollution in Alabama. A geographic information system (GIS) extension allowed loading a database into the GIS interface of the SWAT model. The database included planting and harvesting dates, tillage practices, integrated pest management, irrigation water management, animal waste applications, grazing management and nutrient management among others. The authors concluded that by using a BMP database with SWAT, more accurate estimations of how management practices are affecting water quality can be obtained. In other words, more confident environmental and land management recommendations can be achieved using this approach than using generalized BMP data to represent field operations.

SWAT interfaced with Genetic Algorithms

Several studies have analyzed BMPs' effectiveness using SWAT interfaced with genetic algorithms. For instance, Gitau et al. [2004] interfaced baseline phosphorous estimates from SWAT, with a genetic algorithm and a BMP tool containing site-specific BMP effectiveness estimates to determine the optimal on-farm placement of BMPs so that phosphorous losses and costs were both minimized within the Town Brook watershed in New York. Two scenarios met the target (i.e., 60% phosphorous reduction) while increasing costs, relative to the baseline, by $1,430 and $1,683 per year, respectively.

Muleta and Nicklow [2005] interfaced SWAT with both a genetic algorithm and a Strength Pareto Evolutionary Algorithm (SPEA) to perform single and multi-objective evaluations in the Big Creek watershed in Illinois. Ten percent of the HRUs were converted into conservation programs (cropping system/tillage practice BMPs). This resulted in a 19 percent sediment yield reduction.

Gitau et al. [2006] evaluated the effectiveness of different BMPs to reduce phosphorous losses within the Town Brook watershed in New York. The research combined simulated phosphorous losses obtained from SWAT, practice effectiveness obtained from a BMP tool and selection and placement optimization using genetic algorithms. Nutrient management plans, riparian buffers, crop rotations and contour strip cropping reduced phosphorous by the proposed target, 60 percent. The most cost effective scenario decreased cost by 29 percent per kilogram of phosphorous per year compared to the baseline.

Other studies have examined the application of multi-objective evolutionary algorithms and SWAT. For instance, Confessor and Whittaker [2007] used a non-dominated sorting genetic algorithm II (NSGA-II) to optimize 139 parameters simultaneously to calibrate SWAT within the Calapooia watershed in Oregon over a three year period. The selected solution for calibration resulted in a daily Nash-Sutcliffe efficiency of 0.86 compared with the 0.28 calculated from the simulated daily stream flow using the default SWAT model setup. The daily Nash-Sutcliffe coefficient was 0.81 after validation. Despite the high daily Nash-Sutcliffe efficiency coefficients, the authors concluded that the simulation outputs tend to underestimate high peak flows.

Bekele and Nicklow [2005] evaluated land uses and tillage practices that minimize average annual sediment yield, nitrogen yield and phosphorous yield and maximize average annual gross revenues through the production of agricultural commodities within the Big Creek watershed in Illinois. To accomplish these objectives, the authors combined SWAT and a multi-objective evolutionary algorithm. The results quantified the extent to which certain agricultural landscapes such as perennial crops and a no-till option are able to limit NPS pollution.

Conclusion

The SWAT's use has been documented extensively. In fact, more than 260 peer reviewed publications demonstrated that SWAT is a versatile model that can be used to assess water quality and NPS pollution problems for a wide range of scales and locations. However, like any other model, it is subject to improvements. Gassman et al. [2007] suggested that some processes are not well estimated in SWAT due to inadequate data needed to characterize input parameters, lack of sufficient monitoring data and/or insufficient scientific understanding. For instance, SWAT crop yield output is often inaccurate. Many of parameters used in the temperature, leaf area, biomass, nutrients and harvest routines for plants are information based on personal communications; although a valid approach especially when there is not scientific information available, it is not necessarily generalizable to all locations, soils and weather conditions.

Another area of potential improvement is related to the spatial representation of riparian buffer and filter stripe zones when BMP effectiveness is evaluated. In these cases the width is known but the length is ignored. This issue has implications not only when calculating BMP effectiveness but also crop yields as reduction in area affect production. Additionally, the non-spatial aspect of the HRUs is an extra key weakness of the model as stated by Gassman [2007]. This can have an adverse equity impact in the placement of BMPs suggested for implementation to farmers. However, studies like Arabi et al. [2007] and Volk et al. [2005] are suggesting new approaches that may be functional to improve these aspects of SWAT.

Stochastic Dominance

Introduction

State and local government agencies face the challenge of designing policies that protect water quality and promote economically viable agriculture practices. Unfortunately, conventional agriculture is the most common form of crop and animal production for human consumption. This type of agriculture normally alters the natural environment by tilling and plowing of the soil, by using inorganic fertilizers, herbicides, fungicides and pesticides, and by eliminating diversity when only one crop is planted. Additionally, it requires external inputs that without proper management, could lead to sediment and nutrient movement off the fields into nearby streams, lakes or rivers.

Fortunately, there are several BMPs that when used alone or in combination, can help producers to minimize sediment and nutrient runoff from their fields. However, some BMPs are costly and producers are reluctant to include expensive practices in their management decisions even if they are effective in improving water quality. Producers associate risk with loss. Generally speaking, losses can occur through low yields (due to insufficient or excessive rainfall, extreme temperatures, etc), variable prices (increases in the price of inputs and costs of production; low selling prices, etc) and policy changes (TMDLs, government payments, etc). Most individuals are typically assumed to be risk averse and to have a certain tradeoff between risk and estimated revenue [Albright et al., 2006]. It is expected that producers present the same kind of behavior.

According to Richardson et al. [2006] risk is any management decision that cannot be controlled. As mentioned above, agriculture is a risky business. Therefore, tools that estimate distributions of monetary returns for alternative management strategies are essential in order to facilitate producer management decisions. One of these tools is stochastic dominance.

Stochastic dominance (SD) is defined as a form of ordering between a pair of distributions to rank risky alternatives based on expected utility [Bawa, 1975; Davidson, 2008; Hardaker et al., 2004; Levy, 1998; Richardson et al., 2006]. SD assumes that the decision maker is an expected value maximizer; alternative distributions are mutually exclusive and are based on population probability distributions [Bawa, 1975; Davidson, 2008; Levy, 1998; Richardson et al., 2006]. Precisely, SD integrates the difference between two risky distributions [Richardson et al., 2006]. In general, there are three types of SD: first degree, second degree and stochastic dominance with respect to a function.

First degree stochastic dominance (FSD) relies only on the assumption that utility (U) is non-decreasing (U≥0). In other words, the decision maker prefers more than less [Hardaker et al., 1997]. For instance, given two cumulative distribution functions F and G, distribution F will be preferred to distribution G by FSD if and only if $\mathrm{F(x)} \leq \mathrm{G(x)}$ for all values x with at least one inequality; where x indicates wealth [Levy, 1998]. According to Richardson et al. [2006] distribution F will dominate distribution G if its cumulative distribution function always lies to the right of G's or stating it differently, when cumulative distribution functions do not cross (see figure 4).

Second degree stochastic dominance (SSD) assumes that all decision makers are risk averse or their utility function is concave [Levy, 1998]. That is, their marginal utility is positive $(\mathrm{U}' \geq 0)$ and the rate of change (second derivative of total utility) is negative $(\mathrm{U}'' \leq 0)$. Stating it differently, decision makers prefer to maximize the area between the curves if they cross (see figure 5).

Meyer [1977] introduced the concept of stochastic dominance with respect to a function (SDRF). SDRF weights utility differences between a pair of risky cumulative distribution functions by knowing only the lower and the upper bound of the decision maker's risk aversion coefficient [Richardson et al., 2006]. Risk aversion implies that when facing choices with comparable returns, decision makers tend chose the less-risky alternative. Risk aversion coefficient (RAC) is the marginal rate at which a decision maker is willing to sacrifice expected return in order to lower variance by one unit [Richardson et al., 2006]. Pratt [1964] and Arrow [1971] defined RACs as the negative of the ratio of the second derivative of the utility function to its first derivative i.e., $\mathrm{RAC(x)} = -\mathrm{U}''(\mathrm{x})/\mathrm{U}'(\mathrm{x})$. According to Meyer [1977], the utility function is constrained to lie within specified lower (l) and upper (u) bounds which are the parameters for the utility function; $\mathrm{RAC_l(x)} < -\mathrm{U}''(\mathrm{x})/\mathrm{U}'(\mathrm{x}) < \mathrm{RAC_u(x)}$. Therefore, this coefficient is positive for risk aversion ($\mathrm{U}'' < 0$) and diminishes for increasing x if there is diminishing risk aversion [Hardaker et al., 1997]. Anderson and Dillon [1992] suggested a range of RACs to characterize individual attitudes to risk as follows: risk neutral, RAC = 0; hardly risk averse, RAC = 0.5; somewhat risk averse, RAC = 1.0; rather risk averse, RAC = 2.0; very risk averse, RAC = 3.0 and extremely risk averse, RAC = 4.0.

Stochastic efficiency with respect to a function (SERF) employs certainty equivalent (CE) to determine the subset of utility efficient alternatives given a range of RACs [Hardaker et al. 2004]. Richardson et al. [2006] defined certainty equivalent as the amount of payoff that a decision maker would have to receive to be indifferent between accepting the guaranteed payoff and a higher but uncertain payoff. For a risk averse decision maker, CE is less than the expected value of a risky alternative because the decision maker prefers to reduce uncertainty [Hardaker et al., 2004]. In other words, a decision maker will prefer the risky scenario with the greatest CE. Risk premiums (RP) are calculated as the difference between CEs for each scenario and a base scenario which generally is the most preferred scenario picked best by CE. RP indicates the minimum payment a decision maker requires to be indifferent between two alternatives [Hardaker et al., 2004; Richardson et al., 2006]. A decision maker will select the alternative with the highest RP. Hardaker et al. [2004] claimed that SERF allows for the simultaneous evaluation of alternatives and is therefore more discriminating than SDRF.

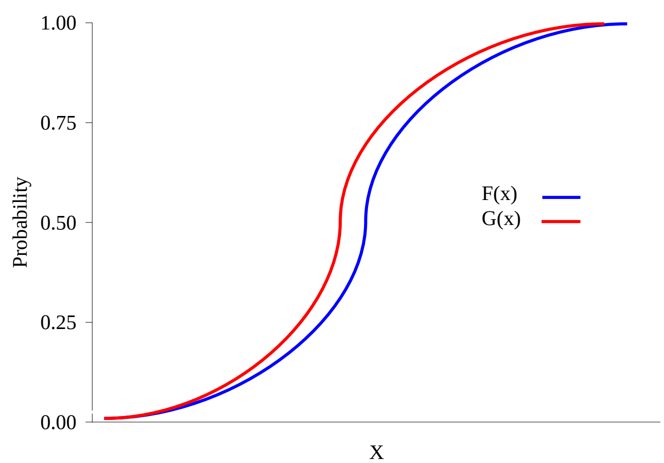

Figure 4. First degree stochastic dominance – CDFs of two different scenarios

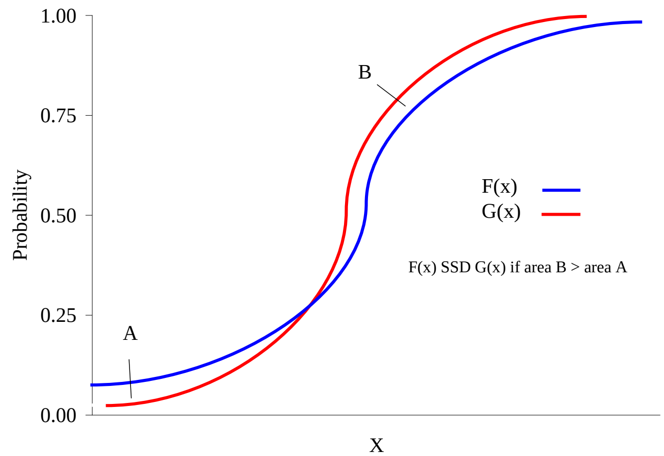

Figure 5. Second degree stochastic dominance – CDFs of two different scenarios

The previous concepts can be demonstrated with an example. Let us assume a person is given the choice between two options, one with a guaranteed payoff and one without. In the guaranteed option, the person receives \$5. In the uncertain scenario, a coin is flipped to decide whether the person receives \$10 or nothing. The expected payoff for both scenarios is \$5, meaning that a person who is indifferent to risk would not care whether he takes the guaranteed payment or the gamble. However, individuals may have different risk attitudes. A person is: 1) risk neutral if he is indifferent between the bet and a certain \$5 payment, 2) risk-averse if he would accept a payoff of less than \$5 (for example, \$4), with no uncertainty (non-risky), rather than taking the gamble and possibly receiving nothing or 3) risk-loving if the guaranteed payment must be more than \$5 (for example, \$6) to induce him to take the guaranteed option, rather than taking the gamble and possibly winning \$10. The average payoff of the gamble is the expected value or \$5 in this case. The dollar amount that the person would accept instead of the bet is the CE, and the difference between the CE and the expected value is the RP.

Simulation & Econometrics to Analyze Risk

The simulation and econometrics to analyze risk (SIMETAR) is an add-in template for Microsoft Excel used to develop, simulate and apply a stochastic model into the spreadsheet. This program is capable of simulating sets of random variables using Monte Carlo or Latin Hypercube sampling procedures [Richardson et al., 2006]. The SIMETAR determines FSD, SSD, SDRF and SERF rankings of risky alternatives and allows sets of cumulative distributions to be compared accounting for the risk in each distribution by using lower and upper RACs the user specifies. The results are display in tables and graphs which are dynamic so the user can adjust RACs and evaluate the effect on scenario rankings.

Review of Literature

The use of stochastic dominance (SD) has been well-documented in several fields especially in investment decision making in financial settings [Levy, 1998]. This review of literature focuses on application of SD to agricultural challenges. Only four studies were considered. This is due to the focus given to studies that use SIMETAR to analyze risk. Consequently, all the studies reported here used SIMETAR as the tool to rank risky alternatives and they were analyzed under three parameters: 1) objectives 2) methods and 3) results and conclusions. The studies analyzed risk in several areas such as conservation policies, tillage systems, irrigation deficiencies and insurance decisions.

Grové et al. [2006] used stochastic efficiency with respect to an exponential utility function to determine utility-efficient water-conserving irrigation schedules for maize and wheat based on certainty equivalents. The authors analyzed deficit irrigation as an economically viable option to follow under conditions of limited water supplies in South Africa. Four alternative water conservation strategies between 8 and 32 percent were analyzed. Results showed that all the deficit irrigation strategies evaluated had a higher maximum gross margin compared to a full irrigation strategy in seasons with high rainfall. This is due to reduce irrigation cost and the more efficient use of rainfall and applied irrigation water. However, risk increased with deficit irrigation.

Decision makers who are risk averse will not adopt deficit irrigation. However, decision makers who are slightly risk averse will adopt deficit irrigation in maize. In contrast, decision makers need to be risk seeking to adopt deficit irrigation practices when irrigating wheat. The authors concluded that risk-averse decision makers will not be willing to adopt deficit irrigation strategies in areas where rainfall is low.

Wilson et al. [2006] developed a model to evaluate the combined crop insurance/contracting decision responses of barley producers in North Dakota. Alternative risk efficient insurance strategies for producers with differing risk attitudes and production practices (i.e., irrigated and dry-land production) were evaluated using stochastic dominance with respect to a function and stochastic efficiency with respect to a function. Price coverage was assumed to be 100 percent while crop insurance yield coverage ranged from 50 to 80 percent. Producers who raise their barley for malt are eligible to purchase malt option A or B.

Option A is for producers who do not have a contract when purchasing their crop insurance and option B is for producers with a malt contract. Results showed that irrigated risk-returns were consistently ranked. The SDRF and SERF rankings for risk averse barley producers implied that more insurance coverage and production with a contract and option B is preferred to alternatives. In contrast, dry-land returns are inconsistent for malting barley producers. Risk averse barley producers prefer option B and contracting over other alternatives; however, premium costs reduce net returns at higher coverage levels but producers commonly prefer more insurance coverage to less. The authors concluded that efficient insurance strategies choices are highly dependent on risk attitudes for dry-land producers, but not for irrigated producers.

Benitez et al. [2006] studied how to preserve forest and agro-forest systems in west Ecuador using conservation payments. The authors used stochastic dominance to demonstrate that conservation payments required for preserving shaded coffee areas compared with alternative land uses (i.e., maize, pasture, upland rice) were much higher than those calculated under risk-neutral assumptions. Results showed that maize dominated rice by first degree stochastic dominance. Also, maize dominated rice and coffee by second degree stochastic dominance and coffee dominated rice by second degree stochastic dominance but there was not dominance relation between maize and pasture.

To guarantee that all risk-averse landowners preferred coffee over pasture may require a risk premium of 70 percent of the average net revenues for coffee (or $55/ha hectare). Therefore, the high variability of coffee revenues discouraged risk-averse landowners from growing shaded coffee. The authors concluded the need for considering risk when implementing conservation policy instruments in Ecuador.

Ribera et al. [2004] compared the net income distributions of conventional tillage and no-tillage systems on grain sorghum, wheat and soybean in south Texas using a Monte Carlo simulation model. Stochastic efficiency with respect to function was used to rank conventional tillage and no-tillage systems for decision makers with different levels of risk preference or aversion. Results showed that from comparing sorghum-wheat-soybean rotation under both tillage systems, no-tillage is preferred by all classes of decision makers. No-tillage has a risk premium ($/ha) over conventional tillage of $8.45 for risk-neutral individuals and $17.79 for risk-averse individuals.

Regardless of risk preference, all decision makers would prefer the no-tillage system for the wheat-soybean rotation. With this rotation, no-tillage has a risk premium ($/ha) over conventional tillage of $18.38 for risk-neutral individuals and $32.57 for risk-averse individuals. The authors concluded that a risk-averse individual would prefer no-tillage over conventional tillage for all crop rotations analyzed in this study.

Conclusion

The previous studies proved that SD is a valuable tool to rank alternatives for different agricultural problems when risk is included in the analysis. However, since the introduction of the concept of stochastic efficiency with respect to a function (SERF) by Hardaker et al. [2004], this methodology has been more appealing for researchers since it evaluates the CE of each alternative over the relevant parameter space of the utility function rather than evaluated only at the boundaries of the specified risk aversion range as occurs with SD. One common limitation expressed through several studies is the lack of historical yield, price and cost data available.

Genetic Algorithm Overview

Introduction

The concept of a genetic algorithm (GA) was introduced by Holland [1975] in his book entitled: “Adaptation in Natural and Artificial Systems.” He originated the framework for predicting the quality of the next generation by applying the principle of the survival of the fittest. Koza [1992, p18] defined GA as a:

> “….. *highly parallel mathematical algorithm that transforms a set (population) of individual mathematical objects (typically fixed-length character strings patterned after chromosome strings), each with an associated fitness value, into a new population (i.e., the next generation) using operations patterned after the Darwinian principle of reproduction and survival of the fittest and after naturally occurring genetic operations (notably sexual recombination).”*

GA is a technique based on evolutionary principles of reproduction, recombination and mutation that seeks for optimal solutions to solve a search problem [Chambers, 2001; Goldberg, 1989; Holland, 1975; Koza, 1992; Reeves and Rowe, 2003]. GA models individuals of a population as chromosomes, with genes on the chromosome encoding a specific trait of an individual. Alleles are the possible settings for a trait. Fitter chromosomes are the most likely to survive into the next generation. This process occurs in generations starting from a random population of generated individuals (chromosomes).

The fitness of each individual in the population is evaluated; multiple individuals are randomly reproduced based on their fitness, and then randomly recombined and randomly mutated to form a new population [Koza, 1992; Reeves and Rowe, 2003]. This occurs in each generation (iteration). The new population is then used in the next iteration of the algorithm. Usually, the algorithm stops when an adequate fitness level has been achieved for the population or a maximum number of generations have been produced [Chambers, 2001; Goldberg, 1989; Koza, 1992; Reeves and Rowe, 2003].

Genetic algorithms have been applied to difficult optimization problems because of their capacity to handle complex and irregular solution spaces when searching for a global optimum [Chambers, 2001]. The search space includes all feasible solutions and their associated fitness which is based on the objective function value. Although, only a few solutions are known at the beginning, GA will generate other solutions, using the principles of reproduction, recombination and mutation, as the process of finding solutions continues.

Koza [1992] divided in four the number of steps needed to solve a problem using a GA: 1) the representation scheme, 2) the fitness measure, 3) the parameters and variables for controlling the algorithm and 4) the way of designing the result and the criterion for terminating a run. The representation scheme is the first step in preparing to solve an optimization problem using GA. This can be demonstrated with an illustration consisting on an optimization problem: searching for the best water quality strategy to reduce phosphorous pollution in a watershed. This example was adapted from Koza [1992].

The strategy to decrease phosphorous runoff will consist of making three binary decisions: 1) poultry litter application, 2) buffer strip area and 3) poultry litter treated with alum. Since there are three decision variables or genes; each of which can assume one of two possible values (i.e., 0 or 1), the search space of this problem consists of $2^3 = 8$ possible cleaning strategies. Table 1 displays four of the eight possible strategies in the representation scheme described above. The goal is to find the combination of these three cleaning decisions that produces the highest phosphorous reduction.

Cleaning Strategy *(i)*	**Litter**	**Buffer Strip**	**Alum**	**Binary String**
1	Low	Long	Yes	011
2	Low	Short	Yes	001
3	High	Long	No	110
4	Low	Long	No	010

Table 1. Representation scheme for a hypothetical water quality problem

The GA will initiate with generation 0 including a population of randomly created individuals. In this case the population size (M), is equal to 4 different cleaning strategies (i.e., chromosomes). To establish individual fitness, each individual in the population is tested against the unknown environment [Koza, 1992]. This process occurs for each generation. Fitness in this case is called phosphorous reduction (i.e., the value of the objective function). Table 2 displays the fitness associated with each of the individuals in the initial random population for this problem (i.e., values were assigned arbitrarily). Now the decision maker knows that cleaning strategy 110 reduce 6 kg and cleaning strategy 001 reduce 1 kg making it the worst in generation 0.

The GA renovates one population of individuals and their respective fitness scores using the principle of reproduction [Chambers, 2001; Goldberg, 1989; Holland, 1975; Koza, 1992]. Individuals are copied into the next generation with a probability proportional to their fitness [Goldberg, 1989; Koza, 1992]. It can be expected that individual 110 will be copied twice (p= 0.50), individuals 011 (p=0.25) and 010 (p=0.17) once whereas it is expected that individual 001 (p=0.08) will be omitted from the new population. This is one of the possible outcomes of generation 0 after reproduction. Table 3 displays one possible outcome after reproduction is applied to the initial random population. One of the goals of reproduction is to improve the average fitness of the population [Chambers, 2001; Goldberg, 1989; Koza, 1992]. The average fitness of the population improved from 3 to 4.25. Also, the worst individual in the original population had a fitness score of 1 whereas the worst individual in the new population has a fitness score of 2. It is important to notice that the diversity of the population have been affected by these improvements. More precisely, individual 001 is now extinct.

	Generation 0		
i	**String** x_i	**Fitness** $f(x_i)$	$\frac{f(x_i)}{\sum f(x_i)}$
1	011	3	0.25
2	001	1	0.08
3	110	6	0.50
4	010	2	0.17
Total		12	
Average		3	
Worst		1	
Best		6	

Table 2. Fitness measure for the initial random population of the water quality problem

New points in the search space can be tested using recombination (crossover). Recombination begins with two parents that are selected proportionate to their fitness [Chambers, 2001; Goldberg, 1989, Koza, 1992]. This operation generates two offspring which contain information from their parents but are different from their parents and each other [Chambers, 2001; Goldberg, 1989, Koza, 1992]. Two parents and a recombination point must be selected. In this case two parents were selected proportionate to their fitness, parent one (011) and parent two (110). Suppose the recombination point is the last digit from the string. Then the recombination fragments from parent one is 01* and parent two 11*. The remainders fragments from the parent one is **1 and **0 for parent two. The remainder fragment of parent one (**1) is combined with the recombination fragments of parent two (11*) and vice versa. Consequently, two offspring are produced by recombination, offspring one (111) and offspring two (010).

In this example an arbitrarily 50 percent recombination probability was used. In other words, two individuals (50 percent of the population) contributed in the process of creating the next generation. As a result, the reproduction probability is also 50 percent. Table 4 displays one possible outcome after applying reproduction and recombination operations to generation 0 to create generation 1.

	Generation 0			**After Reproduction**	
I	**String** x_i	**Fitness** $f(x_i)$	$\frac{f(x_i)}{\sum f(x_i)}$	**String** $f(x_i)$	**Fitness** $f(x_i)$
1	011	3	0.25	011	3
2	001	1	0.08	110	6
3	110	6	0.50	110	6
4	010	2	0.17	010	2
Total		12			17
Average		3			4.25
Worst		1			2
Best		6			6

Table 3. Fitness-proportionate reproduction to the initial random population

Briefly, the primary parameters for controlling a GA are the population size (M) and the maximum number of generations (Gen) to be run (i.e., the termination parameter). GA initiates by randomly creating an initial population of individuals. The fitness of each individual in the population is evaluated. The secondary parameters control reproduction (P_r), recombination (P_c) and mutation (P_m) probabilities.

Individuals that form the next generation are chosen with a probability based on fitness. For instance, some individuals can be copied to the new population; others can be randomly recombined and occasionally randomly mutating. Mutation is used to diversify the population by creating new individuals.

	Generation 0			After Reproduction		After Recombination	
i	**String** x_i	**Fitness** $f(x_i)$	$\frac{f(x_i)}{\sum f(x_i)}$	**String** $f(x_i)$	**Fitness** $f(x_i)$	**String** x_i	**Fitness** $f(x_i)$
1	011	3	0.25	011	3	111	7
2	001	1	0.08	110	6	010	2
3	110	6	0.50	110	6	110	6
4	010	2	0.17	010	2	010	2
Total		12			17		17
Average		3			4.25		4.25
Worst		1			2		2
Best		6			6		7

Table 4. Possible result of applying reproduction and recombination operations to generation zero

By using these three processes, the GA approach evolves by removing poor solutions that do not perform well and repopulating the next generation with only combinations of the best solutions. Only the best individuals remain in successive generations. A flowchart of the basic GA process is display in figure 6. This chart is similar to the one presented by Chambers [2001, p 373] but it was reproduced from Koza [1992] for its simplicity.

Genetic Algorithm Applications

The use of GA has been well-documented in several fields to find optimal solutions to several types of problems. For instance, Chang et al., [2006] studied the use of GA to solve the economic lot scheduling problem with deteriorating food items.

Haldenbilen and Ceylan [2005] estimated a transport demand based on GA approach and evaluated the road tax system in Turkey. Ozyildirim et al. [2005] estimated a dynamic model using GA to optimize tenure (housing policy implications) behavior of an individual who faces the possibility of moving multiple times during his lifetime.

Rubenstein-Montano and Zandi [1999] introduced a GA procedure for creating alternative policy options for municipal solid waste management planning. Pereira and Lapa [2003] applied GAs to a Nuclear Power Plant (NPP) Auxiliary Feed-Water System (AFWS) surveillance tests policy optimization. Marseguerra et al. [2002] used a GA for determining the optimal degradation level beyond which preventive maintenance has to be performed.

Ortega et al. [2004] used GA to identify an optimum cropping pattern and irrigation strategy to maximize the gross margin on a farm in a specific irrigable area in a semi-arid area of Spain, with great deficits and high water costs. Cho et al. [2004] integrated a GA and a mathematical water quality model to calculate treatment type and treatment cost for each wastewater treatment plant in the Youngsan River basin to change wastewater treatment policy in Korea. Juran and Sarma [2005] used a GA model for finding the optimal operating policy of a multi-purpose reservoir in the Pagladia River in India. Rui and Seng [2004] used GA to calibrate a NPS water quality models using sparse field data of the Triadelphia Reservoir in Maryland.

Although GA is a very powerful optimization by itself, GA and other programs have also been combined to solve complex problems. For instance, Reis et al. [2006] applied a hybrid method using GA and linear programming (LP) techniques to determine operational decisions for the Roadford multi-reservoir system over an optimization period in United Kingdom. Linton et al. [2002] showed that a GA approach can be simultaneously combined with simulation to incorporate stochastic elements in the policy option generation phase of a solid waste management system.

Gitau et al. [2004] combined a GA, a watershed-level nonpoint-source model and a BMP tool to determine cost-effective alternative scenarios that meet a phosphorus reduction criterion in a reservoir within New York City's water supply system. Janejira et al. [2005] combined a GA and discrete differential dynamic programming approach (called GA-DDDP) to optimize operating policies by minimizing the total irrigation deficits during a critical drought year of the Mae Klong multiple reservoir system in Thailand.

Systematic Review of Literature

After conducting a systematic search of the literature, sixteen articles, which focused on the use of GA to find optimal solutions to watershed issues, were selected. In order to better comprehend the characteristics and effectiveness of the GA to estimate optimal solutions, this section provides a review of those studies. The studies were analyzed under three parameters: 1) objectives 2) methods and 3) results and conclusions. A brief summary of those studies is displayed in table 5. Only one of the articles was published before year 2000.

Ten articles evaluated sediments yield, three flow control, two nutrients and one waste loads. Three articles analyzed sediments and nutrients. Fourteen of the sixteen studies were conducted in the United States and two in Taiwan. Of those conducted in the United States eight were conducted in the east coast, four in the mid-west, one in the west coast and one in the south. Five watersheds analyzed were small, less than

1,000 hectares and only three were greater than 50,000 hectares. Thirteen of the sixteen watersheds analyzed were agricultural watershed whereas the other three were urban watersheds. Finally, eleven studies analyzed the effect of implementing BMPs to control sediments and nutrients pollution.

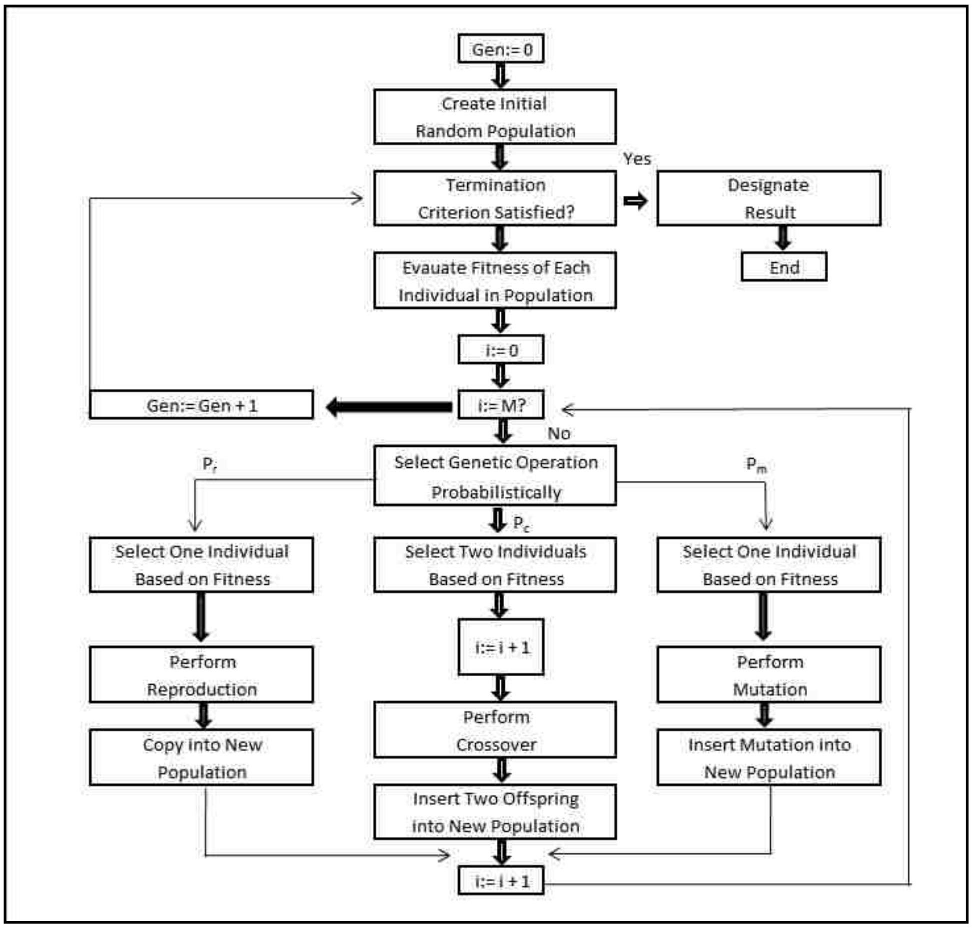

Figure 6. A flowchart of the basic GA process - Source: Koza [1992].

Author(s)	Year	Location	Watershed	Watershed Area (ha)	Optimization Analysis	Reduction Target
Confesor, Whittaker	2007	Oregon	Calapooia River	96,300	Automatic multi-objective calibration	Flow
Arabi, Govindaraju, Hantush	2006	Indiana	Dreisbach & Smith Fry	623 730	Implementation of conservation practices	Sediment, Nitrogen Phosphorous
Chen, Chang	2006	South Taiwan	Tseng-Wen River	117,600	Waste load reduction	Waste
Gitau, Veith, Gburek, Jarrett	2006	New York	Town Brook	3,700	Selection and placement of cost-effective BMPs	Phosphorous
Wan, Labadie, Konyha, Conboy	2006	South Florida	St. Lucie Estuary	200,000	Size and operation of a storm-water detention system	Sediment
Bekele, Nicklow	2005	Southern Illinois	Big Creek	13,300	Evaluation of land uses and tillage practices	Sediment, Nitrogen Phosphorous
Muleta, Nicklow	2005	Southern Illinois	Big Creek	13,300	Sediment pollution reduction	Sediment
Perez-Pedini, Limbrunner Vogel	2005	Massachusetts	Aberjona River (Urban Watershed)	6,514	Number and location of infiltration-based BMPs to reduce peak flood flows	Flow
Gitau, Veith, Gburek	2004	Pennsylvania	Cannonsville Reservoir	300	Selection and placement of cost-effective BMPs	Phosphorous
Veith, Wolfe, Heatwole	2004	Virginia	Muddy Creek	1,014	Selection and placement of cost-effective BMPs	Sediment
Harrell, Ranjithan	2003	North Carolina	City Lake (Urban Watershed)	138	Pond configurations and land use allocations	Sediment, Nitrogen Phosphorous
Srivastava, Hamlett, Robillard	2003	Pennsylvania	Mahantango Creek	725	Selection of cost-effective BMPs	Sediments

Author(s)	Year	Location	Watershed	Watershed Area (ha)	Optimization Analysis	Reduction Target
Veith, Wolfe and Heatwole	2003	Virginia	Ridge and Valley Physiographic Region	1,104	BMP placement based on cost and NPS pollution reduction	Sediment
Srivastava, Hamlett, Robillard, Day	2002	Pennsylvania	Mahantango Creek	725	Selection of BMPs and Net returns increase	Sediments
Randhir, Lee, Engel	2000	Indiana	Animal Science	6.5	Selection of BMPs	Sediment
Yeh, Labadie	1997	Southern Taiwan	Pazam (Urban Watershed)	2,254	Locations and sizes of detention ponds	Flow

Table 5. Summary of previous studies applying GA to watershed management

Single Objective Functions

Several articles used GA to find combinations of BMPs to reduce sediment and nutrient runoff using a single objective function. Arabi et al. [2006b] combined a simulation pollutant load model, a BMP representation method, an economic component and a GA-based spatial optimization model to evaluate a range of agricultural and environmental management plans that reduce pollutant loads below regulatory or target values at minimum cost in two watersheds in Indiana. The model was optimized to evaluate the water quality impacts of grassed waterways, parallel terraces, grade stabilization structures and field borders. Four cases were examined.

Case one was the baseline – no BMPs. Case two represented cost-effectiveness of BMPs allocated by targeting. Case three allocated BMPs to reduce sediment, nitrogen and phosphorous below targeting values and case four only included the cost constraint. Results showed that BMPs selected and placed in the Dreisbach watershed by optimization case three cost 2.5 times less and produced almost three times better benefit-cost ratio than a targeting combination. The benefit-cost ratio attained with case four was almost two times higher than the targeting solution. The authors concluded that the optimization results are likely to achieve the same level of pollutant reduction as targeting strategies at significantly lower costs.

Gitau et al. [2006] evaluated different management solutions to reduce phosphorous losses by 60 percent within the Town Brook watershed in New York. The study assessed BMP effectiveness based on BMP selection and placement using four components: 1) a NPS pollution reduction model – (SWAT), 2) a BMP tool, 3) BMP costs and 4) a GA. GA evaluated the best scenarios for BMP selection and placement based on the effectiveness in reducing total phosphorous and reducing costs by using SWAT phosphorous loadings, BMP effectiveness estimated by the BMP tool (percentage of phosphorous reduced from a baseline) and the costs associated with each BMP.

Four scenarios including different combinations of management practices were examined. Results showed a 60 percent reduction in phosphorous losses in all scenarios. Scenarios 1 and 2 reduced costs by 29 percent and 26 percent respectively. Although, scenario 3 and 4 obtained the same phosphorous pollution reduction, cost increased by 18 percent with scenario 3 and was unchangeable for scenario 4 compared to the baseline. The authors suggested evaluating potential BMP solutions before implementing them everywhere on the watershed. In other words, using this methodology, BMPs can be implemented selectively to areas most in need of the BMPs.

Gitau et al. [2004] developed a methodology to determine optimal selection and placement of cost-effective BMPs to reduce dissolved phosphorous within the Town Brook watershed in New York. The study assessed water quality and economic concerns by incorporating four components: 1) a GA, 2) a watershed level NPS model – (SWAT), 3) a BMP tool and 4) BMP costs. The GA fused average annual pollution loads from SWAT with reduction efficiencies from the BMP tool and annualized BMP costs to optimize BMP placement with respect to cost and phosphorous reduction. This methodology was implemented to a 300 hectares farm within the watershed.

The BMPs used in this study consisted of the combination of nutrient management plans, contour strip cropping and riparian forest buffers. A phosphorous reduction target of 60 percent of the baseline annual loading value was created for comparison purposes. The authors only presented the results of two scenarios. Both scenarios met the established 60 percent dissolved phosphorous pollution reduction target. However, scenario two increased cost by $1,683 compared to the baseline and it was $230 more expensive than scenario one. Overall scenario one was more cost-effective saving $0.29 per year per kilogram of dissolved phosphorous. The authors concluded that the results from this study were not transferable to make decisions at a watershed level.

Veith et al. [2004] used a GA to optimize the search for the combination of site-specific practices that meets sediment reduction requirements as well as the BMPs combination that minimizes cost. This process was compared to targeting strategies that define locations for BMP implementation based on specific criteria uniformly applied across the Muddy Creek watershed in Virginia. The optimization procedure was based on three components: 1) a GA, 2) a NPS pollution reduction model and 3) an economic component. A baseline scenario, one targeting strategy and three optimization plans were applied to the watershed.

Results showed that the targeting strategy reduced sediment by 81 percent compared to the baseline. Optimization plan 1 and 2 reduced costs compared to the targeting strategy by 13 percent and 33 percent respectively. Optimization plan 3 was estimated to cost $2 less than the baseline scenario for every kilogram of sediment loss prevented by year. The authors concluded that the optimization plan with the same BMP choices achieved the same sediment reduction at a lower cost than using the targeting strategy.

Harell and Ranjithan [2003] investigated individually the tradeoffs between removal efficiency and cost for total suspended solids, total nitrogen and total phosphorous using a GA-based method within the City Lake watershed in North Carolina. The model was configured to identify the cost-effective pond configuration (i.e., sites and locations) and the associated land allocation for any given removal efficiency. Results showed removal efficiency for individual pond design of 85 percent for total suspended solids, 20 percent for total nitrogen and 31 percent for total phosphorous. The cost of this pond is the $6.41 million. A system-wide design approach (total suspended solids specific) which allows flexibility in the allocation of future land use achieved 85 percent total suspended solids removal with a cost saving of 35 percent compared to individual ponds. The authors concluded that optimizing specifically for the limiting pollutant of primary concern can yield the most cost-effective pond configurations.

Srivastava et al. [2003] studied the differences in pollutant loads by using 15 different crop rotations (i.e., combinations of corn, soybean, wheat and alfalfa) and related management practices in the Mahantango Creek watershed in Pennsylvania. The goal of their research was to test annual yields of pollutant loads from 2 years and 5 years 24 hour storms and cumulative load from 5 year continuous simulation. The methodology included three components: 1) a continuous simulation model, AnnAGPS, 2) a cost model and 3) a GA.

The AnnAGNPS simulated runoff, sediment, nutrient and pesticide transport resulting from selected BMPs based on continuous events linked in time. Three optimization cases were evaluated using a GA to determine the BMP schemes that minimize pollutant loads from 2 and 5 years storms events and long term accumulated pollutant loads at the watershed outlet. Results showed that the five-year accumulated analysis provide smaller cumulative sediment loads at the watershed outlet. The authors argued that a continuous simulation model is desired rather than an event model which is inadequate in representing long term cropping and management schemes. GA proved to be successful in providing similar levels of sediment reduction while providing a diverse BMP selection on various fields in the watershed.

Veith et al. [2003] developed an optimization procedure that identifies BMP combinations that meet defined pollutant reduction levels while minimizing costs for a 1,014 hectares watershed in Virginia. The optimization procedure was based on three components: 1) a GA, 2) a NPS pollution reduction model and 3) an economic component. The objective of this study was to create an optimization procedure that reduced sediment load by placing an adequate amount of cost-effective BMPs on the watershed. All scenarios that increased sediment pollution were given a fitness score of zero. Results showed that sediment control cost could be reduced by 25.2 percent using this methodology. However, the authors argued that using the three components as a single objective function is not the best alternative.

Srivastava et al. [2002] demonstrated that a GA combined with a NPS pollution model –AnnAGNPS - could optimize BMP selection and maximize net returns within the Mahantango Creek watershed in Pennsylvania. Two objective functions were employed in this study. The first one consisted in maximizing pollution reduction for a given net return constraint ($45,000). The second one consisted in maximize net return associated with various crop rotations (i.e., rotations of corn, soybeans, wheat and alfalfa) including a penalty for an increase in pollutant load.

Results for objective function one showed a sediment reduction of 44 percent, sediment nitrogen reduction of 56 percent and sediment phosphorous reduction of 50 percent whereas net return increased by 41 percent. Objective function two did not decrease pollutant loads compared to the baseline but increased net returns by 109 percent. This occurred mainly because corn and alfalfa generated high net returns and were chosen to cover 79 percent of the total area. The authors argue that because the spatial distribution of BMPs was not studied, the chosen BMPs may not be the best scheme for the watershed. The authors concluded that a more sophisticated and robust objective function should maximize pollutant reduction and net returns at the same time.

Randhir and Engel [2000] optimized land uses (i.e., corn and soybean) in the Animal Science watershed in Indiana by minimizing sediment pollution and economic loss. The optimization procedure was based on four components: 1) a geographic information system (GIS), 2) two biophysical simulation models (AGNPS and EPIC were used to model spatial hydrology and crop growth processes), 3) an economic component and 4) a GA. The authors included two objectives; maximizing net returns from crop production and minimizing sediment loss. Results showed that by varying the type of cropping system at specific locations within the watershed overall sediment pollution is reduced. The authors concluded that it is possible to achieve water quality and economic objectives by spatially optimizing site-specific practices.

Multi Objective Functions

Other studies have evaluated multi-objective functions using GA. Confesor and Whittaker [2007] used a multi-objective evolutionary algorithm (MOEA) and Pareto ordering optimization in the automatic calibration of SWAT. The authors used non-dominated sorting genetic algorithm II (NSGA-II) which is a fast and efficient multi-objective evolutionary algorithm (MOEA). The Calapooia River watershed in Oregon was divided in four dominant land uses (i.e., evergreen forest, mix forest, perennial grass and hay, pasture and rangelands), nine main soil groups and seventeen HRUs. The main goal was to calibrate and validate 139 parameters in SWAT.

Results show that the automatic multi-objective calibration successfully simulated the daily stream flow of the watershed by improving the daily Nash-Sutcliffe coefficient from 0.28 to 0.86 at calibration. However, the authors concluded that the simulated outputs tend to underestimate high peak flows as reported in previous studies.

Chen and Chang [2006] combined grey and fuzzy multi-objective programming with a GA to solve a waste load allocation problem in the Tseng-Wen River basin in south Taiwan. Three fuzzy cases were considered: 1) maximization of the utilization level of TMDL, 2) minimization of wastewater treatment cost and 3) maximization of the benefit due to in-stream water quality improvement. Results showed that case 3 required the lowest investment followed by case 2 and case 1 respectively. The water quality management planning proposed included direct and indirect costs and benefits relevant to the selection of essential treatment levels during the allocation of waste load. Although all three cases were able to provide a set of waste allocation schemes, the authors concluded that future land use planning in the Tseng-Wen River region must adhere to a sustainable development strategy.

Wan et al. [2006] used a GA to optimize sizing and operation of storm-water detention reservoirs within the St. Lucie Estuary watershed in south Florida. A GA and a daily hydrologic simulation model of the drainage network were combined to achieve coastal ecosystem restoration. A multi-objective analysis was employed to match the frequency distribution of storm-water discharges, to satisfy irrigation requirements and to minimize the required storage capacity of the reservoirs. Results showed that this methodology is useful to obtain optimal solutions that achieve target mean monthly frequency distributions for storm-water inflows with significant costs reductions.

Bekele and Nicklow [2005] evaluated land uses and tillage practices that minimize average annual sediment, nitrogen and phosphorous yields and maximize average gross margin of crops (i.e., corn, soybean, sorghum, hay, pasture and tall fescue) within the Big Creek watershed in southern Illinois. The authors combined a comprehensive hydrologic and environmental simulation model (SWAT) with a multi-objective evolutionary search algorithm, strength Pareto evolutionary algorithm (SPEA2), which finds multiple optimal solutions in a single model execution.

Results showed that perennial crops and a no-till option are able to limit sediments and nutrients pollution. However, the degree of pollution reduction depended on the amount of profits farmers were willing to forgo. The authors suggested comparing the results of this study with a non-dominated genetic algorithm (NSGA-II) which has a lower runtime than (SPEA2).

Muleta and Nicklow [2005] studied the potential role of optimal land use and management activity combinations in reducing erosion and sediment in the Big Creek watershed in southern Illinois. The optimization procedure integrated three components: 1) a GA, 2) a water simulation model (SWAT) and 3) an economic model. Automatic calibration of daily flow volume and daily sediment yield was accomplished using an artificial neural network (ANN). The authors used single objective functions (i.e., minimize sediment yield or maximize net profit) and multi-objective functions (i.e., minimize sediment yield while maximizing farm income).

Results showed that sediment yield can be reduced by 39 percent (single-objective function) but it may not be fully economically viable. Although, the multi-objective decision reduced sediment yield by 19 percent, it was found that the total difference in annual profit will differ by $22,492 among solutions that favor maximization of net profit and minimization of sediment yield. The authors concluded that ANN reduced processing time by 84 percent.

Perez-Pedini et al. [2005] combined a distributed hydrologic model with a GA to determine the optimal location of infiltration-based BMPs for storm water management within the Aberjona River watershed in Massachusetts. An event-based hydrologic model was optimized using a GA to establish areas where the application of BMPs would be most effective in reducing flood flows. The model consisted of a system of 4,533 square HRUs that had a side length of 120 meters.

The authors use a Pareto frontier to describe the trade-off between peak flow reduction and number of BMPs. Results showed that by applying BMPs to less than 200 HRUs a 20 percent reduction in the peak flow can be obtained. The authors concluded that it is best to implement BMPs in the most critical areas and then target future action in less critical ones according to budget constraints.

Yeh and Labadie [1997] evaluated the layout and sizing of detention systems for various levels of detention effect of urban drainages within the Pazam watershed in south Taiwan. The objective was to minimize water detention system costs of maintaining desired peak downstream flow. The authors formulated a multi-objective genetic algorithm (MOGA) which generated a wide range of non-dominated solutions with a stream network of 10 junctions, 19 channels and 18 possible dam sites.

Results showed that a detention effect of 2.8 percent cost $548,000 with 7 dam sites. Inclusion of 4 more dam sites produced a detention effect of 3.8 percent but the cost increased by 35 percent. The authors concluded that MOGA demonstrated capabilities in generating trade-off curves for conflicting objectives.

Conclusion

From the previous review of literature, it can be concluded that optimal solutions to water quality problems including excess of sediments and nutrients have been found for several watersheds around the country. This literature review can be divided in two main groups: single objective and multi-objective function studies.

Although, the studies developed for Arabi et al. [2006b], Gitau et al. [2006; 2004], Veith et al. [2004; 2003], Harell and Ranjithan [2003], Randhir and Engel [2000] and Srivastava et al. [2003; 2002] successfully found optimal solutions, a single objective function that joined all different constraints into one was used in all cases. This kind of optimization is functional but it cannot offer a set of alternative solutions that trade different objectives against each other from which decision makers can choose from.

In fact, some of the studies concluded that a single objective function is not the best alternative and that a more sophisticated and robust objective function should maximize pollutant reduction and minimize costs at the same time.

In contrast, Confesor and Whittaker [2007], Chen and Chang [2006], Wan et al. [2006], Bekele and Nicklow [2005], Muleta and Nicklow [2005], Perez-Pedini et al. [2005] and Yeh and Labadie [1997] used multi-objective functions with conflicting objectives. As a result, they did not find single optimal solutions rather they provided trade-off curves between different objectives and alternative solutions. Water degradation is a multi objective problem; therefore, this approach seems to be more accurate because trade-offs between benefits and costs provide decision makers with more flexibility when selecting solutions.

In brief, given the increasing national concern with the quality of the nation's waters and the growing popularity of hydrological simulation models in combination with sophisticated GAs, this methodology seems like a good tool in an effort to find cost-effective optimal BMP solutions to complex multi-objective sediments and nutrients pollution problems as those found in several Arkansas' watersheds.

Overall Conclusions

All the components of this review of literature proved to be successful in given solutions to agricultural problems. Therefore, combining a water simulation model with BMPs' effectiveness, an economic component, stochastic dominance and genetic algorithm techniques will be a comprehensive methodology to evaluate how implementation, timing and spatial distribution of combinations of BMPs can be used within watersheds in Arkansas to reduce nutrient runoff while minimizing the producers' exposure to additional risk. Results from a study using this comprehensive methodology will provide local authorities with quantitative research information to make better water management decisions.

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CHAPTER III

Implementation of Best Management Practices under Cost Risk to Control Phosphorous Pollution in a Crop Based Watershed in Arkansas

Abstract

A stochastic simulation model of a combination of 54 best management practices (BMPs) including two levels of tillage, three fertilization rates and three filter-strip widths was used to address total phosphorous (TP) loading in the L'Anguille Watershed in Arkansas. The purpose of this study was to identify the efficient set of BMPs in terms of its effectiveness to reduce TP and its relative costs to rice and soybean producers. A sub-basin-level simulation model was constructed using the soil and water assessment tool simulated output data for TP. This information was combined with BMP cost data for all 54 scenarios in 31 sub-basins. Scenarios were ranked in terms of their relative cost-effectiveness of reducing TP per dollar spent using stochastic efficiency techniques under a wide range of risk aversion levels. Results suggested that five BMP combinations consistently out rank all others, regardless of sub-basin size or amount of land devoted to agriculture in the sub-basin. Scenario 10 (rice conservation-till, soybeans no-till, low level of phosphorous (P) fertilization for both crops and a filter strip of 5 meters wide for soybeans) was the most preferred regardless of the decision maker's risk preferences. For example, if all producers in sub-basin 18, regardless their risk preferences implement this scenario and invest $4,546 they will reduce 2,913 kg of TP. This methodology demonstrates the benefits of analyzing risk faced by crop producers when they need to deal with the joint effects of water regulations and the cost of implementing BMPs in their farm operations.

Keywords: Total phosphorous, BMPs, SWAT, stochastic efficiency

Introduction

State and local government agencies face the challenge of designing policies that protect water quality and promote economically viable agriculture practices. In the Mississippi Delta, for example, vast acreages of rice and soybean employ high levels of fertilizers, pesticides and water for production. Without proper management, use of these inputs could lead to sediment and nutrient movement off the farm and into nearby rivers and streams, further exacerbating water quality issues that exist in the region.

Best management practices (BMP) exist that, when used alone or in combination, can help crop producers to minimize nutrient and sediment movement off farm. However, some BMPs are costly and producers are reluctant to include expensive practices in their management decisions even if they are effective in reducing water pollution. There are several reasons why costs of implementing BMPs often represent a barrier to adoption. One, producers are facing both increasing costs of production and the diminishing prices for their products every year. Another reason is that producers go through a BMP learning process which can lead to a temporally reduced income (e.g., the cost of installation, grading slopes, vegetation establishment, cost of maintenance, purchases of new equipment to facilitate BMP implementation, loss of acreage for crops, etc). These changes all occur in a stochastic environment that affects both the costs and returns for a farmer. Consequently, identification of BMPs that can reduce nutrient/sediment loss without greatly increasing costs of production is a priority.

Although, BMPs seem to be one of the possible solutions to water degradation, the effectiveness of BMPs should be rated not only in terms of their impact on pollutant loads but by their acceptability to producers, cost-effectiveness and ease of implementation and maintenance (Logan, 1990). Some researchers have identified BMPs effective in reducing sediment and nutrient pollutants (Dillaha, 1990; Chaubey et al., 1994; 1995; Srivastava et al., 1996; Gitau, 2003). Others have optimized placement of effective BMPs within a watershed (Srivastava et al. 2002; Veith, 2002; Gitau et al., 2004; Veith et al., 2004). However, none of these studies includes the cost-risk incurred by producers when implementing such practices.

Description of the Study Site

A watershed level study was initiated in 2004 at the L’Anguille Watershed in the Arkansas Delta region to develop a quality-water conservation decision support system based on linkages among water conservation, water quality and agricultural production. The L’Anguille Watershed with an area of 2,522 km^2 is located in northeastern Arkansas (figure 1). The L'Anguille River is a tributary of the St. Francis River where agriculture is the dominant land use. Many producers draw irrigation water from the L'Anguille along its 110-mile course. Farm activities place runoff back into the river from crop fields. Approximately 76% of the land within the watershed is used for agricultural activities; mostly rice and soybean production. Close to 20% of the total area is covered by forests and the rest of the area is occupied by land surface waters and urban areas (ASWCC, 2003).

Water Quality Problem of the L’Anguille River

Row crop agriculture in this region is the major source of income and largely depends on irrigation. Total irrigated area has increased almost three folds over the past 20 years to almost 40% of total acreage (Scott et al., 1998). The greater part of this irrigation water comes from ground water. Municipalities and manufacturing industries located in this region also depend on ground water to meet their water needs. Increased rates of withdrawal of ground water in this region have created rapid ground water depletion and conflict between agricultural and urban sectors. The Arkansas Water Quality Inventory Report has listed the entire length of the L'Anguille River as impaired to support aquatic life (ADEQ, 2002). Excess sediment originating primarily from row crop agriculture was identified as the source of impairment, resulting in the development of a TMDL for total suspended solids (TSS). Also, the drainage of the low-land areas by ditching and the channelization of streams contribute to high turbidity and silt loads carried into the streams from row crop activities (ASWCC, 2003). Applications of nitrogen (N) and P to support row crop agriculture may create excess nutrient runoff problems and contribute to water quality degradation in the L'Anguille River. Consequently, the objective of this study was to identify the efficient set of BMPs in terms of its effectiveness to reduce total phosphorous (TP) losses and its relative costs to producers. Selected BMPs can enable producers to better manage water resources to reduce TP runoff with the aim of protecting water quality.

Materials and Methods

Fifty-four BMP scenarios were created that consist of combinations of tillage, fertilization rates and filter-strips (FS) that were appropriate for rice and soybean production in the watershed. Each scenario was examined in terms of its effectiveness to reduce TP and its relative costs to producers using Soil and Water Assessment Tool (SWAT), Simulation and Econometrics to Analyze Risk (SIMETAR) and BMP costs.

Soil Water Assessment Tool (SWAT)

SWAT (Arnold et al., 1998) is a watershed simulation model that assesses the impact of management and climate on water supplies, sediment, and nutrient yields. The water quality parameters generated in the model were calibrated and verified against historical stream flow and water quality data collected for the watershed by the United States Geological Survey (USGS, 2006) from 1990 to 2004. In this study, the L'Anguille River Watershed was sub-divided into 31 sub-basins and 433 HRUs (Figure 1). Twenty six of those sub-basins have rice and soybean production, in addition to other land uses. In the remaining five sub-basins (12, 13, 22, 23, and 30), soybean and other land uses were predominant. The model was run for 15 years under each BMP scenario described below. After each model run, soluble, sediment and organic P were gathered from each rice and soybean HRU. These three variables were added together to create a variable called total phosphorous (TP) that represented the total amount of TP that moved into the surface water when each BMP combination was employed in the production process.

$$TP = P\,(Soluble + Sediment + Organic) \tag{1}$$

Simulation & Econometrics to Analyze Risk (SIMETAR)

SIMETAR is an add-in template for Microsoft Excel used to develop, simulate, and apply a stochastic model into the spreadsheet. This program is capable of simulating sets of random variables using Monte Carlo or Latin Hypercube sampling procedures (Richardson et al., 2006). SIMETAR was employed for ranking risky BMP alternatives based on utility using Stochastic Efficiency with Respect to a Function (SERF). First, using an empirical distribution, 15 years (i.e., 1990-2004) of TP data from SWAT output were converted to deviations from the mean in order to estimate the stochastic component (or risk) associated with TP to create a random variable i.e., $\tilde{TP}$. Second, a new random variable called TP reduction ($\tilde{TP}$ red) was created as the difference between $\tilde{TP}$ for each BMP scenario and the baseline (scenario 1). This variable was measured in kg per hectare.

$$\tilde{TP}_{red} = \tilde{TP}_i - \tilde{TP}_{baseline} \tag{2}$$

Where $\tilde{TP}_{\text{red}}$ is TP reduction. $_i$ represents BMP scenario 2 to 54

Best Management Practices (BMPs)

Fifty-four combinations of BMPs were created for rice and soybean production in the watershed. These BMPs included: 1) two levels of tillage, conservation-till (CT) for rice and soybean as well as no-till (NT) for soybean, 2) three levels of P fertility management for each crop: P fertilizer applied at three rates: low, average and high and 3) three filter strip (FS) widths for soybeans, 0, 5 and 10 meters (Table 1). In the study area, CT is the common practice used by rice producers (Tacker, 2006). Consequently, NT was ignored. However, both tillage systems were analyzed for soybeans as both are used throughout the watershed. SWAT optimized rice and soybean production at 24 kg/ha of P and 22 kg/ha of P, respectively. In order to determine the impact of P on nutrient runoff, scenarios including low (25% below optimal) and a high (50% above optimal) levels of P were also created. Filter strips were used to filter sediment and nutrient runoff from crop fields before it reaches surface waters. Three FS width dimensions were selected: 0, 5, and 10 meters based on previous studies (Chaubey et al., 1994; 1995) and NRCS information (NRCS, 2006a).

BMP Cost Estimation

Costs of production including cost of tillage, P fertilization, and FS for rice and soybeans were estimated in dollars per hectare ($/ha) as shown in table 2. Relevant production practices and the costs of those practices were gathered from year 2007 using locally relevant crop production budgets (UACES, 2007). Filter strips were assumed to have a life of 10 years (NCRS, 2006a). Methods used to calculate FS costs came from Chia-Yu and Sohngen (1999) and prices were taken from NRCS (2006b). The opportunity cost of not continuing to produce soybeans on the land where a FS was placed was also added. It was assumed that the producers bear all the costs of establishing and maintaining the FS, and they do not receive financial assistance in the form of government cost-share. Based on the above information costs of production were calculated for each BMP scenario. Per hectare BMP cost were estimated as follows:

$$BMP_C = \left(\sum_{i}^{j} FP_L + FS_{KM} \right) \tag{3}$$

Where, *BMP* is cost of BMPs for crop *c*; *FP* is P fertilizer cost per application rate $_L$; *FS* is the filter strip cost per tillage system $_K$ (CT or NT) with width $_M$. Also, total cost of production for each crop system was calculated including BMP costs.

$$Cost_C = \left(\sum_i^j IC_K + BMP_C \right) * SA_C \tag{4}$$

Where, *IC* is cost of production practices *i* through *j* (where *i* includes typical production expenses such as crop seed, fertilizers, fungicides, herbicides, irrigation, labor, tractor, fuel, repair and maintenance, interest on operating capital, fixed expenses, etc); *k* is tillage system used (where *k* is either CT or NT); *SA* is area in rice or soybeans in each sub-basin. Costs from each BMP scenario were then compared to a baseline (scenario 1). Production costs were calculated using costs weighted by the relative percentage of rice and soybean land area in each sub-basin.

$$Cost_{BMP_i} = Cost_{C_i} - Cost_{Baseline} \tag{5}$$

Where, $_i$ represents scenario 2 through 54.

A stochastic ratio (SR) that measured $\tilde{TP}$ reduction (kg) per dollar spent ($1) was created for each scenario in each sub-basin using equations 2 and 5.

$$SR = \frac{\tilde{TP}_{red}}{Cost_{BMP}} \tag{6}$$

The SR was simulated using a Latin Hypercube procedure. Each scenario was simulated 500 times (iterations) in each sub-basin.

Risk Analysis

The model described above measures the cost-risk producers face when selecting BMP scenarios available for reducing TP. The stochastic efficiency (SERF) analysis was conducted under the following assumptions. First, the decision maker has absolute risk aversion coefficient (ARAC) function and also exhibits a negative exponential utility function (Hardaker et al., 2004; Richardson et al., 2006). Second, the risky alternatives being evaluated are small relative to the decision maker's wealth (Hardaker et al., 2004). Third, to rank risky alternatives using utility, it is essential to estimate the decision maker's risk aversion coefficient (RAC) as it is the parameter for the utility function.

Ranking Scenarios with SIMETAR

SIMETAR was employed to rank BMP scenarios with regard to risk. First, based on the assumptions stated above, SERF identifies an efficient set comparing each BMP scenario with all other alternatives simultaneously selecting only the utility efficient scenarios. This was done for each sub-basin for risk neutral (RAC = 0) and an extremely risk averse (RAC = 1) decision makers following Meyer (1987) and Ribera et al. (2004) procedures. Second, SERF employs certainty equivalence (CE) to determine the sub-set of utility efficient alternatives given a range of RACs (Hardaker et al., 2004). In this study, this procedure implies that the decision maker's risk aversion lies anywhere between 0 and 1 (in this case, RACs could take on 25 different values). A decision maker will prefer the risky scenario with the greatest CE. Third, risk premiums (RP) are calculated as the difference between CEs for each scenario and a base scenario which generally is the most preferred scenario picked best by CE. RP measured the amount of TP that a BMP scenario failed to retain in the field when a sub-optimal alternative was implemented. In others words, less TP was reduced with the same amount of money invested - in this case $1 dollar. This risk methodology builds upon the earlier work of Hardaker et al. (2004); Ribera et al. (2004); and Richardson et al. (2006). These studies provide additional information concerning the method and its application.

Results

As explained above, 54 combinations of BMPs were analyzed for each sub-basin. Focus was given to the top-five scenarios consistently selected by SERF across all sub-basins. Scenarios were ranked using CE and RP techniques. These procedures provide the same ranking results in all sub-basins. For illustrative purposes, results from only two sub-basins (18 and 23) are reported here. These sub-basins were chosen because they represent the two general categories of agricultural related sub-basins, those with both rice and soybean production and those sub-basins with only soybean production. However, results for all sub-basins are available upon request.

Sub-basin 18

The stochastic efficiency analysis resulted in an efficient set that contains only one scenario (scenario 10) regardless decision makers' risk preferences. On average, scenario 10 will reduce 0.64 kg of TP per dollar spent. If this scenario is not available, scenario 19 is preferred, and so on as shown in table 3. Implementing any scenario other than scenario 10 will increase the total amount of TP leaving this sub-basin. For example, if all producers in sub-basin 18 implement scenario 10, they will need to invest $4,546[2] to reduce 2,913 kg of TP. However, if all decide to implement scenario 19 (the second most preferred scenario), even if they spend the same amount of money, they will reduce on average only 1,789 kg of TP. In other words, scenario 19 will reduce 1,124 kg of TP less than scenario 10. It is important to highlight that the only difference between scenario 10 and 19 is the width of the FS employed. A smaller FS proved to be more cost-efficient to reduce TP in this sub-basin.

SERF involved 2 types of analyses – CE and RP. Values for each analysis were calculated for each alternative at 25 different RAC levels. Table 4 displays CE and RP for five RACs. BMP alternatives were ranked with respect to their CE and their RP values. Under both types of analysis scenario 10 is the preferred scenario (Figures 2 and 3). Scenario 10 has the highest CE value for the CARA range of 0 to 1 (Table 4). Under this RP analysis, a decision-maker that chooses a different scenario will reduce less TP for the same dollar spent. In other words, any scenario other than scenario 10 will reduce less TP load for all risk neutral and risk averse decision-makers. For instance, if a risk neutral decision-maker chooses scenario 19 instead of scenario 10, this producer will reduce TP by 0.25 kg less than he/she would have under scenario 10. An extremely risk averse decision maker will reduce TP by 0.14 kg less than he/she would have under scenario 10 (Table 4).

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[2] Sub-basin 18 covers 4,546 hectare.

Sub-basin 23

The stochastic efficiency analysis for this sub-basin resulted in an efficient set that contains three scenarios. However, these scenarios have the same BMP composition as shown in table 1. Therefore, decision makers regardless their risk preferences will be indifferent among scenarios 10, 13 and 16. Table 3 displays the top-five BMP alternatives for this sub-basin. On average, scenarios 10, 13 and 16 will reduce 0.37 kg of TP per dollar spent. If these scenarios are not available, scenario 19 or 22 are preferred. If all producers in sub-basin 23, regardless their risk preferences, implement either scenario 10, 13 or 16, they will need to invest $926[3] to reduce 344 kg of TP. However, if all of them decide to implement either scenario 19 or 22, they will reduce on average 211 kg of TP investing the same amount of money. In other words, if all producers in this sub-basin implement either scenario 19 or 22 instead of either scenario 10, 13 or 16 they will reduce less TP pollution by 133 kg. Therefore, implementing any scenario other than the scenarios mentioned before will increase the total amount of TP leaving this sub-basin.

Table 5 displays CE for the previously identified efficient set (top-five scenarios). Scenarios 10, 13 and 16 have the highest CE; therefore, either of these is the preferred scenario. This is corroborated graphically in figure 3. In this sub-basin, a risk neutral or an extremely risk averse decision-maker will be indifferent among these scenarios. If none of these scenarios are available scenarios 19 or 22 are preferred by both those who are risk neutral or extremely risk averse. RPs were also calculated using scenario 10 as the base scenario. Table 5 and figure 3 illustrate that scenarios 10, 13, and 16 are

[3] Sub-basin 23 covers 926 hectare.

preferred for all risk averse decision-makers. A decision-maker that chooses a different scenario will reduce less TP for the same dollar spent. In other words, any scenario other than scenarios 10, 13 or 16 will reduce less TP regardless decision maker's risk preferences. For example, if a risk neutral decision-maker chooses scenario 19 or 22 this producer will reduce TP pollution by 0.14 kg less than he/she would under scenario 10, 13, and 16. An extremely risk averse decision-maker will decrease TP pollution by 0.10 kg less than he/she would under scenarios 10, 13 and 16 as shown in table 5.

Discussion

The economy of the Arkansas Delta region relies greatly upon production of field crops. Among all crops, rice and soybeans are some of the most important from an economic perspective. Few studies have analyzed crop revenue risk in the state of Arkansas but no one has specifically addressed the issue of cost-risk incurred by producers when implementing BMP practices as a possible solution to water degradation. However, it is important to highlight that the effectiveness of BMPs should be rated not only in terms of their impact on pollutant loads but also by their acceptability to producers. Considering this last point, this study aims to enhance the body of water conservation literature by evaluating the risk faced by crop producers when they need to deal with the joint effects of water regulations and the cost of implementing BMPs in their farm operations. Consequently, the stochastic model developed in this study allows producers making better or more informed decisions.

The model consisted of combinations of three common used BMPs (54 scenarios) in the L'Anguille River Watershed that were ranked, for each sub-basin, using SERF techniques. Certainty equivalents and risk premiums procedures consistently selected scenario 10 as the most preferred regardless decision maker's risk preferences. Sub-optimal solutions were also analyzed but they reduced less TP with the same amount of money invested. One limitation in this study is the cost data used. A general 2007 cost of production budget was chosen to characterize the cropping system used in the entire watershed. Therefore, such cost data represent only estimates of the actual BMP costs. In addition, it was assumed that the producers bear all the costs of establishing and maintaining filter strips. Historically in the state only a small percent of farmers do get cost share. Presumably, the upcoming farm bill will be cutting farm payments. So the authors believe this is a reasonable assumption for this analysis. Nevertheless, this study has immense value as a tool for comparing BMP alternatives to be implemented in crop-based watersheds to reduce TP pollution.

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Table 1. Best management practice scenarios matrix

Scenario	Crop	Tillage [1]	Kg of P/Ha [2]	Crop	Tillage	Kg of P/Ha [2]	Filter Strip
1	Rice	Cons	18	Soybean	No-Till	16.5	0
2	Rice	Cons	18	Soybean	No-Till	22.0	0
3	Rice	Cons	18	Soybean	No-Till	33.0	0
4	Rice	Cons	24	Soybean	No-Till	16.5	0
5	Rice	Cons	24	Soybean	No-Till	22.0	0
6	Rice	Cons	24	Soybean	No-Till	33.0	0
7	Rice	Cons	36	Soybean	No-Till	16.5	0
8	Rice	Cons	36	Soybean	No-Till	22.0	0
9	Rice	Cons	36	Soybean	No-Till	33.0	0
10	Rice	Cons	18	Soybean	No-Till	16.5	5
11	Rice	Cons	18	Soybean	No-Till	22.0	5
12	Rice	Cons	18	Soybean	No-Till	33.0	5
13	Rice	Cons	24	Soybean	No-Till	16.5	5
14	Rice	Cons	24	Soybean	No-Till	22.0	5
15	Rice	Cons	24	Soybean	No-Till	33.0	5
16	Rice	Cons	36	Soybean	No-Till	16.5	5
17	Rice	Cons	36	Soybean	No-Till	22.0	5
18	Rice	Cons	36	Soybean	No-Till	33.0	5
19	Rice	Cons	18	Soybean	No-Till	16.5	10
20	Rice	Cons	18	Soybean	No-Till	22.0	10
21	Rice	Cons	18	Soybean	No-Till	33.0	10
22	Rice	Cons	24	Soybean	No-Till	16.5	10
23	Rice	Cons	24	Soybean	No-Till	22.0	10
24	Rice	Cons	24	Soybean	No-Till	33.0	10
25	Rice	Cons	36	Soybean	No-Till	16.5	10
26	Rice	Cons	36	Soybean	No-Till	22.0	10
27	Rice	Cons	36	Soybean	No-Till	33.0	10
28	Rice	Cons	18	Soybean	Cons	16.5	0
29	Rice	Cons	18	Soybean	Cons	22.0	0
30	Rice	Cons	18	Soybean	Cons	33.0	0
31	Rice	Cons	24	Soybean	Cons	16.5	0
32	Rice	Cons	24	Soybean	Cons	22.0	0
33	Rice	Cons	24	Soybean	Cons	33.0	0
34	Rice	Cons	36	Soybean	Cons	16.5	0
35	Rice	Cons	36	Soybean	Cons	22.0	0
36	Rice	Cons	36	Soybean	Cons	33.0	0
37	Rice	Cons	18	Soybean	Cons	16.5	5
38	Rice	Cons	18	Soybean	Cons	22.0	5
39	Rice	Cons	18	Soybean	Cons	33.0	5
40	Rice	Cons	24	Soybean	Cons	16.5	5
41	Rice	Cons	24	Soybean	Cons	22.0	5
42	Rice	Cons	24	Soybean	Cons	33.0	5
43	Rice	Cons	36	Soybean	Cons	16.5	5
44	Rice	Cons	36	Soybean	Cons	22.0	5
45	Rice	Cons	36	Soybean	Cons	33.0	5
46	Rice	Cons	18	Soybean	Cons	16.5	10
47	Rice	Cons	18	Soybean	Cons	22.0	10
48	Rice	Cons	18	Soybean	Cons	33.0	10
49	Rice	Cons	24	Soybean	Cons	16.5	10
50	Rice	Cons	24	Soybean	Cons	22.0	10
51	Rice	Cons	24	Soybean	Cons	33.0	10
52	Rice	Cons	36	Soybean	Cons	16.5	10
53	Rice	Cons	36	Soybean	Cons	22.0	10
54	Rice	Cons	36	Soybean	Cons	33.0	10

[1] Cons: Conservation [2] P: Phosphoruos [3] Meters width

Table 2. Estimate costs of production for rice and soybean 2007

	Tillage System ($/ha)		
	Rice	Soybean	
	Conservation	Conservation	No-Till
Variable Expenses			
Custom Work	255.61	78.00	78.00
Diesel Fuel	36.02	36.02	21.99
Fertilizer			
Nitrogen	104.37	n/a	n/a
Phosphorous 25% Below	51.41	45.46	45.46
Phosphorous Optimal	68.54	60.61	60.61
Phosphorous 50% Above	102.82	90.92	90.92
Filter Strips			
5 meters width	n/a	14.79	14.67
10 meters width	n/a	29.57	29.35
Fungicide & Seed Treatment	33.01		
Herbicides & Insecticides	128.92	38.77	61.53
Interest on Operating in Capital	46.87	11.84	11.74
Irrigation Expenses	256.05	122.31	122.31
Operator Labor	26.79	14.49	9.91
Repair & Maintenance	32.50	18.13	12.15
Seed	35.76	92.58	92.58
Fixed Expenses			
Machinery & Equipment	147.75	83.18	53.31

Table 3. Efficient set based on SERF for sub-basins 18 and 23

	Sub-basin 18					Sub-basin 23				
Variable	**S10**[a]	**S13**	**S19**	**S20**	**S22**	**S10**	**S13**	**S16**	**S19**	**S22**
Mean	0.64	0.21	0.39	0.17	0.20	0.37	0.37	0.37	0.23	0.23
StDev[b]	0.54	0.20	0.26	0.15	0.14	0.35	0.36	0.36	0.17	0.17
CV[c]	84.18	93.64	66.39	88.57	71.59	94.22	96.30	96.32	73.04	73.93
Min[d]	-0.63	-0.27	-0.24	-0.19	-0.14	-0.23	-0.23	-0.23	-0.04	-0.04
Max[e]	1.95	0.68	0.99	0.53	0.52	1.07	1.07	1.07	0.55	0.55
Level of Preference	1st	3rd	2nd	5th	4th	3rd	2nd	1st	4th	5th

[a] S, scenario [b] Standard Deviation [c] Coefficient of Variation [d] Minimum [e] Maximum

Table 4. SERF -Certainty equivalent and Risk premium values for five ARACs for the top-five scenarios in sub-basin 18

Certainty Equivalents

ARAC[a]	S10[b]	S13	S19	S20	S22
0.00	0.6407	0.2141	0.3936	0.1727	0.1962
0.25	0.6047	0.2091	0.3851	0.1698	0.1938
0.50	0.5693	0.2042	0.3767	0.1669	0.1913
0.75	0.5346	0.1992	0.3684	0.1640	0.1889
1.00	0.5007	0.1943	0.3601	0.1611	0.1865

[a] Absolute Risk Aversion Coefficient, [b] S, Scenario

Risk Premiums

ARAC[a]	S10[b]	S13	S19	S20	S22
0.00	0.0000	-0.4266	-0.2471	-0.4680	-0.4445
0.25	0.0000	-0.3956	-0.2196	-0.4349	-0.4109
0.50	0.0000	-0.3651	-0.1926	-0.4024	-0.3780
0.75	0.0000	-0.3354	-0.1662	-0.3706	-0.3471
1.00	0.0000	-0.3064	-0.1406	-0.3396	-0.3142

Table 5. SERF -Certainty equivalent and Risk premium values for five ARACs for the top-five scenarios in sub-basin 23

Certainty Equivalents

ARAC[a]	S10[b]	S13	S16	S19	S22
0.00	0.3710	0.3710	0.3710	0.2279	0.2279
0.25	0.3559	0.3552	0.3552	0.2244	0.2243
0.50	0.3411	0.3398	0.3398	0.2210	0.2209
0.75	0.3266	0.3248	0.3247	0.2177	0.2174
1.00	0.3125	0.3102	0.3100	0.2143	0.2140

[a] Absolute Risk Aversion Coefficient, [b] S, Scenario

Risk Premiums

ARAC[a]	S10[b]	S13	S16	S19	S22
0.00	0.0000	0.0000	0.0000	-0.1431	-0.1431
0.25	0.0000	-0.0006	-0.0006	-0.1315	-0.1315
0.50	0.0000	-0.0012	-0.0013	-0.1200	-0.1202
0.75	0.0000	-0.0018	-0.0019	-0.1089	-0.1091
1.00	0.0000	-0.0022	-0.0025	-0.0981	-0.0984

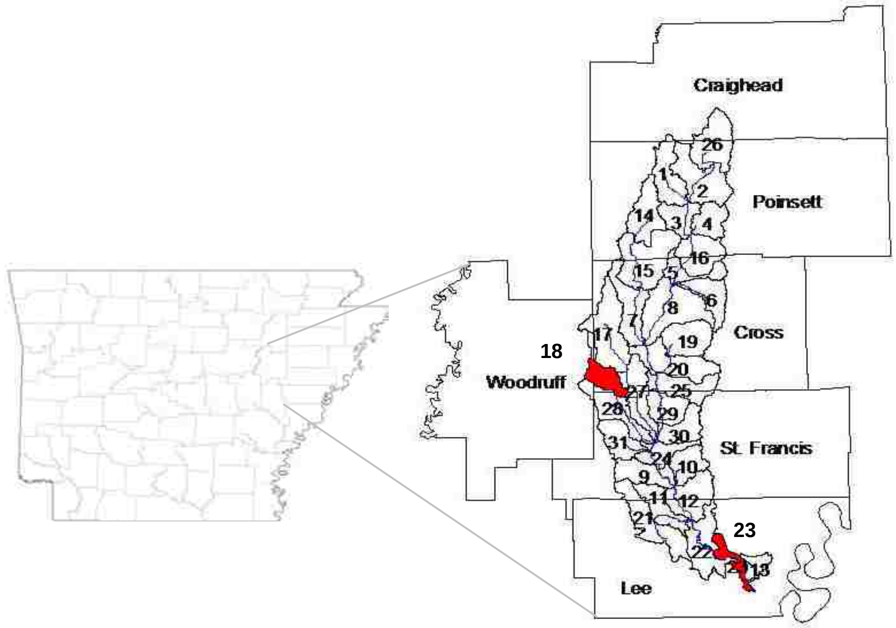

Figure 1. Location of the L'Anguille Watershed in Arkansas

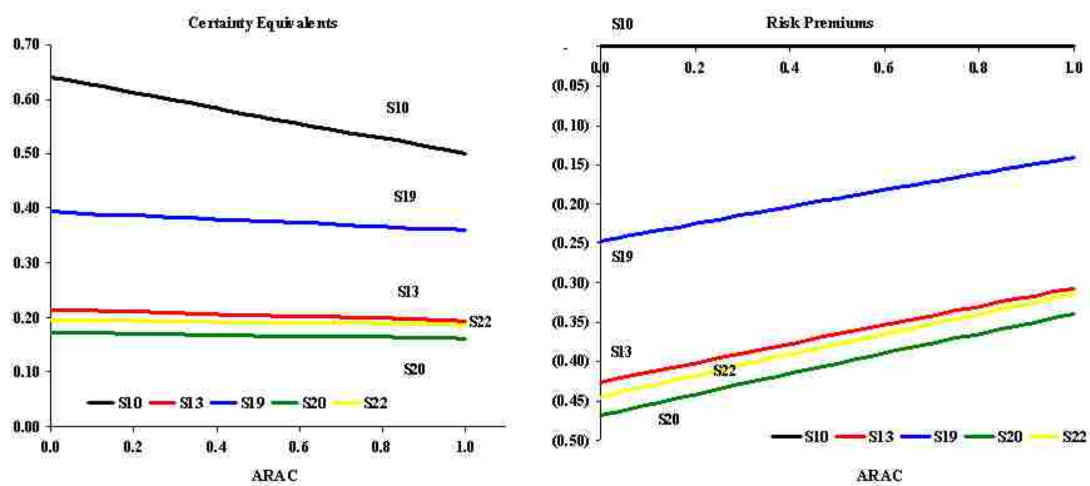

Figure 2. SERF – Certainty equivalents and Risk premiums for TP reduction in Sub-basin 18

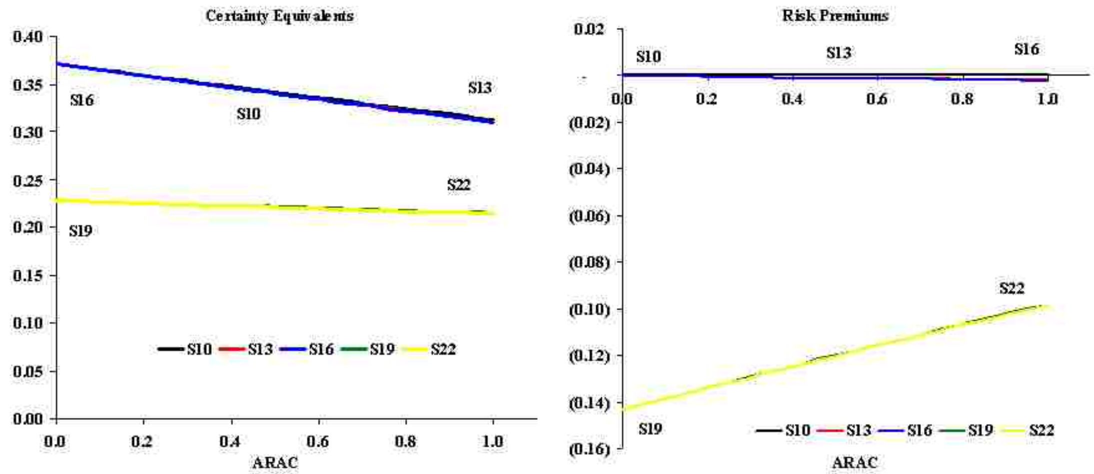

Figure 3. SERF – Certainty equivalents and Risk premiums for TP reduction in Sub-basin 23

CHAPTER IV

Evaluation of Best Management Practices to Reduce Total Phosphorous Runoff under Net Returns Risk

Abstract

An environmental-economic modeling approach linked output data from SWAT with a risk model to assess the impact of total phosphorous (TP) runoff reduction under current and alternative best management practices (BMPs) to improve water quality in year 2008. The major contribution of this study is to determine the risk impact of different BMPs on net returns under different TP runoff reduction schemes at the watershed and subbasin levels. The main objective of this study was to provide decision makers with more information about TP runoff reduction benefits and the net returns risk impact of using BMPs in their hay production operations. To accomplish this objective, TP loads and bermudagrass net returns were calculated for 59 different scenarios. Scenarios were ranked in terms of TP loadings and net returns in each of the 69 pasture subbasins of the watershed using stochastic dominance techniques.

A stochastic dominance analysis revealed environmentally and economically preferred BMPs and their trade-offs. This simulation provided evidence that TP runoff in the Lincoln Lake watershed could be reduced without affecting producers' expected net returns when environmentally efficient and economically acceptable BMPs are implemented. Results at the watershed and subbasin levels showed that decision makers will be reluctant to adopt BMPs that reduce drastically their net returns regardless of their water quality benefits. Although the analysis was conducted at the watershed and subbasin levels, the same management practices were chosen to reduce

TP runoff. Similar results were found when management practices were ranked in terms of net returns. As expected, the top ten management practices to reduce TP runoff decreased net returns considerably.

Nevertheless, there were other scenarios that could reduce TP runoff and increase net returns simultaneously. Consequently, these results highlight the importance of evaluating the effectiveness of BMPs not only based on their potential to reduce TP runoff but also in their positive or negative economic impact.

Results at the subbasin level confirmed that decision makers should compare the net returns risks and environmental benefits of implementing BMPs to reduce TP runoff, so that producers will be able to select BMPs with the lowest negative economic impact in their hay production operations. Ignoring producers risk preferences would lead to inappropriate policy recommendations since the model revealed that producers' risk preferences matter. For instance, slightly risk averse decision makers would prefer different BMPs than more risk averse decision makers. If producers are reluctant to change their current management practice, the risk premiums calculated for each BMP would be used to create a tax or a subsidy instrument.

Introduction

Agriculture plays a major role in Arkansas' economy as it does in other southern states. Arkansas' different types of climates and soils sustain a well diversified and productive agriculture. In 2007, over $15 billion of the value added to the Arkansas economy was due to agricultural activities [Popp et al., 2009]. In the production of livestock Arkansas ranked among states second in broilers, third in turkeys, twelfth in beef cows and sixteenth in cattle and calves in 2008 [NASS, 2009]. In 2007, the direct impact of animal agriculture in the state was significant. It counted for 57,610 jobs, over $1.6 billion in labor income, over $1.4 billion in wages and almost $2.3 billion in value added [Popp et al., 2009]. From those values, the poultry production and processing industry alone employed over 70.0% of the labor accounting for almost 80.0% of the labor income and over 78.0% of the wages [Popp et al., 2009].

Large scale intensive confined poultry production generates about 1.4 million tons of litter each year in geographic areas where it is concentrated [Tabler and Berry, 2003]. Since poultry litter has high levels of nitrogen and phosphorous, it has been predominantly used as fertilizer for pasture and hay fields [Coblentz et al., 2004]. Even though these nutrients are essential macronutrients plant growth, plants need more nitrogen than phosphorous.

Excessive poultry litter application over the years has resulted in phosphorous build-up in soils as litter application rates have been based on crop nitrogen requirements [Coblentz et al., 2004; Slaton et al., 2004]. Eutrophication of fresh water systems is generally accelerated by excessive phosphorous concentration [Coblentz et al. 2004; Edwards et al., 1996, Edwards et al., 1997; Nelson et al., 2004; Sharpley et al., 2007].

As environment awareness increases, management of animal waste has become a crucial issue for livestock producers, poultry producers, the poultry industry and the general public [Tabler and Berry, 2003]. Currently, there is legislative activity focusing on minimizing impact of animal agriculture on water quality in Arkansas.

Accordingly, federal and state water quality policy standards have been proposed to reduce pollution from sediments, nutrients and pesticides runoff [EPA, 2008a].

Several studies have provided evidence of the effectiveness of BMPs in reducing sediment and nutrient runoff [Chaubey et al., 1995; Moore and Edwards, 2005; Shreve et al., 1995; Srivastava et al., 1996]. However, an economic evaluation of producers' options when implementing BMPs to control water pollution in nutrient surplus areas is scarce. Consequently, the objective of this research was to develop a procedure to economically and environmentally evaluate a range of BMP alternatives under uncertain production conditions using stochastic dominance techniques. This study compares 59 different BMPs in terms of net return risk reduction for hay producers in the Lincoln Lake watershed located in northwest Arkansas. Special emphasis was devoted to identifying cost-effective BMPs to reduce TP runoff while maintaining the profitability of agriculture in the watershed.

Water Quality Problem

The Illinois River has been the focus of environmental and political debate due to nutrient enrichment and consequently accelerated eutrophication [Ekka et al., 2006]. In 1992, the U.S. Supreme Court ruled that the Environmental Protection Agency (EPA) may require upstream states to adhere to downstream states' water quality standards [Ekka et al., 2006; Soerens et al., 2003]. The Illinois River is listed as a scenic river in Oklahoma and therefore is subject to a standard of 0.037 milligrams of phosphorous per liter (mg/L) of water [Smith, 2002]. In 2002, the average flow weighted TP concentration at the Illinois River near the Arkansas-Oklahoma border was approximately 0.40 mg/L; over ten times greater than the TP criteria suggested by the Oklahoma Water Resources Board [Green and Haggard, 2001].

Section 303 (d) of the Clean Water Act requires states to identify and list impaired waters that do not support designated uses and thus may require development of a total maximum daily load (TMDL) for the pollutants of concern [U.S. EPA, 2008b]. The EPA has reported the Illinois River in the 303(d) list as an impaired water body in the state of Arkansas [ADEQ, 2008; EPA, 2009]. Total phosphorous has been recognized as the nutrient of concern in this watershed.

Description of the Lincoln Lake Watershed

Lincoln Lake watershed was one of 13 watershed projects funded through the Conservation Effects Assessment Project (CEAP) competitive grants program to evaluate the effects of watershed conservation practices on water quality in the United States. This agricultural watershed is located in Washington County in northwest Arkansas (figure 1) and it is a subbasin of the Illinois River watershed. The drainage area of the watershed is approximately 3,240 hectares [Nelson et al., 2004].

In 2004, forest and pasture were the major land uses in the watershed, accounting for 39.0% and 36.0% of the land, respectively. Other key land uses included urban, 12.0%, woody, 10.0%, and poultry, 2.0% [Gitau et al., 2007]. The dominant agricultural activities in the watershed are poultry and beef cattle operations [Storm et al., 2006; Stubblefield, 2006]. Consequently, water quality degradation caused by TP runoff from surface applied animal manure in the watershed is a major concern since the city of Lincoln uses water from Lincoln Lake as the secondary drinking water supply for the city [Cotter et al., 2002].

Previous Research

Federal, state and local government agencies face the challenge of designing policies that protect water quality and promote economically viable agriculture practices. However, economic and production tradeoffs are necessary to obtain abatement goals. Conventional agriculture is the most common form of crop and animal production for human consumption. This type of agriculture requires external inputs that without proper management, could lead to nutrient movement off the fields into nearby rivers, streams or lakes [Isik, 2002].

Fortunately, there are several BMPs that when used alone or in combination, might help producers to minimize nutrients runoff from their fields. However, before settling on a particular BMP to reduce pollution, policymakers need to know what impacts each BMP could have on producer's income and the local economy [Westra et al., 2002]. Producers are reluctant to voluntary implement expensive practices that diminish their net returns even if they are effective in improving water quality [Intarapapong et al., 2005].

Producers associate risk with loss. Generally speaking, losses might occur through low yields (due to insufficient or excessive rainfall, extreme temperatures, etc), variable prices (increases in the price of inputs and costs of production; low selling prices, etc) and policy changes (TMDLs, input taxes, government payments, etc). Most individuals are typically assumed to be risk averse and to have a certain tradeoff between risk and estimated revenue [Albright et al., 2006]. It is expected that agricultural producers possess the same kind of behavior. Tools that estimate distributions of monetary returns for alternative management strategies are essential in order to facilitate producer management decisions. Several modeling techniques have been employed to compare the effects of policies and the tradeoffs between economic and environmental goals. One of these tools is stochastic dominance.

Stochastic dominance (SD) is defined as a form of ordering between a pair of distributions to rank risky alternatives based on expected utility [Bawa, 1975; Davidson, 2008; Hardaker et al., 2004; Levy, 1998; Richardson et al., 2006]. It assumes that the decision maker is an expected value maximizer; distributions are mutually exclusive and are based on population probability distributions [Bawa, 1975; Davidson, 2008; Levy, 1998; Richardson et al., 2006]. Precisely, SD integrates the difference between two risky distributions and ranks them from most preferred to less preferred [Richardson et al., 2006]. In general, there are three types of SD: first degree, second degree (SSD) and SD with respect to a function (SDRF).

First degree SD (FSD) relies only on the assumption that utility is non-decreasing [Hardaker et al., 1997]. In other words, the decision maker prefers more than less. This assumption has very low discriminatory power since it includes all decision makers who prefer more than less. Second degree SD (SSD) assumes that all decision makers are risk averse [Levy, 1998]. Decision makers who prefers higher to lower returns and are also risk averse are in this group. The assumption that the decision maker is averse to risk gives SSD more discriminatory power than FSD.

Stochastic dominance with respect to a function (SDRF) weights utility differences between a pair of risky cumulative distribution functions by knowing only the lower and the upper bound of the decision maker's risk aversion function [Meyer, 1977; Richardson et al., 2006]. According to Meyer [1977], the utility function is constrained to lie within specified lower (*l*) and upper (*u*) bounds which are the parameters for the utility function. In general, scenario analysis results in only a partial ordering of alternatives into efficient and dominated sets. The decision maker must then make the final choice [Hardaker et al., 2004; Richardson et al., 2006].

Stochastic efficiency with respect to a function (SERF) is a variation of SDRF. It orders a set of risky alternatives in terms of certainty equivalents calculated for specified ranges of risk attitudes [Hardaker et al., 2004]. It employs certainty equivalent (CE) to determine the subset of utility efficient alternatives given a range of absolute risk aversion coefficients (ARACs). The ARAC represents a decision maker's degree of risk aversion [Anderson and Hardaker, 2003; Hardaker et al., 1997; Hardaker et al., 2004]. Richardson et al. [2006] defined CE as the amount of payoff that a decision maker would have to receive to be indifferent between accepting the guaranteed payoff and a higher but uncertain payoff. For a risk averse decision maker, CE is less than the expected value of a risky alternative because the decision maker prefers to reduce uncertainty [Hardaker et al., 2004]. In other words, a decision maker will prefer the risky scenario with the greatest CE. Risk premiums (RP) are calculated as the difference between CEs for each scenario and a base scenario. A RP indicates the minimum payment a decision maker requires to be indifferent between two alternatives [Hardaker et al., 2004; Richardson et al., 2006]. A decision maker will select the alternative with the highest RP. Hardaker et al. [2004] claimed that SERF allows for the simultaneous evaluation of alternatives rather than pair-wise comparison making it more discriminating than SDRF.

The use of SD has been well-documented especially in investment decision making in financial settings [Levy, 1998]. In agricultural economics, researchers have analyzed risky management practices that might alleviate pollution by using SD. Numerous studies analyzed risk in several areas such as conservation payments [Benitez et al., 2006], irrigation [Grové et al., 2006; Sun et al., 1996], tillage systems [Ribera et al., 2004; Watkins et al., 2008; Westra et al., 2002], and reduction of nitrogen [Sun et al., 1996] and phosphorous fertilizer applications [Westra et al., 2002]. In most studies, researchers have sought solutions to alleviate pollution by recommending BMPs and try to compare the tradeoffs between environmental and economic goals.

Often research focuses on the evaluation of the efficiency of alternative policies and management practices to achieve environmental goals. Although choice among risky alternatives can be achieved in a number of ways, the simplest is to assume producers are profit maximizers and consequently indifferent to risk. In practice, profit maximization is a poor predictor of the actual decision making process, since variability in income as well as decision maker's risk attitudes influence decisions.

For instance, Benitez et al. [2006] demonstrated that conservation payments required for preserving shaded coffee areas compared with alternative land uses were much higher than those calculated under risk-neutral assumptions. Watkins et al. [2008] found that risk neutral rice landlords would be indifferent between conventional till and no-till management practices. However, risk averse landlords had a slight preference for no-till management. Likewise, Ribera et al. [2004] showed that under risk-neutral rankings no-till practices would be preferred over conventional till in three out of five crop rotations tested while risk-averse decision makers would prefer no-till over conventional till for all five crop rotations.

How the presence of risk (and risk attitudes) affects BMP decisions is well documented [Grové et al., 2006; Ribera et al., 2004; Watkins et al., 2008; Westra et al., 2002]. Some risk analyses have used SERF to rank few BMPs at the farm level by calculating CEs and RPs between alternatives [Grové et al., 2006; Ribera et al., 2004; Watkins et al., 2008]. However, environmental and agricultural uncertainties may have opposite impacts on net returns when BMPs are analyzed on a larger scale than at the farm level.

Research Method and Data Requirements

To assess the value of BMPs to reduce TP runoff, SDRF was employed to analyze risky scenarios[1]. This analysis requires a systems approach combining a number of different models covering hydrologic, economic and risk analysis components of a hay (i.e., bermudagrass) production farming system. The first two models were run for 25 years. The hydrologic model was run to generate TP loading and bermudagrass yield data for each scenario for each subbasin in the watershed. Bermudagrass yield data sets were inputs to the economic model. Yield data were utilized to calculate net returns for each scenario analyzed in this study. Outcomes from the hydrologic and economic models were input to the risk model. This last model was employed to evaluate the impact of decision-makers' risk attitudes on scenario preferences under both net returns and TP runoff reductions.

[1] Throughout the rest of the document, the words scenarios and BMPs are being used interchangeably.

Best Management Practices Selection

Seventy-six scenarios were created using combinations of BMPs. The BMPs used in this study were: a) suggested by stakeholders including producers, landowners and regulators with stakes in agriculture [Pennington et al., 2008; Popp and Rodríguez, 2007], b) used in the development of the Arkansas phosphorous index [DeLaune et al., 2004, DeLaune et al., 2006]; or c) used in previous studies [Chaubey et al., 1994; Chaubey et al., 1995; Moore and Edwards, 2005; Moore et al., 1999; Moore et al., 2004; Shreve et al., 1995; Srivastava et al., 1996]. This study focuses only on the TP reduction and economic impacts of these practices on pasturelands.

Practices were grouped into pasture management (no grazing and optimum grazing); buffer zones (0 and 15 meters wide) and poultry litter application practices. Poultry litter contained three factors: poultry litter application rates (0, 1.0, 1.5, 2.0, 2.5 and 3.0 tons/acre), litter characteristics (non-amended litter and alum amended litter) and application timing (spring, summer or fall).

Hydrologic Model

The Soil and Water Assessment Tool (SWAT), one of the most widely used water quality models in the United States [Gassman et al., 2007], was employed in this analysis. The SWAT model divided the Lincoln Lake watershed into 72 subbasins (figure 1); 69 of which included pastureland. The SWAT model was calibrated for flow and nutrient loads. The average annual TP load and the annual total bermudagrass yield for each BMP in each pasture subbasin was calculated across 250 different weather scenarios. All scenarios were compared against a baseline, which assumes commonly used practices (scenario 41, optimal grazing and two tons of litter per acre spread during the fall) in the watershed [Pennington and Gunsaulis, 2008]. Since the goal of this study was to reduce TP loads, 17 scenarios that have TP loads greater than the baseline were excluded. Table 1 displays the remaining 59 scenario combinations analyzed. A preliminary analysis showed that TP runoff reductions were similar overtime. Thus, information for year 2008 is presented as an example.

Economic Model

The economic variable of interest was net returns. Net returns were calculated in dollars per hectare per year 2008 ($/ha) for each scenario (see table 1). Net returns were a function of bermudagrass yield, price and total costs of production.

$$\mathrm{NR} = \mathrm{Y_{BERM}} * \mathrm{P} - \mathrm{TCP}$$

Where, NR represents net returns ($/ha), $\mathrm{Y_{BERM}}$ represent bermudagrass yield (tons/ha), P represents the price of one ton of bermudagrass hay ($/ton) and TCP represents total cost of production including the cost of implementing BMPs ($/ha).

1) **Bermudagrass Yield (tons/ha)**

Bermudagrass yield was a function of adjusted bermudagrass yield, buffer zone and poultry litter application (PLA).

$$\mathrm{Y_{BERM}} = \mathrm{AY_{BERM}} * \mathrm{BZ} * \mathrm{PLA}$$

Where, Y_{BERM} represents bermudagrass yield (tons/ha), AY_{BERM} represents adjusted bermudagrass yield in tons per hectare (tons/ha). BZ[2] is a buffer zone where BZ is 0.954 if a buffer is present and 1 otherwise. PLA[3] represents poultry litter application where PLA is 0.800 if poultry litter is applied and 1.000 otherwise. AY_{BERM} was estimated using the following equation:

$$AY_{BERM} = YSWAT + [3.707 + 0.043(N)]$$

Where, YSWAT represents bermudagrass yield (tons/ha) from SWAT. The second part of this equation is an equation[4] obtained from results of pasture research conducted in northwest Arkansas. The yield equation was modified to account for bermudagrass yield in tons per hectare (tons/ha) and to adjust for region differences. The constant value 3.707 represents expected bermudagrass yield without application of nitrogen (N). Yield will increase by 0.043 tons/ha per each pound of N applied. It was assumed that each ton of poultry litter contains 60 pounds of N [Coblentz et al., 2004; VanDevender et al., 2003].

2) **Bermudagrass Hay Price ($/ha)**

Price for dry hay was collected from the National Agricultural Statistic Service [NASS, 2008a]. The hay price was calculated as a five-year average (2003-2007) by using the most recent data available at the time of the calculation. This value was

[2] Scenarios with a 15 meters wide buffer were assumed to have a constant length of 30 meters [NRCS, 2002]. The product of these two values generated a buffer zone area (0.046 ha) that was subtracted from one hectare to account for reduction in yield (1.000 - 0.046 = 0.954).
[3] Finally, studies have shown that poultry litter applications produce 80.0% of the bermudagrass yields obtained using inorganic nitrogen fertilizers [Slaton et al., 2006; Massey et al., 2007].
[4] Bermudagrass yield (lbs/ac) = 3,000 + 35 (N); where N represents pounds of nitrogen West [2007]. One hectare equals 2.471 acres and one ton equals 2,000 pounds.

deflated to 2004 dollars (i.e., to match the year of the SWAT simulation) by using the index for prices received by farmers for feed grain and hay [NASS, 2008b]. This value was used as a constant to calculate net returns for each scenario. A constant increase of two percent was added each year (starting in year 2005) to adjust hay price by inflation [Dixon, 2008].

3) **Total Cost of Production ($/ha)**

A bermudagrass budget was developed in Microsoft Excel using information generated by the Mississippi budget generator [Laughlin and Spurlock, 2008]. Bermudagrass total costs of production ($/ha) were a function of standard cost of production and BMP cost

$$\mathrm{TCP} = \mathrm{CP} + \sum \mathrm{BMPC}_{\mathrm{i,j,k}}$$

Where, TCP represents total cost of production, CP represents cost of production practices (including typical production expenses such as labor, tractor, fuel, twine, etc), BMPC is cost of BMPs where *i* represents buffer zone cost [NRCS, 2002; NRCS, 2006], *j* represents poultry litter cost including field application [Goodwin, 2007], and *k* represents cost of amending poultry litter with alum [Johns, 2007]. Total cost for each scenario was calculated by adding costs of production and the respective costs for each BMP combination for year 2007. Total cost was deflated to 2004 dollars by using the index for prices paid by farmers for commodities and services, interest, taxes and wage rates [NASS, 2008c]. In addition, a fixed rate of two percent was used to account for inflation effects each year starting in year 2005 [Dixon, 2008].

Risk Analysis Modeling

Hay profitability is one of the key factors that will determine whether a BMP is implemented or not. However, selecting BMPs exclusively for the desire of maximizing producer's expected annual net returns is not a sufficient criterion for BMP adoption [Sun et al., 1996]. Thus, in this study TP reduction and economic performance (in terms of net returns) of each BMP were ranked and compared with the baseline to evaluate the tradeoffs between these two competing objective functions.

Stochastic dominance performs pair-wise comparison of mutually exclusive sets of alternative scenarios based on their cumulative probability distributions [Richardson et al., 2006]. Rankings were done in both TP and net returns and then the top ten scenarios in terms of both TP reduction and net returns increase were evaluated.

Watershed vs. Subbasin Level Analysis

The goal of the watershed level analysis was to determine which BMP resulted in higher TP reductions with less variability in bermudagrass net returns. To accomplish this goal, BMPs were ranked in terms of TP loadings and in terms of net returns using SDRF. The same SDRF analysis was conducted for one subbasin, subbasin 63 (chosen because this subbasin possessed the largest pasture area of any subbasin in the watershed). However, the analysis focused on the effects that decision makers' attitudes towards risk have on selecting BMPs. To accomplish this goal, scenarios at the subbasin level were analyzed using SERF.

According to Anderson and Hardaker [2003] decision makers are risk preferring if ARAC < 0, neutral if ARAC $= 0$ and risk averse if ARAC > 0. The ARAC range used in this analysis was from 0 (risk neutral) to 0.016 (very risk averse). The upper bound (0.016) was calculated using the formula[5] proposed by Hardaker et al. [2004]. Since the utility function of the producers in the Lincoln Lake watershed is unknown, the negative exponential utility function was used to calculate CE and RP values for each ARAC as suggested by Hardaker et al. [2004].

Scenarios Ranking

The simulation and econometrics to analyze risk (SIMETAR) is used to develop, simulate and apply a stochastic model to a spreadsheet [Richardson et al., 2006]. The SIMETAR determines FSD, SSD, SDRF and SERF rankings of risky alternatives. Hence, the SIMETAR was used to rank TP loadings for all 59 scenarios and their corresponding net returns in each of the 69 pasture subbasins analyzed in this study based on SDRF criterion.

Decision makers were assumed to be risk neutral regarding their environmental attitudes. Therefore, they are expected to choose the scenario with the highest TP reduction. However, since decision makers risk attitudes may strongly affect their economic behavior a SERF analysis was performed on subbasin 63 (the biggest pasture subbasin in the watershed).

[5] Anderson and Dillon [1992] classified degrees of risk aversion based on the relative risk aversion with respect to wealth (r_r (w)) in the range of 0.5 (somewhat risk averse) to 4.0 (very risk averse). The upper bound value was calculated by using the formula proposed by Hardaker et al. [2004]; $r_a(w) = r_r(w)/(w)$ where $r_a(w)$ represents absolute risk aversion with respect to wealth (w); net returns in this case and $r_r(w)$ is the relative risk aversion with respect to wealth. In this analysis a very risk averse decision maker was assumed; $r_r(w) = 4$ and w (net returns) equaled the average net returns obtained with the baseline ($255.01) in subbasin 63 in year 2008.

Results and Discussion

Watershed Level Analysis

The results are presented in terms of TP rankings first and then in terms of net returns and shown in table 2. All 59 of the BMPs analyzed in this study were effective reducing TP runoff. However, the most preferred BMPs to reduce TP runoff decreased net returns considerably. In fact, 45 BMPs decreased, and three produced negative, net returns when compared to the baseline. The remaining 10, in addition of reducing TP runoff, also increased net returns (table 2). However, none of the top ten TP scenarios made the top ten for net returns and vice versa. As expected rankings of BMPs in terms of TP or net returns differ from each other. These results highlight the importance of evaluating the effectiveness of BMPs not only on their potential to reduce TP runoff but also in their positive or negative economic impact to producers.

Total Phosphorous Ranking

For TP, the top ten BMPs were all nongrazing scenarios with a 15 meter buffer. Producers might find these BMPs difficult to implement for four reasons: 1) this pasture management differs considerably from the baseline, 2) buffers increase the cost of production, 3) very low poultry litter applications might not be preferred by producers and 4) they produced lower expected net returns. A producer would need to receive an incentive to implement any of the top ten BMPs. This will be explored later in the subbasin analysis.

In terms of TP, the most preferred BMP (ranked first in 66 of the 69 subbasins) was S20[6] (nongrazing, buffer, no poultry litter). Its distribution across subbasins was

[6] In this section, S stands for scenario.

fairly symmetric about the median (figure 2). The median TP value was 0.05 kg per ha, a value 19 times lower than the baseline. In contrast, in terms of net returns, S20 ranked 37^{th} to 44^{th} with a median ranking of 43^{rd}; the median ranking distribution was skewed to the left (figure 3). The median net return value was only $33.06 per ha, equivalent to an 87.7% reduction compared to the baseline.

The second most preferred scenario in terms of TP reductions was S24 (nongrazing, buffer, one ton of litter per acre, summer). The median TP value was 0.07 kg per ha, a value 14 times lower than the baseline (table 2). The only difference between S20 and S24 is that this last scenario included the spread of one ton of poultry litter during the summer. In terms of net returns, S24 performed better (at $68.06) than S20 but still 62.5% worse than the baseline. It ranked from 25^{th} to 29^{th} with a median ranking of 28^{th} (figure 3). The rest of the top ten scenarios behaved similarly. Compared to the baseline, they reduced TP runoff considerably but decreased net returns drastically.

Net Returns Ranking

After scenarios were ranked for TP reduction, all 59 scenarios were re-evaluated in terms of net returns. Although two optimal grazing scenarios ranked in the top ten, nongrazing scenarios were again preferred (table 2). Fifteen-meter buffers were included in five scenarios; only one of those scenarios was in the top five. Poultry litter applications ranged from two to three tons per acre being spread mostly during the fall. Alum was not used. It seems that alum amendments and buffers although recommended to reduce TP are cost prohibitive. All top ten BMPs had a mean dollar value per ha greater than the baseline. Nevertheless, none of the top ten net returns BMPs made the top ten for TP.

For net returns, the most preferred was S10 (nongrazing, no buffer, three tons of litter per acre, fall). This scenario actually increased net returns by 49.3% and reduced TP by 33.9%. However, it is expected that producers will evaluate other alternatives that reduce TP runoff without affecting net returns or their current practices drastically. In the Lincoln Lake watershed is common to find that producers raise poultry and cattle and grow perennial forage crops on their lands to help to diversify and stabilize their farm income. This kind of production association cannot be based solely on nongrazing practices.

Since all scenarios reduced TP runoff, the focus was on optimal grazing scenarios that also increased net returns. S45 and S50 were optimal grazing scenarios that increased net returns by 14.2% and 4.2%, respectively. However, they also decreased TP runoff by 81.6% and 80.6%, respectively. When compared to the baseline the main difference is the inclusion of the buffer. Consequently, producers actually can select BMPs that reduce TP runoff, increase net returns and do not differ considerably from their current management practices.

Figure 2 shows that the ranking distribution across all subbasins of S45 was fairly symmetric about the median kilogram value of TP. In some subbasins, this scenario ranked in the top ten and in two subbasins it was the most preferred scenario. However, in figure 3 it is clear that S45 was skewed in terms of net returns. A large number of outliers above the median dollar value indicate that this scenario will not always produce net returns greater than the baseline. A more detailed analysis was conducted at the subbasin level to avoid generalizations of the results since not always the same scenario is preferred in all subbasins. Consequently, a SERF analysis was conducted in subbasin 63 to evaluate if: 1) there are differences in rankings, 2) nongrazing scenarios are still preferred and 3) decision makers' attitudes towards risk have an impact on selecting BMPs.

Subbasin Level Analysis

Subbasin 63 is comprised of 81.0% pasture; it represents 4.4% of the pasture area in the watershed. Results of the TP and net returns rankings at the subbasin level were generally consistent with the findings at the watershed level. Therefore, since it had the largest land area for BMP application, it was chosen as an example of the SERF analysis.

Stochastic Efficiency with Respect to a Function (SERF)

The previous SDRF analysis showed that TP runoff could be reduced when compared to the baseline by implementing any of the BMPs analyzed in this study. Although the top ten BMPs for TP reduced TP by more than 90.0%, producers would continue implementing their current practices since all of these BMPs resulted in lower or even negative net returns (table 3). In other words, SDRF results suggested that producers would not implement BMPs based on their potential to reduce TP runoff.

The previous results also revealed that compared to the baseline, nine BMPs reduced TP runoff and increased net returns simultaneously (figure 4). Accordingly, these scenarios were analyzed using SERF to determine if producer's risk attitudes would affect selection of BMPs. Producers who are risk averse might be willing to pay a risk premium (i.e., tax) to avoid changes in management systems. However, some producers might have to receive an incentive (i.e., subsidy) or risk premium to switch to an alternative BMP. In this specific case, producers that prefer the baseline over any of these nine BMPs are demonstrating some risk aversion. Table 4 exhibits the rankings, certainty equivalents (CEs) and risk premiums (RPs) for these scenarios. Figure 4 displays results as a percentage change from the baseline.

Regardless of risk preference, a profit maximizer will prefer the BMP with the highest CE, in this case, S10 (nongrazing, no buffer, three tons of litter per acre, fall). Although, this scenario increases net returns by 53.5%, it does not reduce as much TP as the other eight BMPs (figure 4). Furthermore, selecting S10 implies that producers would shift their current pasture management system (i.e., from optimal to nongrazing).

The next most preferred scenarios were S4 (nongrazing, no buffer, two tons of litter per acre, spring) then S29 (nongrazing, buffer, three tons of litter per acre, fall) and S9 (nongrazing, no buffer, two and a half tons of litter per acre, fall). Comparing these three scenarios revealed that producers' risk preferences matter (table 4). For instance, slightly risk averse producers will prefer S4 (ARAC < 0.006) while producers who are slightly more risk averse would prefer S29 (figure 5). Similarly, producers who are slightly more risk averse to very risk averse would prefer S9 over S4 (ARAC > 0.012). Since S29 has greater CEs than S9, it would be preferred over S9 regardless producers' risk preferences (table 4, figure 5).

If producers are not interested in changing their current pasture management system, S45 and S50 are good alternatives given that they do not differ much from the baseline. Regardless of decision makers risk preferences, S45 would be preferred over S50 since the CE values are higher for all levels of risk (table 4). In order for profit maximizing producers to be indifferent between S10 (the highest net returns scenario) and S45, they have to receive a RP. The amount of this RP would vary according to producers' risk aversion levels as shown in table 4. For risk neutral producers, it will be $98.30 per ha. Assuming that producers will be reluctant to change their current pasture management system, RPs can be used to create a tax or a subsidy instrument. If neither of these instruments is implemented, producers might continue to implement their current practices regardless of their risk attitudes or their environmental effect.

Conclusions and Recommendations

This study examined the environmental and economic impacts of different BMPs used to reduce TP runoff as compared to conventional management practices used by producers in the Lincoln Lake watershed. Although the analysis was conducted at the watershed and subbasin levels, the same management practices (but in a slightly different order) were chosen to reduce TP runoff. The same rankings were obtained for the watershed and sub-basin analyses when BMPs were ranked in terms of net returns.

As expected, the preferred management practices to reduce TP runoff decreased net returns considerably. Consequently, BMP selection differs when environmental and economic impacts are analyzed separately. Nevertheless, the environmental-economic model revealed that there were other scenarios that could reduce TP runoff and increase net returns simultaneously.

Results suggested that producers will be reluctant to adopt BMPs that reduce net returns regardless of their water quality benefits. To encourage adoption of such practices, producers would have to be paid (i.e., receive a subsidy) some risk premium. The amount of that premium will be related to producers' risk attitudes.

Focusing only in environmental goals prove to be extremely expensive. In subbasin 63, 49 scenarios decreased net returns when compared to the baseline; 13 generated negative net returns. Consequently, these results highlight the importance of comparing the net returns risks and environmental benefits of implementing BMPs without ignoring producers risk preferences.

Recommendations for Future Research

The following four recommendations are derived from this study:

- Policymakers should review costs of achieving environmental goals to find the most cost efficient means of reaching water quality goals.
- Decision makers should compare the net returns risks and environmental benefits of implementing BMPs without ignoring producers risk preferences.
- Future studies should analyze BMPs cost-share programs available to producers since some management practices that are very effective reducing TP might be cost prohibitive. It is expected that rankings change but several BMPs analyzed in this study will be still preferred.
- An optimization model would use information from the SERF analysis to select and place BMPs within the watershed without ignoring producers' risk attitudes.

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Table 1. Best Management Practice Combinations and Associated Total Cost – 2008

BMP Scenario #	Pasture Land Grazing	Buffer Width (meters)	Litter Amount (ton/ac)	Time of Application (season)	Litter Treated with Alum	Total Cost ($/ha)
S1	No	0	0.0	N/A	No	273
S2	No	0	1.0	Spring	No	300
S3	No	0	1.5	Spring	No	313
S4	No	0	2.0	Spring	No	327
S5	No	0	1.0	Summer	No	300
S6	No	0	1.5	Summer	No	313
S7	No	0	2.0	Summer	No	327
S8	No	0	2.0	Fall	No	327
S9	No	0	2.5	Fall	No	340
S10	No	0	3.0	Fall	No	353
S11	No	0	1.0	Spring	Yes	407
S12	No	0	1.5	Spring	Yes	473
S13	No	0	2.0	Spring	Yes	540
S14	No	0	1.0	Summer	Yes	407
S15	No	0	1.5	Summer	Yes	473
S16	No	0	2.0	Summer	Yes	540
S17	No	0	2.0	Fall	Yes	540
S18	No	0	2.5	Fall	Yes	607
S19	No	0	3.0	Fall	Yes	674
S20	No	15	0.0	N/A	No	293
S21	No	15	1.0	Spring	No	324
S22	No	15	1.5	Spring	No	340
S23	No	15	2.0	Spring	No	357
S24	No	15	1.0	Summer	No	324
S25	No	15	1.5	Summer	No	340
S26	No	15	2.0	Summer	No	357
S27	No	15	2.0	Fall	No	357
S28	No	15	2.5	Fall	No	373
S29	No	15	3.0	Fall	No	389
S30	No	15	1.0	Spring	Yes	431
S31	No	15	1.5	Spring	Yes	501
S32	No	15	2.0	Spring	Yes	570
S33	No	15	1.0	Summer	Yes	431
S34	No	15	1.5	Summer	Yes	501
S35	No	15	2.0	Summer	Yes	570
S36	No	15	2.0	Fall	Yes	570
S37	No	15	2.5	Fall	Yes	640
S38	No	15	3.0	Fall	Yes	710
S39	Optimal	0	0.0	N/A	No	273
S40	Optimal	0	1.0	Spring	No	300
S42	Optimal	15	0.0	N/A	No	293
S43	Optimal	15	1.0	Spring	No	324
S44	Optimal	15	1.5	Spring	No	340
S45	Optimal	15	2.0	Spring	No	357
S46	Optimal	15	1.0	Summer	No	324
S47	Optimal	15	1.5	Summer	No	340
S48	Optimal	15	2.0	Summer	No	357
S49	Optimal	15	2.0	Fall	No	357
S50	Optimal	15	2.5	Fall	No	373
S51	Optimal	15	1.0	Spring	Yes	431
S52	Optimal	15	1.5	Spring	Yes	501
S53	Optimal	15	2.0	Spring	Yes	570
S54	Optimal	15	1.0	Summer	Yes	431
S55	Optimal	15	1.5	Summer	Yes	501
S56	Optimal	15	2.0	Summer	Yes	570
S57	Optimal	15	2.0	Fall	Yes	570
S58	Optimal	15	2.5	Fall	Yes	640
S59	Optimal	15	3.0	Fall	Yes	710
S41[a]	Optimal	0	2.0	Fall	No	327

[a] baseline

Table 2. Scenario Rankings in terms of Total Phosphorous and Net Returns – Watershed Level

Organized by Total Phosphorous

BMP Scenario #	Total Phosphorous		Net Returns	
	Ranking [b]	Median [c]	Ranking [b]	Median [d]
S20	1	0.05	43	33.06
S24	2	0.07	28	101.12
S21	3	0.08	26	114.55
S33	4	0.08	56	0.27
S25	5	0.08	21	159.43
S30	6	0.08	53	1.12
S22	7	0.09	19	198.59
S27	9	0.10	15	215.95
S34	9	0.10	52	4.53
S26	10	0.10	13	217.91
S31	11	0.10	44	26.41
S23	12	0.10	6	291.72
S28	13	0.11	8	275.88
S36	14	0.11	55	0.70
S35	15	0.11	49	8.75
S29	17	0.12	3	340.36
S32	17	0.11	37	57.65
S37	18	0.12	50	5.72
S38	19	0.14	48	11.49
S42	20	0.15	45	23.65
S43	21	0.16	25	125.99
S46	22	0.18	29	92.81
S51	23	0.17	47	11.23
S54	24	0.19	59	-8.58
S44	25	0.17	15	215.90
S47	26	0.19	23	151.57
S49	27	0.19	15	215.18
S45	29	0.19	5	307.63
S48	29	0.20	16	213.74
S52	30	0.18	42	40.14
S50	31	0.20	7	280.82
S55	32	0.20	57	-3.78
S53	34	0.20	32	73.48
S57	34	0.21	58	-5.98
S56	35	0.22	54	1.29
S58	36	0.22	51	3.80
S59	37	0.23	46	17.18
S1	38	0.31	33	66.80
S5	39	0.44	24	142.49
S2	40	0.45	22	155.74
S14	41	0.48	41	40.66
S6	42	0.50	18	207.27
S11	43	0.50	40	42.10
S3	44	0.51	12	246.17
S8	46	0.58	10	269.86
S15	46	0.56	39	51.59
S7	47	0.58	9	272.07
S12	48	0.57	31	73.55
S4	49	0.57	2	346.96
S9	50	0.63	4	334.41
S17	51	0.66	38	54.76
S16	52	0.66	35	62.47
S13	53	0.66	27	112.04
S10	54	0.68	1	402.18
S18	55	0.73	34	65.54
S19	56	0.81	30	77.25
S39	57	0.90	36	57.35
S40	58	0.96	20	166.40
S41 [a]	59	1.03	11	269.38

Organized by Net Returns

BMP Scenario #	Total Phosphorous		Net Returns	
	Ranking [b]	Median [c]	Ranking [b]	Median [d]
S10	54	0.68	1	402.18
S4	49	0.57	2	346.96
S29	17	0.12	3	340.36
S9	50	0.63	4	334.41
S45	29	0.19	5	307.63
S23	12	0.10	6	291.72
S50	31	0.20	7	280.82
S28	13	0.11	8	275.88
S7	47	0.58	9	272.07
S8	46	0.58	10	269.86
S3	44	0.51	12	246.17
S26	10	0.10	13	217.91
S27	9	0.10	15	215.95
S44	25	0.17	15	215.90
S49	27	0.19	15	215.18
S48	29	0.20	16	213.74
S6	42	0.50	18	207.27
S22	7	0.09	19	198.59
S40	58	0.96	20	166.40
S25	5	0.08	21	159.43
S2	40	0.45	22	155.74
S47	26	0.19	23	151.57
S5	39	0.44	24	142.49
S43	21	0.16	25	125.99
S21	3	0.08	26	114.55
S13	53	0.66	27	112.04
S24	2	0.07	28	101.12
S46	22	0.18	29	92.81
S19	56	0.81	30	77.25
S12	48	0.57	31	73.55
S53	34	0.20	32	73.48
S1	38	0.31	33	66.80
S18	55	0.73	34	65.54
S16	52	0.66	35	62.47
S39	57	0.90	36	57.35
S32	17	0.11	37	57.65
S17	51	0.66	38	54.76
S15	46	0.56	39	51.59
S11	43	0.50	40	42.10
S14	41	0.48	41	40.66
S52	30	0.18	42	40.14
S20	1	0.05	43	33.06
S31	11	0.10	44	26.41
S42	20	0.15	45	23.65
S59	37	0.23	46	17.18
S51	23	0.17	47	11.23
S38	19	0.14	48	11.49
S35	15	0.11	49	8.75
S37	18	0.12	50	5.72
S58	36	0.22	51	3.80
S34	9	0.10	52	4.53
S30	6	0.08	53	1.12
S56	35	0.22	54	1.29
S36	14	0.11	55	0.70
S33	4	0.08	56	0.27
S55	32	0.20	57	-3.78
S57	34	0.21	58	-5.98
S54	24	0.19	59	-8.58
S41 [a]	59	1.03	11	269.38

[a] baseline; [b] median of ranking across 69 subbasins; [c] kg/ha; [d] $/ha

Table 3. Scenario Rankings in Terms of Total Phosphorous and Net Returns –Subbasin 63

Organized by Total Phosphorous

BMP Scenario #	Total Phosphorous Ranking	Percentage Change from Baseline	Net Returns Ranking	Percentage Change from Baseline [b]
S20	1	94.52	43	-93.44
S24	2	92.67	28	-66.68
S33	3	92.15	56	-106.70
S21	4	92.13	26	-61.01
S30	5	91.58	53	-105.38
S25	6	91.48	21	-43.89
S22	7	91.20	19	-28.20
S34	8	90.70	52	-105.07
S27	9	90.44	16	-21.77
S26	10	90.42	14	-21.04
S31	11	90.40	44	-95.57
S23	12	90.07	6	7.66
S28	13	89.45	8	1.74
S35	14	89.22	49	-103.40
S36	15	89.22	55	-106.16
S32	16	88.96	37	-83.79
S29	17	88.45	3	27.29
S37	18	88.04	51	-104.25
S38	19	86.80	48	-101.92
S42	20	85.11	45	-96.72
S43	21	83.83	25	-55.55
S46	22	83.53	29	-69.80
S51	23	83.12	47	-100.34
S54	24	82.89	59	-109.96
S44	25	82.64	13	-20.75
S47	26	82.55	23	-46.54
S49	27	81.97	15	-21.33
S48	28	81.83	17	-22.22
S52	29	81.65	40	-89.18
S45	30	81.48	5	14.99
S55	31	81.47	58	-108.21
S50	32	81.37	7	6.97
S57	33	80.34	57	-108.05
S56	34	80.29	54	-106.00
S53	35	80.22	31	-76.61
S58	36	79.45	50	-103.93
S59	37	78.55	46	-97.91
S1	38	69.53	33	-80.26
S5	39	59.10	24	-50.60
S14	40	56.41	42	-90.59
S2	41	56.26	22	-44.91
S11	42	53.27	41	-89.27
S6	43	52.70	18	-25.17
S3	44	51.11	12	-9.49
S15	45	48.29	39	-86.36
S8	46	46.92	11	-0.44
S7	47	46.83	9	0.29
S12	48	46.69	32	-76.85
S4	49	44.82	2	28.98
S9	50	41.51	4	25.38
S17	51	40.19	38	-84.83
S16	52	40.14	35	-82.07
S13	53	38.67	27	-62.46
S10	54	35.93	1	53.54
S18	55	33.59	34	-80.61
S19	56	26.72	30	-75.67
S39	57	17.39	36	-83.55
S40	58	10.20	20	-39.45
S41 [a]	59	0.00	10	0.00

Organized by Net Returns

BMP Scenario #	Total Phosphorous Ranking	Percentage Change from Baseline	Net Returns Ranking	Percentage Change from Baseline [b]
S10	54	35.93	1	53.54
S4	49	44.82	2	28.98
S29	17	88.45	3	27.29
S9	50	41.51	4	25.38
S45	30	81.48	5	14.99
S23	12	90.07	6	7.66
S50	32	81.37	7	6.97
S28	13	89.45	8	1.74
S7	47	46.83	9	0.29
S8	46	46.92	11	-0.44
S3	44	51.11	12	-9.49
S44	25	82.64	13	-20.75
S26	10	90.42	14	-21.04
S49	27	81.97	15	-21.33
S27	9	90.44	16	-21.77
S48	28	81.83	17	-22.22
S6	43	52.70	18	-25.17
S22	7	91.20	19	-28.20
S40	58	10.20	20	-39.45
S25	6	91.48	21	-43.89
S2	41	56.26	22	-44.91
S47	26	82.55	23	-46.54
S5	39	59.10	24	-50.60
S43	21	83.83	25	-55.55
S21	4	92.13	26	-61.01
S13	53	38.67	27	-62.46
S24	2	92.67	28	-66.68
S46	22	83.53	29	-69.80
S19	56	26.72	30	-75.67
S53	35	80.22	31	-76.61
S12	48	46.69	32	-76.85
S1	38	69.53	33	-80.26
S18	55	33.59	34	-80.61
S16	52	40.14	35	-82.07
S39	57	17.39	36	-83.55
S32	16	88.96	37	-83.79
S17	51	40.19	38	-84.83
S15	45	48.29	39	-86.36
S52	29	81.65	40	-89.18
S11	42	53.27	41	-89.27
S14	40	56.41	42	-90.59
S20	1	94.52	43	-93.44
S31	11	90.40	44	-95.57
S42	20	85.11	45	-96.72
S59	37	78.55	46	-97.91
S51	23	83.12	47	-100.34
S38	19	86.80	48	-101.92
S35	14	89.22	49	-103.40
S58	36	79.45	50	-103.93
S37	18	88.04	51	-104.25
S34	8	90.70	52	-105.07
S30	5	91.58	53	-105.38
S56	34	80.29	54	-106.00
S36	15	89.22	55	-106.16
S33	3	92.15	56	-106.70
S57	33	80.34	57	-108.05
S55	31	81.47	58	-108.21
S54	24	82.89	59	-109.96
S41 [a]	59	0.00	10	0.00

[a] baseline; [b] negative numbers indicate decrease from the baseline

Table 4. Rankings, Certainty Equivalents and Risk Premiums - Net Returns - Subbasin 63

Scenario Rankings

	S4	S7	S9	S10	S23	S28	S29	S45	S50	S41[a]
TP [b]	49	47	50	54	12	13	17	30	32	59
NR [c]	2	9	4	1	6	8	3	5	7	10

Certainty Equivalents

ARAC [d]	S4	S7	S9	S10	S23	S28	S29	S45	S50	S41[a]
0.000	328.93	255.76	319.74	391.55	274.54	259.44	324.60	293.25	272.78	255.01
0.002	326.92	255.61	319.57	391.24	272.53	259.27	324.29	290.67	272.22	254.75
0.004	324.98	255.47	319.40	390.93	270.59	259.09	323.98	288.18	271.67	254.48
0.006	323.10	255.33	319.23	390.63	268.71	258.93	323.68	285.76	271.13	254.23
0.008	321.28	255.19	319.06	390.34	266.89	258.76	323.39	283.42	270.61	253.97
0.010	319.52	255.06	318.89	390.05	265.14	258.59	323.10	281.15	270.11	253.72
0.012	317.82	254.92	318.73	389.77	263.43	258.43	322.82	278.94	269.61	253.48
0.014	316.16	254.78	318.56	389.49	261.78	258.26	322.54	276.81	269.13	253.24
0.016	314.56	254.65	318.40	389.21	260.17	258.10	322.26	274.73	268.66	253.00

Risk Premiums (baseline)

ARAC [d]	S4	S7	S9	S10	S23	S28	S29	S45	S50	S41[a]
0.000	73.91	0.74	64.73	136.54	19.53	4.43	69.59	38.24	17.77	0.00
0.002	72.17	0.87	64.82	136.49	17.78	4.52	69.54	35.93	17.47	0.00
0.004	70.49	0.99	64.91	136.45	16.10	4.61	69.50	33.69	17.19	0.00
0.006	68.87	1.11	65.00	136.41	14.49	4.70	69.46	31.53	16.91	0.00
0.008	67.31	1.22	65.09	136.37	12.92	4.79	69.42	29.44	16.64	0.00
0.010	65.80	1.33	65.17	136.33	11.41	4.87	69.38	27.42	16.38	0.00
0.012	64.34	1.44	65.25	136.29	9.95	4.95	69.34	25.47	16.13	0.00
0.014	62.93	1.55	65.33	136.25	8.54	5.03	69.30	23.57	15.89	0.00
0.016	61.56	1.65	65.40	136.21	7.17	5.10	69.26	21.73	15.66	0.00

ɔaseline, [b] total phosphorous, [c] net returns, [d] absolute risk aversion coefficient

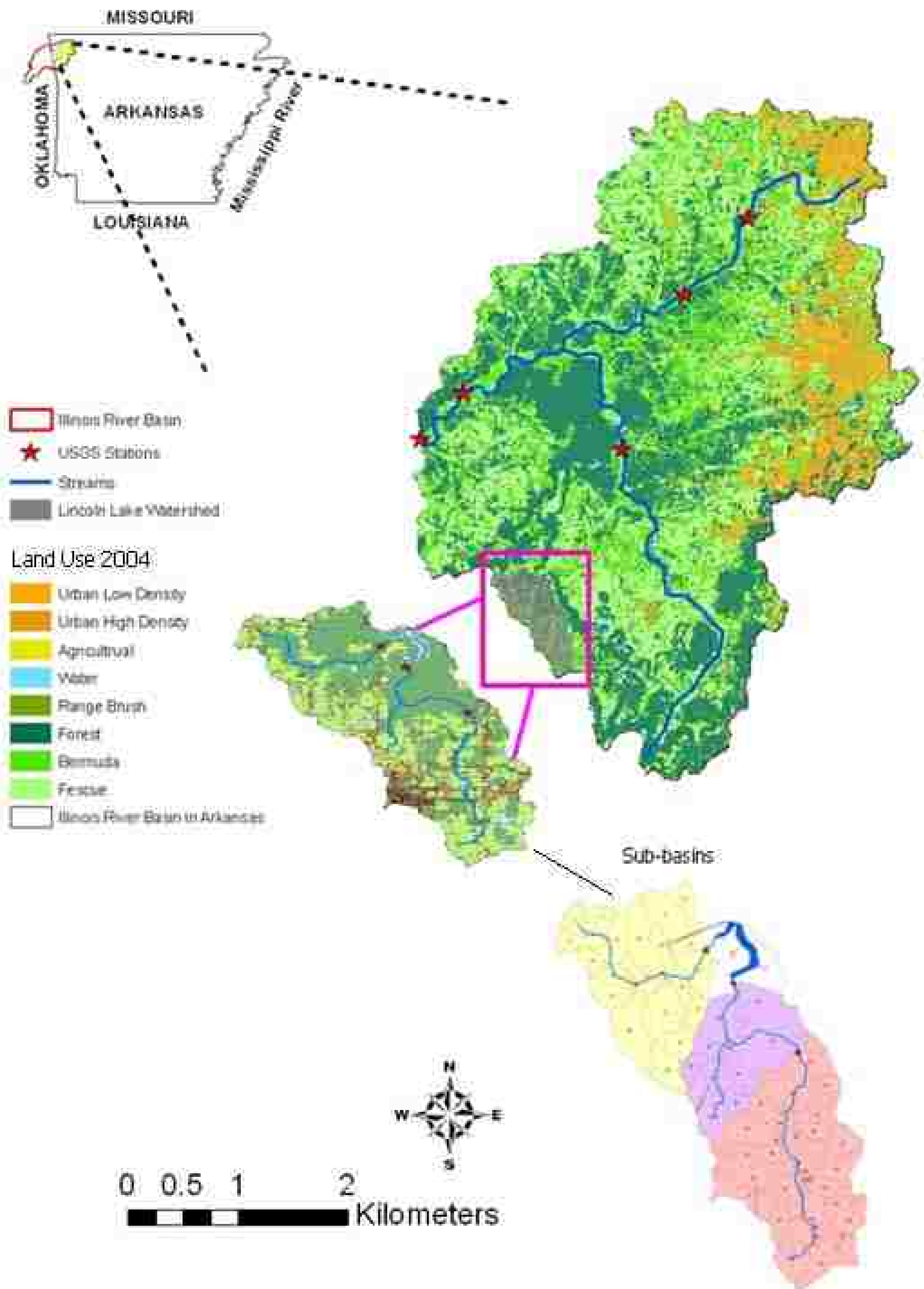


Figure 1. Illinois River Watershed and Lincoln Lake Watershed - Subbasins

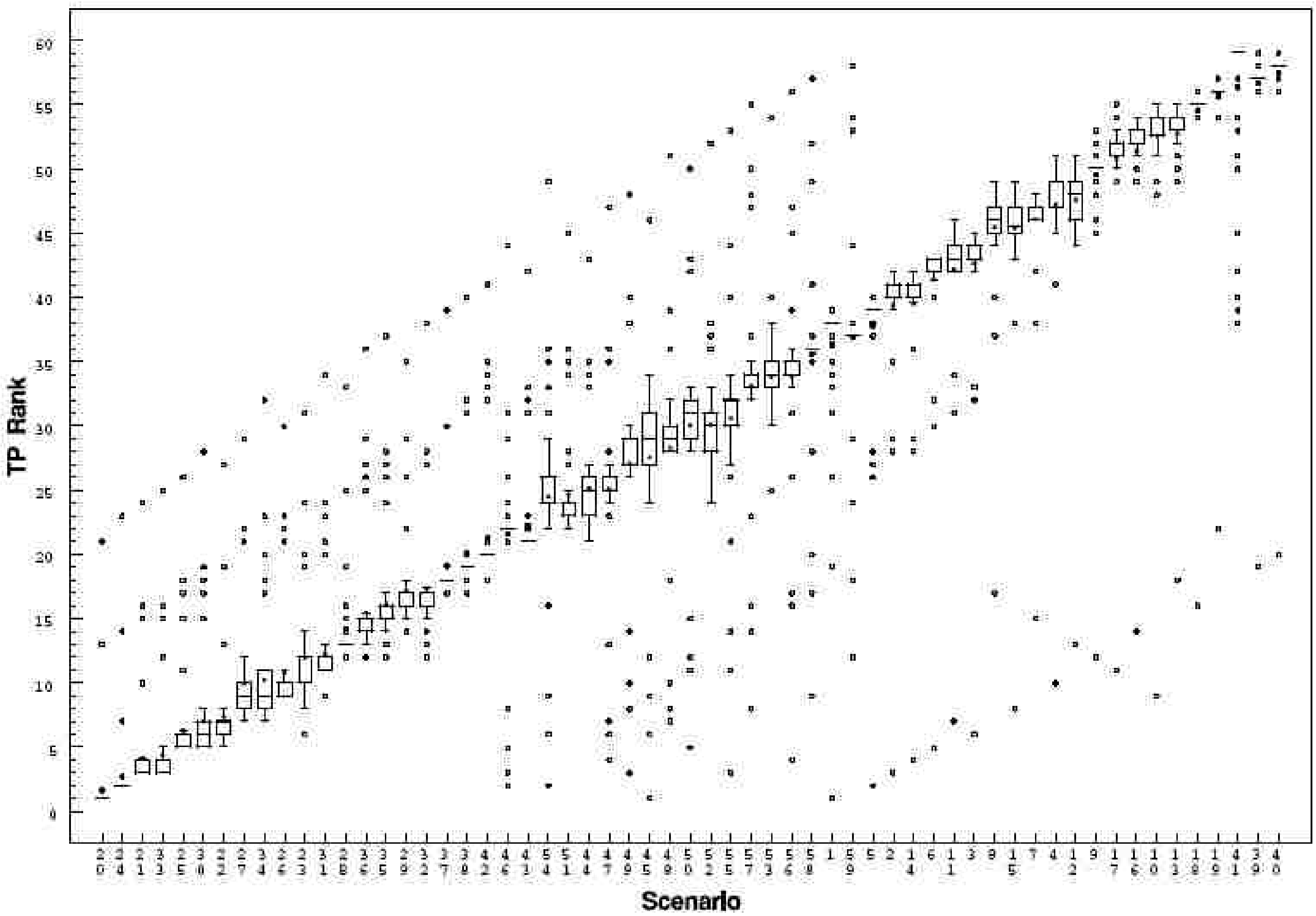


Figure 2. Boxplots for Scenario Rankings in Terms of Total Phosphorous Reduction – Watershed Level

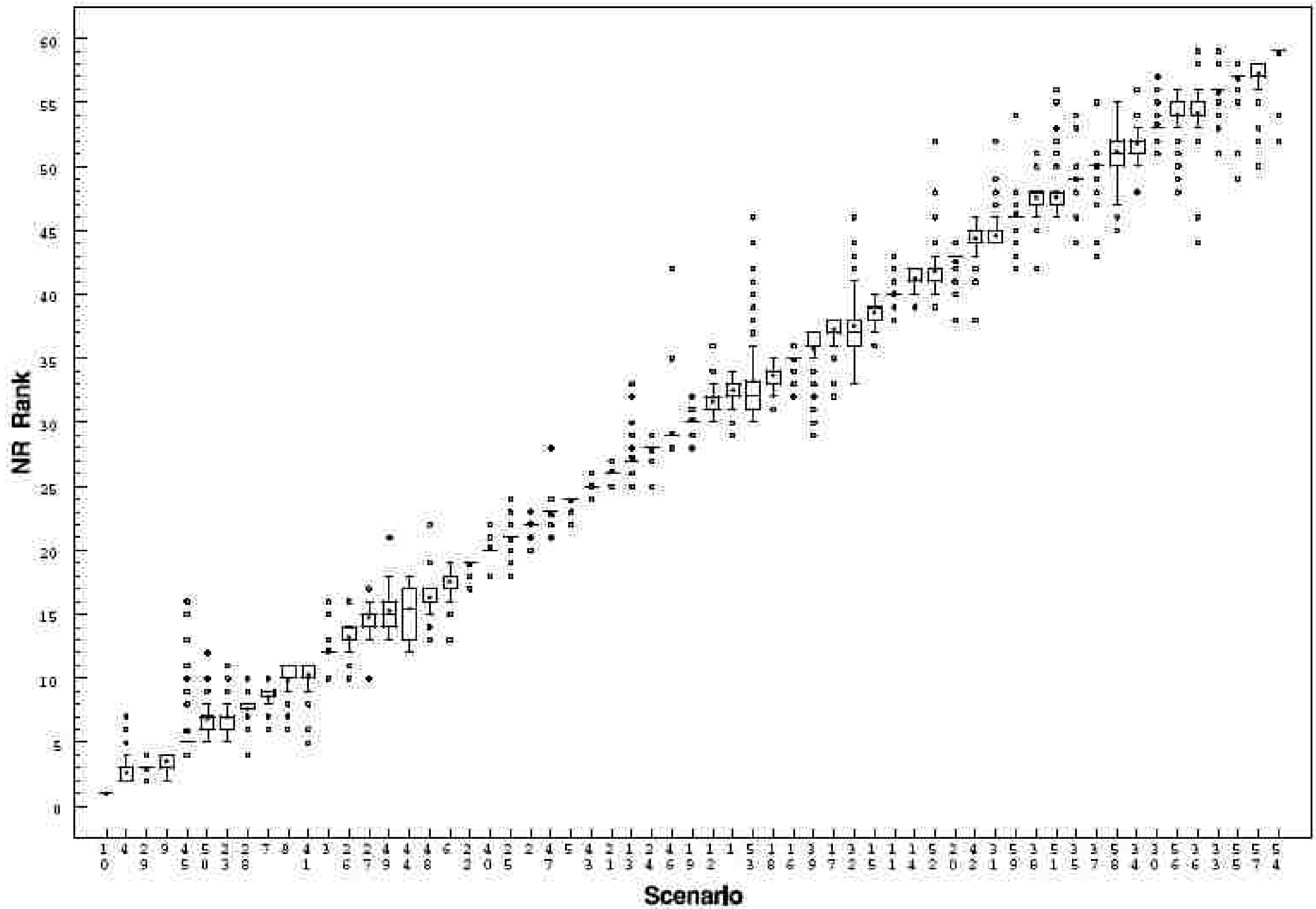


Figure 3. Boxplots for Scenario Rankings in Terms of Net Returns – Watershed Level

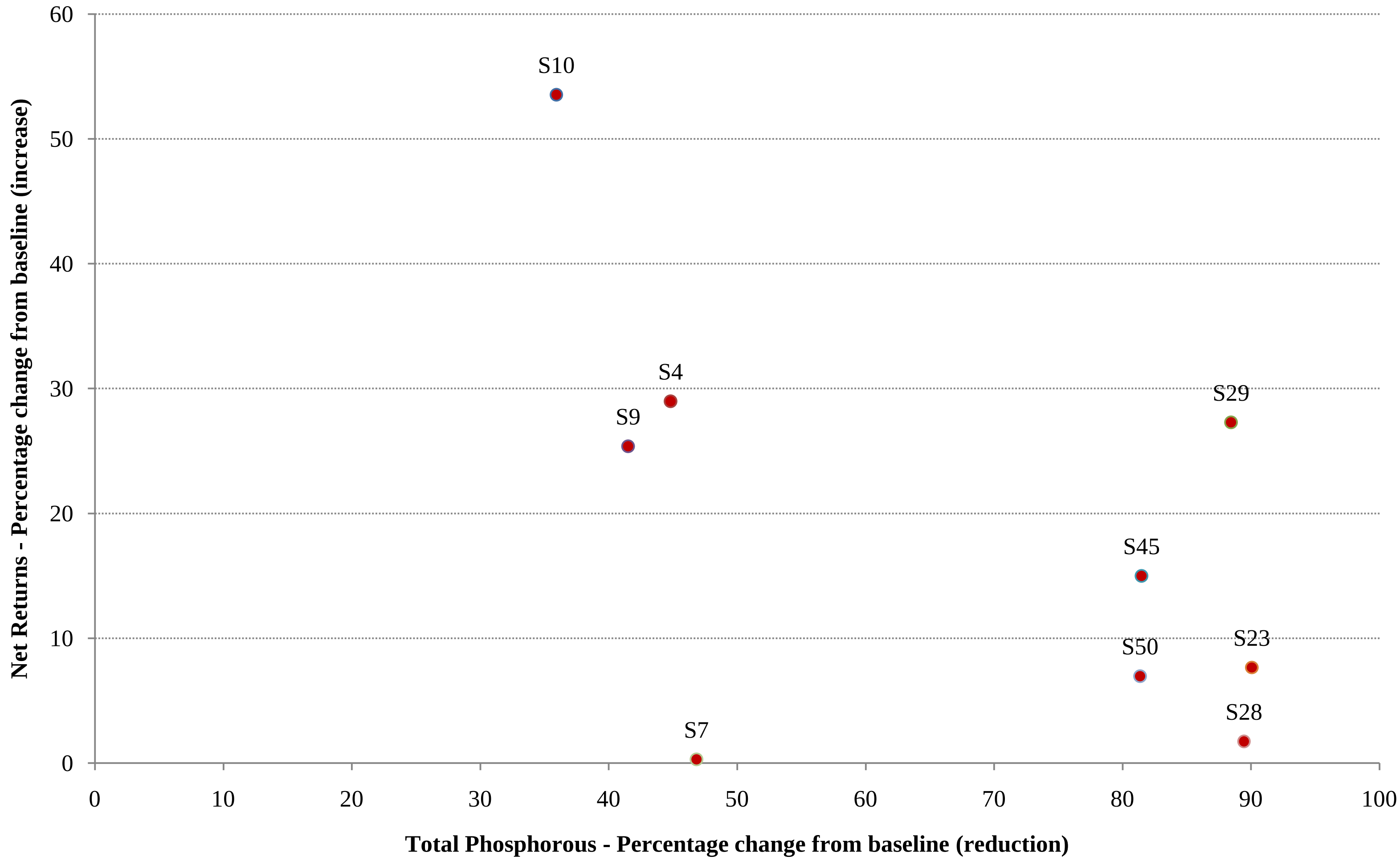
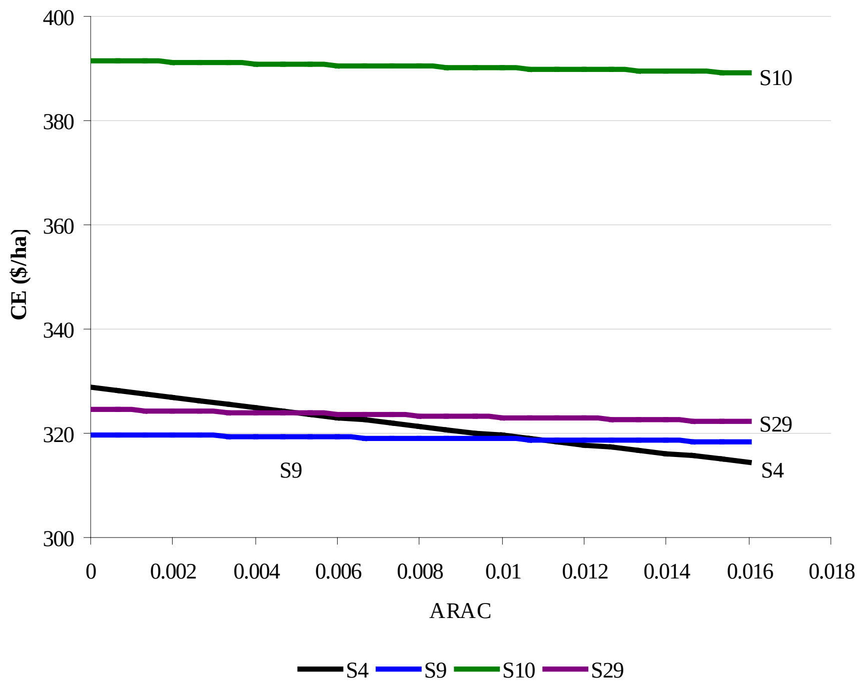


Figure 4. Total Phosphorous vs. Net Returns – (Scenarios that decreased Total Phosphorous and increased Net Returns) Subbasin 63



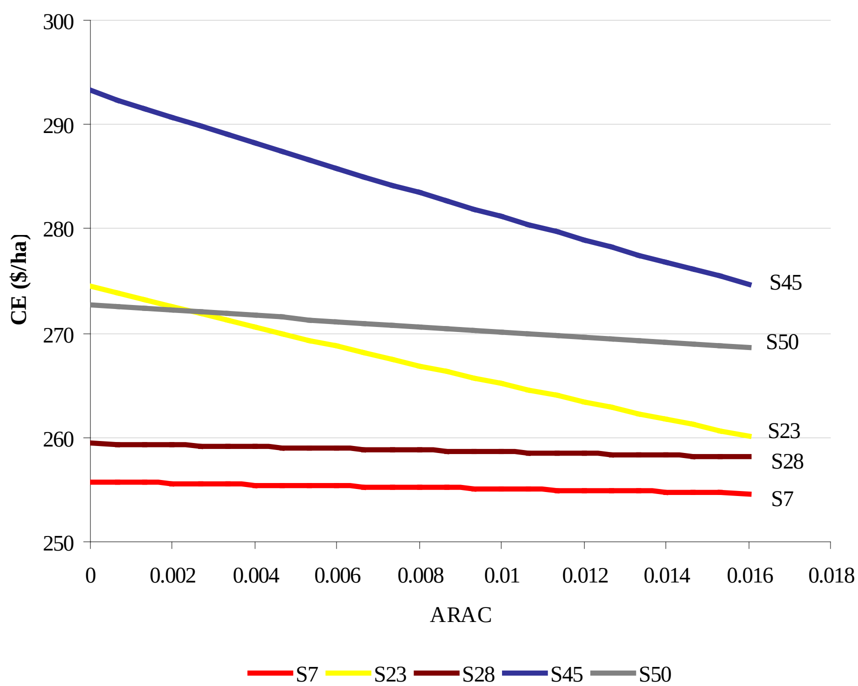


Figure 5. Stochastic Efficiency with Respect to a Function (SERF) - Certainty Equivalents for alternative Absolute Risk Aversion Coefficients when compared to Scenario 41 (baseline)

CHAPTER V

Selection and Placement of Best Management Practices Used to Reduce Water Quality Degradation in Lincoln Lake Watershed

Abstract

An increased loss of agricultural nutrients is a growing concern for water quality in Arkansas. Several studies have shown that best management practices (BMPs) are effective in controlling water pollution. However, those affected with water quality issues need water management plans that take into consideration BMPs selection, placement and affordability. This study used a non-dominated sorting genetic algorithm (NSGA-II). This multi-objective algorithm selects and locates BMPs that minimize nutrients pollution cost effectively by providing trade-off curves (Pareto-optimal front) between pollutants reduction (total phosphorous or total nitrogen) and net cost increase. The usefulness of this optimization framework was evaluated in the Lincoln Lake watershed. The final NSGA-II optimization model generated a number of near-optimal solutions by selecting from 95 BMPs (combinations of pasture management, buffer zones and poultry litter application practices). Selection and placement of BMPs were analyzed for low, medium and high cost schemes. Results suggested that total phosphorous was reduced by 98.3 percent while increasing cost by no more than 4.6 percent when compared to a baseline (high cost scheme). Similarly, total nitrogen runoff loads could be reduced from a baseline by 91.0 % while increasing cost by no more than 1.5 % (high cost scheme). The NSGA-II provides multiple solutions that could fit the water management plan for the watershed. Results

from this study confirmed the value of presenting policy decision makers, agricultural decision makers and the public with a wide range of optimal solutions when trade-offs between environmental and economic conditions must be analyzed simultaneously.

Introduction

Agriculture is a leading contributor to the global economy. As world population continues to grow, pressure to produce enough food impacts how and where food is produced. During recent decades, globalization has allowed for the expansion of industrialized agriculture and therefore making agribusinesses become more competitive while increasing the production of food [Braun and Diaz-Bonilla, 2008]. Although globalization provides opportunities, it also brings challenges. Today agribusinesses spend a considerable amount of resources addressing governmental regulations and even sometimes environmental litigation. These extra expenses will increase production costs, diminishing agribusinesses profitability.

Throughout the centuries, human beings have relied on the consumption of plants and animals to satisfy their food needs. Although vast areas of land have been devoted to crop production, frequently animal production has been confined to small areas. Intensive confined animal feeding operations are a specialized part of the livestock production process [Kellogg et al., 2000]. Waste from animal agriculture, including point and non-point source discharges, has become a significant environmental quality concern. Precisely, animal waste is being linked to some environmental problems, especially water pollution. Managing the environmental effects of point and non-point source problems in watersheds has received more attention as pollution problems reach beyond agricultural land.

Consequently, the United States Environmental Protection Agency (U.S. EPA) has proposed a watershed approach to address priority water problems. This approach includes a coordinating framework that is strengthened through the involvement of stakeholders within the public (federal, state, and local) and private sectors. The inclusion of stakeholders is essential since many might have different interests (i.e., economic, social, political, etc) than exclusively attainment of water quality improvement. The U.S. EPA argues that the watershed approach is economically efficient and provides the most technically sound (i.e., based on sound science) means of addressing water quality problems [U.S. EPA, 2008].

In this study, a genetic algorithm technique is used to determine cost-effective watershed level scenarios through optimization in the Lincoln Lake watershed in northwest Arkansas. This optimization technique determines alternative BMP combinations that reduce pollution in the most cost effective manner possible. The genetic algorithm generates a number of near-optimal solutions by selecting and placing BMPs that minimize nutrients (total phosphorous and total nitrogen) runoff and minimize net costs for hay (bermudagrass) producers.

Water Quality Issues in Arkansas

Often producers raise poultry and cattle and grow perennial forage crops on their lands to help to diversify and stabilize their income in northwest Arkansas. Animal manure is rich in nutrients especially nitrogen and phosphorus [Coblentz et al., 2004]. Bermudagrass is one of the most common grass crops. For optimal growth, it requires high levels of nitrogen but low levels of phosphorus [Coblentz et al., 2004; Massey et al., 2007; Sandage and Kratz, 1999; Slaton et al., 2006]. For many years scientists based manure and litter applications rates on forage nitrogen needs [Coblentz et al., 2004; Slaton et al., 2006]. As a result, some nutrients especially phosphorus may be unused by the crop [Coblentz et al., 2004; Slaton et al., 2004]. Excess nutrients have the potential to leave the field and enter surface waters, where they lead to accelerated algal and bacterial growth [Coblentz et al., 2004; Corell, 1998; Daniel et al., 1994; Edwards et al., 1996; Edwards et al., 1997].

High levels of nutrients runoff can threaten the water supplies available for recreational, municipal and other uses. Some rivers flow from Arkansas into Oklahoma apparently with elevated levels of nutrients which can have negative impacts in surface and ground water quality [Edwards et al., 1994; Ekka et al., 2006; Vendrell et al., 1997]. One potential source of excess of nutrients is animal manure applied as a fertilizer to pastures [Coblentz et al., 2004]. Some suggest that it is the manure from the Arkansas poultry and cattle farms that is contaminating the water, leading to high levels of phosphorous in the water as it reaches the Oklahoma border [Edwards et al., 1996; Edwards et al., 1997; Ekka et al., 2006].

These issues have triggered state and interstate water quality disputes [Soerens et al., 2003]. For instance, in 1992, a water quality dispute between Oklahoma and Arkansas reached the U.S. Supreme Court. The Supreme Court ruled that the U.S. EPA may force upstream states to adhere to downstream states' water quality standards [Ekka et al., 2006; Soerens et al., 2003]. In 2003, the U.S. EPA approved an in-stream limit of 0.037 milligrams of phosphorous per liter of water in scenic rivers in Oklahoma.

As a result, the Arkansas legislature passed several acts to minimize nutrients runoff from applications of animal manure. Now producers must follow provisions of Acts

1059, 1060 and 1061 by: 1) certifying all those who apply nutrients to crops or pastures land, 2) certifying nutrient management plan writers, 3) registering all cattle and poultry feeding operations and 4) developing and implementing nutrient management plans [Wilson et al., 2007]. The Arkansas Natural Resources Commission (ANRC) imposes penalties on those who fail to comply with the regulations developed under these acts. Additionally, a new water quality based phosphorous index requires that manure and litter be spread based on the potential risk of phosphorus movement to water bodies [DeLaune et al., 2004; DeLaune et al., 2006].

Since the above situation has placed pressure on agriculture to implement nutrient management strategies, the research interest in selecting BMPs to control water quality degradation has grown in the past decade. A frequent approach is to consider the individual effectiveness of a BMP in a pool of several ones that may reduce a target pollutant. Nevertheless, strong evidence is found suggesting that placement of BMPs is as crucial as the selection of practices [Chang et al., 2007; Gitau et al., 2006]. This is due to the fact that BMPs' effectiveness tends to vary at different locations within the watershed [Chang et al., 2007].

The objective of this study is to provide policy-makers, agricultural decision makers and the public with comprehensive quantitative (i.e., technical) information about the costs and water quality benefit trade-offs associated with different watershed water management strategies to assist in environmental water policy-making in Arkansas. It is hypothesized that the reduction of nutrient runoff can be achieved without increasing net cost considerably (when compared to a baseline) by optimizing selection and placement of BMPs within a watershed.

Lincoln Lake Watershed

The usefulness of the optimization framework explained above was evaluated in the Lincoln Lake watershed which is a sub-watershed within the Illinois River basin located in northwest Arkansas. The U.S. EPA reported the Illinois River in the 303(d) list as an impaired water body in the state of Arkansas with total phosphorous as the major parameter of concern [U.S. EPA, 2006]. Moores Creek and Beatty Branch are two major tributaries that flow into Lincoln Lake (figure 1). The drainage area of this watershed is 32 km^2. Moores Creek and Beatty Branch drain 21 km^2 and 11 km^2, respectively [Gitau et al., 2007]. Several hundred of chicken houses and livestock operations are located within this watershed (R. Stubblefield, preprint, 2006). Forest (39%), pasture (37%), urban (12%), transitional (10%) and poultry (2%) were the predominant land uses in 2004 [Gitau et al., 2007].

Hydrological Models

Hydrological models are powerful tools for assessing non-point sources of pollution and evaluating effectiveness of BMPs on large watersheds [Arnold and Fohrer, 2005; Gassman et al., 2007; Neitsch et al., 2005]. The Soil and Water Assessment Tool (SWAT) is a watershed scale model widely used for quantifying the impact of land management practices. It helps to identify sources and causes of water impairment as well as to plan management strategies to control non-point sources of pollution in complex watersheds [Arnold and Fohrer, 2005; Gassman et al., 2007; Neitsch et al., 2005].

SWAT has eight main components: hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, pesticides and agricultural management [Arnold and Fohrer, 2005; Gassman et al., 2007; Neitsch et al., 2005]. It simulates these processes by dividing watersheds into subbasins (see figure 1). Subbasins are also divided into hydrologic response units (HRUs) which are areas of land that have unique characteristics such as land use, soil or land management practices [Arnold and Fohrer, 2005; Gassman et al., 2007; Neitsch et al., 2005].

The overall hydrologic balance is simulated for each HRU [Gassman et al., 2007]. Primary input needed to run the SWAT model include digital elevation data, climate data, soils data, land cover data, and land management information. The land management module of SWAT makes the model a powerful tool for evaluating BMPs and for predicting non-point source pollutant loads [Gassman et al., 2007; Neitsch et al., 2005].

Genetic Algorithm

A genetic algorithm (GA) is a technique based on evolutionary principles of reproduction, recombination and mutation that seeks optimal solutions to solve a search problem [Chambers, 2001; Goldberg, 1989; Holland, 1975; Koza, 1992; Reeves and Rowe, 2003]. A genetic algorithm models individuals of a population as chromosomes, with genes on the chromosome encoding a specific trait of an individual. Alleles are the possible settings for a trait. Fitter chromosomes are the most likely to survive into the next generation.

This process occurs in generations starting from a random population of generated individuals (chromosomes). The fitness (i.e., the value of the objective function) of each individual in the population is evaluated; multiple individuals are randomly reproduced based on their fitness and then randomly recombined and randomly mutated to form a new population [Koza, 1992; Reeves and Rowe, 2003]. This occurs in each generation (iteration). The new population is then used in the next iteration of the algorithm. Usually, the algorithm stops when an adequate fitness level has been achieved for the population or a maximum number of generations have been produced [Chambers, 2001; Goldberg, 1989; Koza, 1992; Reeves and Rowe, 2003].

Genetic algorithms have been applied to difficult optimization problems because of their capacity to handle complex and irregular solution spaces when searching for a global optimum [Chambers, 2001]. The search space includes all feasible solutions and their associated fitness which is based on the objective function value. Although, only a few solutions are known at the beginning, GA will generate other solutions, using the principles of reproduction, recombination and mutation, as the process of finding solutions continues.

The literature is rich in examples of the use of GAs to find combinations of BMPs to reduce sediment runoff, nutrients runoff or both at the watershed level. Several studies [Arabi et al., 2006; Gitau et al., 2004; Gitau et al., 2006; Veith et al., 2003; 2004; Srivastava et al., 2002] linked at least three components (a non-point source of pollution reduction model, an economic component and an optimization model - GA) in a single objective function to find optimal solutions to water quality problems for several watersheds around the country. This kind of optimization is functional but it does not offer a set of alternative solutions that trade different objectives against each other from which decision makers can choose from. In fact, some of the studies concluded that a single objective function is not the best alternative and that a more sophisticated and robust objective function should maximize pollutant reduction and minimize costs at the same time.

In contrast, other studies [Bekele and Nicklow, 2005; Chen and Chang 2006; Confesor and Whittaker, 2007; Muleta and Nicklow, 2005; Perez-Pedini et al., 2005; Wan et al., 2006; Yeh and Labadie, 1997] used multi-objective functions with conflicting objectives. As a result, these studies did not find single optimal solutions; rather they provided trade-off curves between different objectives and alternative solutions. Agricultural water quality degradation is a multi-objective problem; therefore, this second approach seems to be more accurate because trade-offs between benefits and costs provide decision makers with more flexibility when selecting solutions.

In this study a non-dominated sorting genetic algorithm (NSGA-II) was employed. This GA is a fast and efficient multi-objective evolutionary algorithm which finds multiple near optimal solutions in a single model execution [Deb et al., 2002]. The work of Deb [2001] and Deb et al. [2002] provide a detailed mathematical description of this algorithm.

Materials and Methods

The approach proposed in this study linked pollutant loads (i.e., total phosphorous and total nitrogen) generated in SWAT under alternative BMPs and their corresponding net cost with a NSGA-II multi-objective optimization technique. A MATLAB® interface was created to link all components together.

Best Management Practices Characterization

Agricultural BMPs suggested by a collaborative dialogue among northwest Arkansas stakeholders [Pennington et al., 2008; Popp and Rodríguez, 2007], practices used in the development of the Arkansas phosphorous index [DeLaune et al., 2004; DeLaune et al., 2006] and previous BMPs studies in the region [Chaubey et al., 1994; Chaubey et al., 1995; Srivastava et al., 1996; Moore et al., 1999; Moore et al., 2004; Moore and Edwards, 2005; Shreve et al., 1995] served as the basis for initial choice of BMP factors for inclusion in this analysis. The factors were grouped into three general categories: grazing and pasture management, buffer zones, and nutrient management (table 1).

The study was designed to allow analysis of the individual and the interaction effects of these categories on nutrient runoff. Grazing and pasture management contained one factor at three levels (no grazing, optimum grazing and over grazing). Buffer zones contained one factor, buffer zone width at three levels (0, 15, and 30 meters). Poultry litter contained three factors: poultry litter application rates (0, 1.0, 1.5, 2.0, 2.5, and 3.0 tons/acre), litter characteristics (non amended litter and alum amended litter) and application timing (spring, summer and fall).

The above categories lead to 171 different scenario combinations. For comparison purposes, a baseline (Optimal grazing and two tons of litter spread during the fall season, without alum) that represented the common practices that producers performed in the Lincoln Lake watershed was used. The number of scenarios analyzed was reduced to 96 based on three rules. First, the baseline was excluded because it served as the basis for comparison for all other scenarios. Second, all the overgrazing scenarios were excluded (57 scenarios) because overgrazing is not a sustainable agricultural practice and a preliminary analysis showed that all the overgrazing scenarios have pollution levels greater than the baseline. Third, any other scenario with pollution values greater than the baseline was also excluded since the goal of this study is to reduce pollutant loads. Table 2 displays the 95 BMP scenario combinations and the baseline analyzed in this study.

Data from SWAT

Although, total phosphorous is the limiting nutrient in this watershed, total nitrogen was also evaluated since data for this nutrient was also available. The hydrological model used in this study, SWAT, divided the Lincoln Lake watershed into 72 subbasins and 1465 HRUs. SWAT simulations generated total phosphorous and total nitrogen pollutant loads for 96 management practice combinations (including a baseline) using 250 weather scenarios for a 25-year period (2004 to 2028).

Since poultry litter is used to fertilize hay fields (i.e., bermudagrass fields), only pasture areas (461 HRUs – or 34.5 % of the overall land area) were considered for implementation of management practices within the watershed. Average HRU weighted (by area) pollutant loads were estimated for the entire watershed to develop a single pollution (i.e., total phosphorous or total nitrogen) value for the particular management practice combination. This value was then compared to scenario 36 (i.e., baseline) to obtain a percentage pollutant reduction value for each management practice. A preliminary analysis showed that total phosphorous and total nitrogen reductions were very similar overtime. Consequently, it was decided to analyze only information in the first five years (i.e., an average from 2004-2008) for each pollutant.

Total Cost of Production (Including BMP costs)

Standard costs of production and costs of BMPs were estimated using information for year 2007. The total cost of production for each scenario was deflated to 2004 (i.e., since it was the starting year of the simulation) dollars by using the index for prices paid by farmers for commodities and services, interest, taxes and wage rates [NASS, 2008]. Standard costs of production included herbicides, implements, repair and maintenance, fuel diesel, interest on capital and labor. This information was calculated using the Mississippi budget generator [Laughlin and Spurlock, 2008] and was constant for all the scenarios. However, a fixed rate of two percent was suggested by B. L. Dixon (unpublished data, 2008) to account for inflation effects each year.

The BMP costs for each scenario were calculated based on the different practices used. Buffer zone costs were estimated using the Natural Resources Conservation Service "Practice Standards and Specifications" technical guide provided by NRCS (unpublished data, 2006). Buffer zone costs were calculated assuming a predetermine buffer area. The area was estimated by multiplying the width (15 and 30 meters) with a constant length of 30 meters provided by NRCS-AR (unpublished data, 2002). Costs included establishment of the buffer every 10 years and maintaining the buffer each year for a period of 25 years. Practices included fertilizer, warm season grass seeding, and herbicide costs. Additionally, loss in yield due to pasture area reduction was also added as an extra (opportunity) cost. The cost of litter, including field application, was assumed to be $12 per ton this information was provided by H.L. Goodwin (unpublished data, 2007). Alum was applied at a rate of 10 percent by weight of the litter (i.e., 20,000 broilers produce approximately 20 tons of moist litter per grow-out) to precipitate soluble phosphorous and consequently reduce phosphorous runoff [Moore et al., 1999; Moore et al., 2004].

Total cost for each scenario was calculated by adding costs of production and the respective costs for each BMP combination. These costs can be expressed as follows:

$$TC_i = CP + \sum_i CBMP_{j,k,l} \qquad [1]$$

where, TC represents total cost of production, CP represents cost of production, $CBMP$ represents BMP cost; *i* represents scenario, *j* is buffer cost, *k* is poultry litter cost and *l* is alum cost. Best management practice combination cost effectiveness was estimated by calculating the percentage reduction in cost when compared to the cost of the baseline (scenario 36). Table 2 displays the total cost per hectare including BMP cost associated with each scenario for year 2004.

NSGA-II Multi-Objective Optimization Model Development

Pollution output data from SWAT and cost data were the inputs used in the optimization model (i.e., NSGA-II). The SWAT generated pollutant (i.e., total phosphorous and total nitrogen) loads at HRU level for each of the 96 BMPs (including a baseline) analyzed in this study. This information was used to estimate each BMP effectiveness (percentage change for the baseline) to reduce total phosphorous and total nitrogen. Cost data for each scenario was used to calculate the percentage cost increase from the baseline.

These two components, BMP effectiveness and cost increase from a baseline, were linked with a NSGA-II multi-objective optimization technique. Since placement of BMPs was planned to be at the HRU level, the searching space consist of 461^{95} possible combinations (i.e., any BMP of the 95 available can be placed in any of the 461 HRUs). A weighted average of the pollutant loading (i.e., total phosphorous or total nitrogen) and the net cost increase from the baseline for each BMP at the HRU level is estimated at the watershed level.

The objective is to minimize two objective functions: 1) total pollutant (f(x) = total phosphorous or total nitrogen) runoff reduction and 2) net cost (g(x)) increase at the watershed level. The following were the two objective functions that needed to be minimized during the optimization process:

$$\mathrm{f(x)} = \left(\sum_{\mathrm{HRU=i}}^{461} \overline{\mathrm{TP}}_{\mathrm{i}} * (1 - \mathrm{BMPR_i}) * \mathrm{Area_i}\right)^2 \qquad [2]$$

$$\mathrm{g(x)} = \left(\sum_{\mathrm{HRU=i}}^{461} \overline{\mathrm{Cost}}_{\mathrm{BMPi}} * (\mathrm{NCI_i}) * \mathrm{Area_i}\right)^2 \qquad [3]$$

where, $\overline{TP}$ is the average total pollutant (i.e., total phosphorous or total nitrogen) output from a particular HRU, i. $BMPR_i$ represents the pollutant reduction efficiency (i.e., total phosphorous or total nitrogen) which was calculated as the percentage change from the baseline. $Area_i$ is the area of each HRU. $\overline{Cost}_{BMP}$ is the cost production plus the cost of each management practice. NCI_i is the net cost increase calculated as the percentage change increase from the baseline.

The genetic algorithm (GA) models individuals of a population as chromosomes which in turn contain genes as the building blocks (in this case each chromosome consists of 461 genes), and each of these genes represent a particular set of BMPs on the chromosome encoding a specific trait. This GA starts by initiating randomly the genes in all the chromosomes of the selected population. The gene structure in each chromosome then undertakes mutation and crossover processes to form a new fitter population. This process continues until the final generation number is reached. Fitter populations (better objective function values) when compared to the previous generation are the most likely to survive into the next generation. The GA stops (in this particular case) when a maximum number of generations have been produced.

Two different optimization models were developed in this study, one for total phosphorous and one for total nitrogen. Near optimal solutions are graphically represented by a Pareto-optimal front. Trade-offs between the two objective functions (i.e., total phosphorous or total nitrogen reduction and net cost increase) allow selection of the best pollution reduction schedule corresponding to minimal net cost.

Sensitivity Analysis - Genetic Algorithm Parameters Estimation

The genetic algorithm results are very sensitive to the operational parameters that define the search algorithm. In order to search effectively for near optimal solutions, the optimal GA operational parameters, such as population size, number of generations, crossover and mutation rates, need to be estimated. This task is performed by using a non-linear sensitivity analysis in which different values of the GA operational parameters are incremented one at a time and the response final generation, the Pareto-optimal front, is plotted to visually estimate the optimal parameter values. Values that were closer to the origin were the best to minimize the two objective functions (i.e., total phosphorous or total nitrogen reduction and net cost increase) analyzed in this study.

Figure 2 exhibits the progress of the Pareto-optimal front for each of the parameters needed for optimization. The final optimization model ran for 800 populations and 10,000 generations (figures 2a and 2b). Although the Pareto-optimal front for generation 20,000 seems to be closer to the origin than generation 10,000, the latter was preferred. Both generations (10,000 and 20,000) perform equally well. However, too many generations are computationally inefficient and take excessive amounts of time to find an optimal solution.

The crossover and mutation probabilities generated the offspring. These probabilities were set up at 0.7 for crossover and 0.005 for mutation since both values were closer to the origin. Figures 2c and 2d are graphical representations of these parameters. The parameters values that resulted from the sensitivity analyses were used for optimizing the selection and placement of BMP combinations for the total phosphorous and total nitrogen models developed in this study. These optimization models (with 10,000 generations and 800 populations for generation) were completed in less than one hour using a SiCortex 5832 supercomputer that consists of 812 Dell PowerEdge 1950 Dual Quad-Core computer nodes.

Results and Discussion

The NSGA-II optimally selected and placed BMP combinations according to their pollutant load reduction and net cost increase in each of the 461 pasture HRUs after comparing them against a baseline. The study was conducted from 2004-2008. The results are divided in three sections, total phosphorous, total nitrogen, and a discussion about modeling more than two objective functions. Figures 3 through 6 focus on the solutions obtained for each of the pollutants evaluated in this study.

Total Phosphorous and Net Cost

The first model evaluated the cost-effectiveness of selecting and placing BMPs to reduce total phosphorous while simultaneously minimizing net cost. The five-year weighted average for total phosphorous loading estimated at the watershed level was 0.505 kilogram per hectare. The spread of the solution was improved significantly during the optimization process (figure 3a).

As expected, the NSGA-II generated a number of near-optimal solutions by selecting and placing BMP combinations that minimized total phosphorous runoff and minimized net costs increase for hay producers at the watershed level. The final solution, obtained after generation number 10,000, displays a range of populations that when compared to the baseline reduce total phosphorous by either 1) 96.9 percent without increasing cost or 2) by 98.3 percent while increasing cost by no more than 4.63 percent per hectare (figure 3b). The Pareto-optimal front was wide spread without solutions being concentrated either in the lower or in the higher net cost solutions giving decision makers a broader set of options to select from (figure 3b).

To illustrate this process, three populations were chosen; the lowest cost population (population 1), the medium cost pollution (population 550) and the highest cost population (population 138) for generation 10,000. Table 3 displays the value of the objective functions for each of the populations analyzed in this example and table 4 shows the frequency of BMPs selected under these three cost schemes. Figure 4 exhibits the selection and spatial placement of BMP combinations within the watershed (at the HRU level) under low, medium and high cost schemes.

For these three populations, total phosphorous loads were reduced by at least 96.9 percent under all cost implementation schemes. The NSGA-II assigned mainly BMP combinations (scenarios 77, 81, 87, and 88) with optimal grazing practices, 30 meters wide buffers and low litter application rates for all three levels of costs. Optimal-grazing practices were placed on 48.8, 57.5 and 67.2 percent of the HRUs for low, medium and high cost schemes, respectively. The optimal grazing management practices are preferred because producers need to maintain a minimum biomass per hectare during grazing [Neitsch et al., 2005]. In other words, this practice guaranties permanent ground cover while reducing runoff.

The most common optimal grazing strategy for both medium and high cost was BMP combination 88 (30 buffer, 1.5 tons litter applied during the summer with alum). This combination was placed on 19.3 percent of the HRUs under medium cost scheme and in 28.4 percent of the HRUs for high cost schemes. The most common optimal grazing strategy for low cost was BMP combination 87 (30 buffer, 1.0 tons litter applied during the summer without alum). This combination was placed on 12.4 percent of the HRUs under low cost schemes. The most common non-grazing practice combination was scenario 115 (15 buffer, no litter application) for both low (15.2 percent) and medium (10.2 percent) cost schemes. Scenario 58 (30 buffer, no litter application) was the most preferred non-grazing practice for high cost schemes (8.7 percent).

Not surprisingly, high total phosphorous load reductions were obtained when buffer zones were used. In at least 94.1 percent of the HRUs, buffer zones were placed for all three levels of costs. This confirms the results obtained in several studies conducted in northwest Arkansas [Chaubey et al., 1994; Chaubey et al., 1995; Srivastava et al., 1996] regarding the effectiveness of buffer zones to reduce runoff losses of nutrients from land areas treated with animal manure. Thirty meters wide buffers were preferred over 15 meters wide buffers. Under the low, medium and high cost schemes they were placed on 67.2, 79.2, and 89.2 percent of the HRUs, respectively.

Best management practice combinations with application of two or less tons of poultry litter per hectare were placed on 59.7, 69.2 and 79.0 percent of the HRUs for low cost, medium cost and high cost schemes, respectively. Population one allocated low cost BMPs (see table 2 and 4) especially scenarios without poultry litter application. Those scenarios represent 34.9 percent of all the BMPs implemented in the watershed. In general, low poultry litter applications (less than two tons per acre) may be preferred for two reasons: 1) they are less expensive and 2) phosphorous concentration in soil may be decreased since less phosphorous is available for runoff. In other words, the amount of phosphorous available for runoff will decrease with lower poultry litter application rates and vice versa.

Surprisingly, BMP combinations that amended poultry litter with alum were not preferred at all under any of the cost schemes. Even though studies have proved that alum reduces total phosphorous [Moore et al., 1999; Moore et al., 2004; Moore and Edwards, 2005; Shreve et al., 1995]; it seems to be cost-prohibitive. Consequently, these kinds of BMP combinations were not included in the final solution.

Scenario combinations that spread litter during the summer season were preferred under all three cost schemes. This choice is predictable since less rainfall is likely to occur during the summer season. Summer litter applications represented 40.1, 52.7 and 61.8 percent of the HRUs for low, medium and high cost schemes, respectively.

Total Nitrogen and Net Cost

The second model evaluated the cost-effectiveness of selecting and placing BMPs to reduce total nitrogen while simultaneously minimizing net cost. The five-year weighted average for total nitrogen loading estimated at the watershed level was 0.952 kilograms per hectare. Figure 5a displays the progress of the Pareto-optimal front for total nitrogen and net cost. The final solution, obtained after generation number 10,000, displays a range of populations that when compared to the baseline reduce total nitrogen by either 1) 90.3 percent without increasing cost or 2) by 91.0 percent while increasing cost by no more than 1.48 percent per hectare (figures 5a and 5b).

The Pareto-optimal front for generation number 10,000 got closer to the origin than the previous generations (figure 5a). Although, this Pareto-optimal front was vertically spread (i.e., wider range of net cost solutions) it provided decision makers with a narrower range (i.e., a range of approximately 0.00015 kg/ha/year) of total nitrogen reduction solutions (figure 5b). Therefore, it is expected that decision makers will choose populations that do not increase cost as the total nitrogen reduction benefits are marginal when selecting more expensive alternatives (figure 5b).

As with the previous case, three populations were chosen; the lowest cost population (population 1), the medium cost pollution (population 490) and the highest cost population (population 776) for generation 10,000. Table 3 displays the value of the objective functions for each of the populations analyzed in this example and table 4 shows the frequency of BMPs selected under three cost schemes. Figure 6 exhibits the selection and spatial placement of BMP combinations within the watershed (at the HRU level) under low, medium and high cost schemes for total nitrogen.

For these three populations, total nitrogen loads were reduced by at least 90.3 percent under all cost implementation schemes. The NSGA-II assigned mainly best management combinations with non-grazing practices, buffer zones and low litter application rates (scenarios 58, 64, 115 and 119) for all three levels of costs. Non-grazing practices were placed on 73.8, 80.7 and 80.7 percent of the HRUs for low, medium and high cost schemes, respectively. Preferences for non grazing practices are due to the fact that they act like big buffer. Consequently, total nitrogen runoff reductions are expected. The most common optimal grazing strategy was BMP 134 (15 meter buffer, no litter). This combination was placed on 7.6 percent of the HRUs under low cost scheme and in 10.0 percent of the HRUs for both medium cost and high cost schemes. In at least 73.8 percent of the HRUs, buffer zones were placed for all three levels of costs.

High total nitrogen load reductions were obtained when buffer zones were employed. In at least 73.8 percent of the HRUs, buffer zones were placed for all three levels of costs. Specifically, 15 meters wide buffers were placed on over 39.7 percent of the HRUs while 30 meters wide buffers were placed on over 34.1 percent of the HRUs under all cost implementation schemes. Previous studies [Chaubey et al., 1994; Chaubey et al., 1995; Srivastava et al., 1996] have shown that buffer zones are effective in improving the quality of the total nitrogen runoff from a source area treated with poultry litter.

Best management practice combinations with application of two or less tons of poultry litter per acre were placed on 67.9, 60.3 and 60.3 percent of the HRUs for low cost, medium cost and high cost schemes, respectively. Low poultry litter applications may be preferred for three reasons: 1) they are less expensive, 2) they contain less nitrogen than higher application rates and 3) since bermudagrass requires high levels of nitrogen for optimal growth [Coblentz et al., 2004] it is expected that bermudagrass will increase nitrogen uptakes since lesser amounts of this element are available. Consequently, less amounts of this element are available for runoff.

Scenario combinations that amended poultry litter with alum were more preferred under high cost schemes (15 percent of the HRUs). They were less preferred under low cost schemes (13.4 percent of the HRUs). However, it is unclear why scenarios that included alum were part of the final solution. Previous studies [Moore et al., 1999; Moore et al., 2004; Moore and Edwards, 2005] have shown that the addition of alum to poultry litter reduces total phosphorous runoff and ammonia volatilization in poultry houses [Moore and Edwards, 2005]. However, there is no evidence of total nitrogen runoff reductions when poultry litter is amended with alum.

Scenario combinations with litter applications during the spring season were preferred under all three cost schemes. These scenario combinations were placed on over 54.7 percent of the HRUs for all cost schemes. Preference for scenarios where poultry litter is applied during the spring semester can be explained by the ability of bermudagrass to responds promptly (i.e., nutrient uptake) to applied fertilizer, especially nitrogen [Slaton et al., 2006].

To sum up, these six populations (i.e., three for total phosphorous and three for total nitrogen) represent the benefits of the NSGA-II optimization model when reducing total phosphorous (or total nitrogen) runoff and reducing net cost increase from a baseline are considered simultaneously. Decision makers can choose any population in the Pareto-optimal front (i.e., there are 800 non dominant solutions for each pollutant). In selecting the best set of BMPs to reduce nutrients pollution at lower cost at the watershed level, decision makers need to understand that each population (i.e., a solution that includes a combination of 461 BMPs that need to be placed in specific locations within the watershed to obtain the pollutant and net cost reduction benefits) will allocate some combination of grazing pasture management practices (non-grazing or optimal grazing), a buffer zone (0, 15, and 30 meters wide) and poultry litter (including application rate, time and amendments) at once. It is the task of the decision maker to weigh trade-offs between the two objective functions to find the solution that better fit the water management plan for the watershed.

Modeling More Than Two Objective Functions

Developing multi objective optimization models is not a trivial task. Modelers need to have a good understanding not only of programming techniques but also the interrelationships among conflicting objective functions. Multi objective modeling programming gets more difficult when the number of objectives is larger than two (for instance, modeling simultaneously total phosphorous, total nitrogen and net cost). As mentioned before, the NSGA-II optimization model forms a set of compromised trade-off solutions (a Pareto-optimal front) from which the best solution can be chosen. Pareto-optimal fronts are visualized for the purpose of comparing among solutions according to their location on the front. However, even visualizing a front for more than two objective functions becomes problematic. Although, it was not the scope of this study, this section focuses on scenarios that reduced both pollutants runoff.

There are several BMP combinations that were selected and placed to reduce total phosphorous or total nitrogen (see table 4 and figures 4 and 6); however, only two scenarios (58 and 115) were effective reducing both nutrients simultaneously. These two BMP combinations are non grazing scenarios with a buffer zone and without poultry litter applications. Although, there appear to be scenarios that control total phosphorous and total nitrogen simultaneously, these scenarios are part of a set (i.e., population) of BMPs (in this case 461) that need to be implemented and placed simultaneously in specific locations within the watershed in order to obtain the benefits of the NSGA-II methodology.

A decision maker, in this case a watershed management expert, is needed to help to determine which of the Pareto-optimal solutions is the most satisfying to be the final solution. This includes analyzing Pareto-optimal fronts from both nutrients, if pollution control of both pollutants is desired. Decision makers that consider non grazing scenarios without poultry litter applications to be unrealistic management practices must select another population (i.e., another set of 461 BMPs solutions) that better fit the production and environmental goals of the watershed. This can be difficult since comparing the numerical values of the solutions is complex (i.e., HRUs numbers, scenarios numbers, objective functions values, etc). Thus, some additional information such as pollution reduction targets and producers grazing preferences are needed to support the decision making process.

Conclusions and Recommendations

To help modeling and predicting water quality impairment more accurately, state regulators, agricultural and non-agricultural stakeholder groups' perceptions regarding BMPs effectiveness and cost were included in this analysis. This study uses a non-dominated genetic algorithm (NSGA- II), which allows pollutant runoff reduction and net cost to be minimized simultaneously. This optimization technique is able to determine the specific combination of BMPs to reduce a pollutant of interest in a cost-effective way. The methodology used in this study linked pollutant loadings from the SWAT model (a non-point source pollution model), BMPs reduction effectiveness (as a percentage change from a baseline) and net cost increase from a baseline with a genetic algorithm. The methodology was demonstrated in the Lincoln Lake watershed where total phosphorous pollution has been a major concern.

Results from the two analyses conducted in this study provided some optimal solutions with zero net cost increase. This is only possible by placing optimal selected BMP combinations in specific locations through the watershed. However, if a decision maker does not want to shift between grazing preferences or between poultry litter application rates, several populations will provide different management combinations to be placed in different locations within the watershed to obtain similar results at different costs (Pareto-optimal front). For instance, if the nutrient of concern is total phosphorous, decisions makers should select populations that include scenarios with wide buffers (i.e., scenarios 58, 77, 81, 87, and 88). However, if the decision maker is interested on reducing total nitrogen, populations that include BMP combinations with a narrower buffer are preferred (i.e., scenarios 115, 119 and 134).

Results from this study provide decision makers with a wide range of optimal solutions when trade-offs between environmental and economic conditions must be analyzed simultaneously. Although the methodology proved to be effective in finding near optimal solutions, future modeling approaches should include stricter restrictions. For instance, shifting land from optimal grazing to non-grazing operations, using big buffer zones or decreasing poultry litter rates to a minimum level could be impractical for some profit maximizers decision makers. While net cost increase from a baseline is a good economic proxy, a better variable will be net returns. The reason is that higher yields (and consequently higher net returns) could offset the cost of more effective but more expensive BMPs that otherwise could be in the optimal solution (for instance, poultry litter amended with alum).

While proposing individual watershed management plans for a specific pollutant is a valid and significant contribution, a methodology that could select and place BMPs that reduce total phosphorous, total nitrogen and other pollutants simultaneously is desired. This is a more comprehensive strategy to control water pollution, especially when pollutant criteria must be developed on a watershed by watershed basis instead of pollutant driven. This is an area that needs more research since a number of challenging issues will arise such as data availability, methods used to collect data, handling more than two objective functions, simultaneous visualization of solutions (Pareto-optimal fronts for more than two objective functions), solution spaces, software, modeling and optimization time, etc.

In summary, real partnerships at the federal, state and among all stakeholders involved in water quality issues are needed to coordinate all available tools to improve water quality. As communication among stakeholders improve and more data become available, results from studies like this one will provide policy-makers, decision makers and the public with better cost and water quality benefit trade-offs associated with different water management strategies that are acceptable and understandable by all the stakeholders in the watershed.

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Table 1. Best Management Practice Factors

Grazing and Pasture Management	Buffer Width (meters)	Nutrient Management		
		Poultry Litter [b]	Application Time	Alum Application
No, Optimal, Overgrazing [a]	0, 15 , 30	1, 1.5, 2	Spring	Yes/No
			Summer	
		2, 2.5, 3	Fall	
		0	N/A	No

[a] overgrazing was not analyzed in this study [b] (tons/acre)

Table 2. Best Management Practice Combinations and Associate Total Cost

BMP Scenario #	Pasture Land Grazing	Buffer Width (meters)	Litter Amount (ton/acre)	Time of Application (season)	Litter Treated with Alum	Total Cost ($/ha)	BMP Scenario #	Pasture Land Grazing	Buffer Width (meters)	Litter Amount (ton/acre)	Time of Application (season)	Litter Treated with Alum	Total Cost ($/ha)
1	No	0	0.0	N/A	No	252	75	No	30	2.5	Fall	No	375
20	Optimal	0	0.0	N/A	No	252	94	Optimal	30	2.5	Fall	No	375
115	No	15	0.0	N/A	No	271	2	No	0	1.0	Spring	Yes	376
134	Optimal	15	0.0	N/A	No	271	8	No	0	1.0	Summer	Yes	376
5	No	0	1.0	Spring	No	277	76	No	30	3.0	Fall	No	393
11	No	0	1.0	Summer	No	277	116	No	15	1.0	Spring	Yes	398
24	Optimal	0	1.0	Spring	No	277	122	No	15	1.0	Summer	Yes	398
6	No	0	1.5	Spring	No	289	135	Optimal	15	1.0	Spring	Yes	398
12	No	0	1.5	Summer	No	289	141	Optimal	15	1.0	Summer	Yes	398
58	No	30	0.0	N/A	No	290	59	No	30	1.0	Spring	Yes	420
77	Optimal	30	0.0	N/A	No	290	65	No	30	1.0	Summer	Yes	420
119	No	15	1.0	Spring	No	299	78	Optimal	30	1.0	Spring	Yes	420
125	No	15	1.0	Summer	No	299	84	Optimal	30	1.0	Summer	Yes	420
138	Optimal	15	1.0	Spring	No	299	3	No	0	1.5	Spring	Yes	437
144	Optimal	15	1.0	Summer	No	299	9	No	0	1.5	Summer	Yes	437
7	No	0	2.0	Spring	No	302	117	No	15	1.5	Spring	Yes	462
13	No	0	2.0	Summer	No	302	123	No	15	1.5	Summer	Yes	462
17	No	0	2.0	Fall	No	302	136	Optimal	15	1.5	Spring	Yes	462
36 [a]	Optimal	0	2.0	Fall	No	302	142	Optimal	15	1.5	Summer	Yes	462
18	No	0	2.5	Fall	No	314	60	No	30	1.5	Spring	Yes	487
120	No	15	1.5	Spring	No	314	66	No	30	1.5	Summer	Yes	487
126	No	15	1.5	Summer	No	314	79	Optimal	30	1.5	Spring	Yes	487
139	Optimal	15	1.5	Spring	No	314	85	Optimal	30	1.5	Summer	Yes	487
145	Optimal	15	1.5	Summer	No	314	4	No	0	2.0	Spring	Yes	499
62	No	30	1.0	Spring	No	322	10	No	0	2.0	Summer	Yes	499
68	No	30	1.0	Summer	No	322	14	No	0	2.0	Fall	Yes	499
81	Optimal	30	1.0	Spring	No	322	118	No	15	2.0	Spring	Yes	527
87	Optimal	30	1.0	Summer	No	322	124	No	15	2.0	Summer	Yes	527
19	No	0	3.0	Fall	No	326	128	No	15	2.0	Fall	Yes	527
121	No	15	2.0	Spring	No	329	137	Optimal	15	2.0	Spring	Yes	527
127	No	15	2.0	Summer	No	329	143	Optimal	15	2.0	Summer	Yes	527
131	No	15	2.0	Fall	No	329	147	Optimal	15	2.0	Fall	Yes	527
140	Optimal	15	2.0	Spring	No	329	61	No	30	2.0	Spring	Yes	555
146	Optimal	15	2.0	Summer	No	329	67	No	30	2.0	Summer	Yes	555
150	Optimal	15	2.0	Fall	No	329	71	No	30	2.0	Fall	Yes	555
63	No	30	1.5	Spring	No	339	80	Optimal	30	2.0	Spring	Yes	555
69	No	30	1.5	Summer	No	339	86	Optimal	30	2.0	Summer	Yes	555
82	Optimal	30	1.5	Spring	No	339	90	Optimal	30	2.0	Fall	Yes	555
88	Optimal	30	1.5	Summer	No	339	15	No	0	2.5	Fall	Yes	561
132	No	15	2.5	Fall	No	345	129	No	15	2.5	Fall	Yes	591
151	Optimal	15	2.5	Fall	No	345	148	Optimal	15	2.5	Fall	Yes	591
64	No	30	2.0	Spring	No	357	72	No	30	2.5	Fall	Yes	622
70	No	30	2.0	Summer	No	357	91	Optimal	30	2.5	Fall	Yes	622
74	No	30	2.0	Fall	No	357	16	No	0	3.0	Fall	Yes	623
83	Optimal	30	2.0	Spring	No	357	130	No	15	3.0	Fall	Yes	656
89	Optimal	30	2.0	Summer	No	357	149	Optimal	15	3.0	Fall	Yes	656
93	Optimal	30	2.0	Fall	No	357	73	No	30	3.0	Fall	Yes	689
133	No	15	3.0	Fall	No	360	92	Optimal	30	3.0	Fall	Yes	689

[a] Baseline

Note: Total costs were estimated in 2004 dollars and were assumed to increase by 2% each year.

Table 3. Objective Function Values for Different Populations

Population	Total Phosphorous (Kg/Ha/Year)	Total Cost ($/Ha/Year)
1	0.016	0.00
550	0.010	7.30
138	0.009	15.11

Population	Total Nitrogen (Kg/Ha/Year)	Total Cost ($/Ha/Year)
1	0.092	0.00
490	0.086	3.12
776	0.086	4.82

Table 4. Best Management Practice Frequencies for Low, Medium and High Costs Schemes for Total Phosphorous and Total Nitrogen – Generation 10,000

Total Phosphorous						
Population	**1**		**550**		**138**	
Scenario	**Low Cost**		**Medium Cost**		**High Cost**	
#	**Frequency**	**%**	**Frequency**	**%**	**Frequency**	**%**
0	5	1.08	0	0.00	0	0.00
1	5	1.08	0	0.00	0	0.00
11	16	3.47	16	3.47	16	3.47
20	1	0.22	0	0.00	0	0.00
58	36	7.81	40	8.68	40	8.68
59	1	0.22	1	0.22	1	0.22
62	12	2.60	14	3.04	14	3.04
63	4	0.87	1	0.22	1	0.22
64	1	0.22	2	0.43	2	0.43
68	29	6.29	30	6.51	30	6.51
69	16	3.47	16	3.47	16	3.47
70	2	0.43	1	0.22	0	0.00
77	50	10.85	51	11.06	51	11.06
81	39	8.46	41	8.89	42	9.11
87	57	12.36	77	16.70	78	16.92
88	43	9.33	89	19.31	131	28.42
89	1	0.22	0	0.00	0	0.00
91	0	0.00	0	0.00	1	0.22
93	2	0.43	2	0.43	3	0.65
94	0	0.00	0	0.00	1	0.22
115	70	15.18	47	10.20	3	0.65
119	12	2.60	14	3.04	14	3.04
120	3	0.65	0	0.00	0	0.00
121	2	0.43	0	0.00	0	0.00
125	11	2.39	11	2.39	11	2.39
126	9	1.95	3	0.65	3	0.65
127	1	0.22	0	0.00	0	0.00
131	1	0.22	0	0.00	0	0.00
134	24	5.21	4	0.87	3	0.65
138	5	1.08	1	0.22	0	0.00
139	1	0.22	0	0.00	0	0.00
140	1	0.22	0	0.00	0	0.00
150	1	0.22	0	0.00	0	0.00
Total	461	100	461	100	461	100

Total Nitrogen						
Population	**1**		**490**		**776**	
Scenario	**Low Cost**		**Medium Cost**		**High Cost**	
#	**Frequency**	**%**	**Frequency**	**%**	**Frequency**	**%**
0	3	0.65	0	0.00	0	0.00
1	33	7.16	42	9.11	42	9.11
2	25	5.42	30	6.51	30	6.51
3	2	0.43	0	0.00	0	0.00
5	21	4.56	25	5.42	25	5.42
6	4	0.87	0	0.00	0	0.00
7	1	0.22	0	0.00	0	0.00
8	1	0.22	0	0.00	0	0.00
11	18	3.90	16	3.47	16	3.47
12	1	0.22	0	0.00	0	0.00
13	2	0.43	0	0.00	0	0.00
14	1	0.22	0	0.00	0	0.00
20	2	0.43	0	0.00	0	0.00
24	6	1.30	0	0.00	0	0.00
36	1	0.22	0	0.00	0	0.00
58	23	4.99	40	8.68	40	8.68
59	13	2.82	26	5.64	39	8.46
60	2	0.43	0	0.00	0	0.00
61	1	0.22	0	0.00	0	0.00
62	24	5.21	30	6.51	17	3.69
63	18	3.90	3	0.65	3	0.65
64	30	6.51	50	10.85	50	10.85
65	4	0.87	0	0.00	0	0.00
66	1	0.22	0	0.00	0	0.00
68	7	1.52	0	0.00	0	0.00
70	1	0.22	0	0.00	0	0.00
77	21	4.56	15	3.25	15	3.25
78	1	0.22	0	0.00	0	0.00
81	8	1.74	0	0.00	0	0.00
83	1	0.22	0	0.00	0	0.00
88	1	0.22	0	0.00	0	0.00
93	1	0.22	0	0.00	0	0.00
115	34	7.38	40	8.68	40	8.68
116	1	0.22	0	0.00	0	0.00
118	3	0.65	0	0.00	0	0.00
119	32	6.94	48	10.41	48	10.41
120	21	4.56	22	4.77	22	4.77
121	4	0.87	0	0.00	0	0.00
122	1	0.22	0	0.00	0	0.00
125	2	0.43	0	0.00	0	0.00
126	6	1.30	0	0.00	0	0.00
134	35	7.59	46	9.98	46	9.98
135	1	0.22	0	0.00	0	0.00
136	2	0.43	0	0.00	0	0.00
138	10	2.17	2	0.43	2	0.43
139	15	3.25	1	0.22	0	0.00
140	11	2.39	25	5.42	26	5.64
142	3	0.65	0	0.00	0	0.00
145	2	0.43	0	0.00	0	0.00
Total	461	100	461	100	461	100

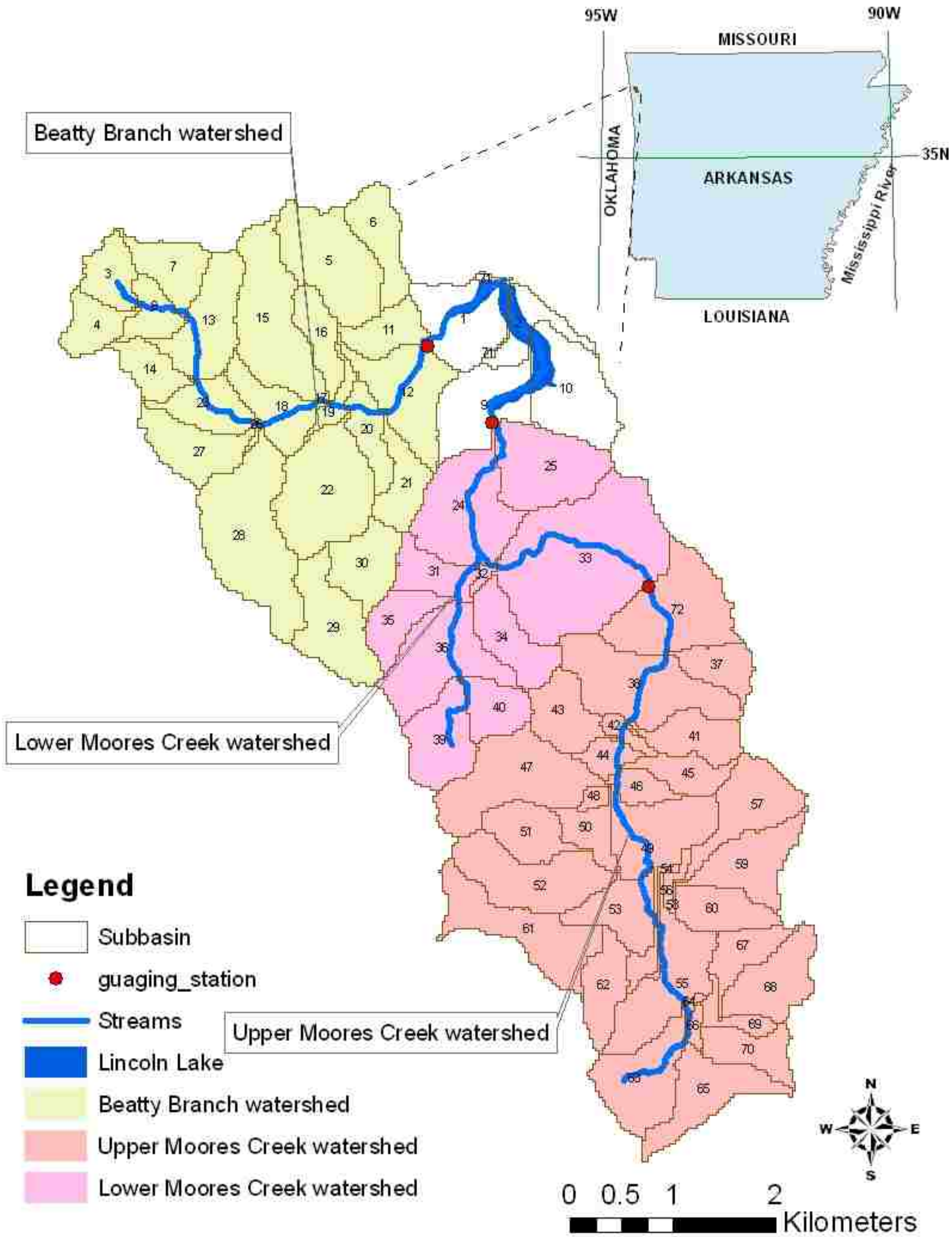


Figure 1. Lincoln Lake Watershed and Subbasins

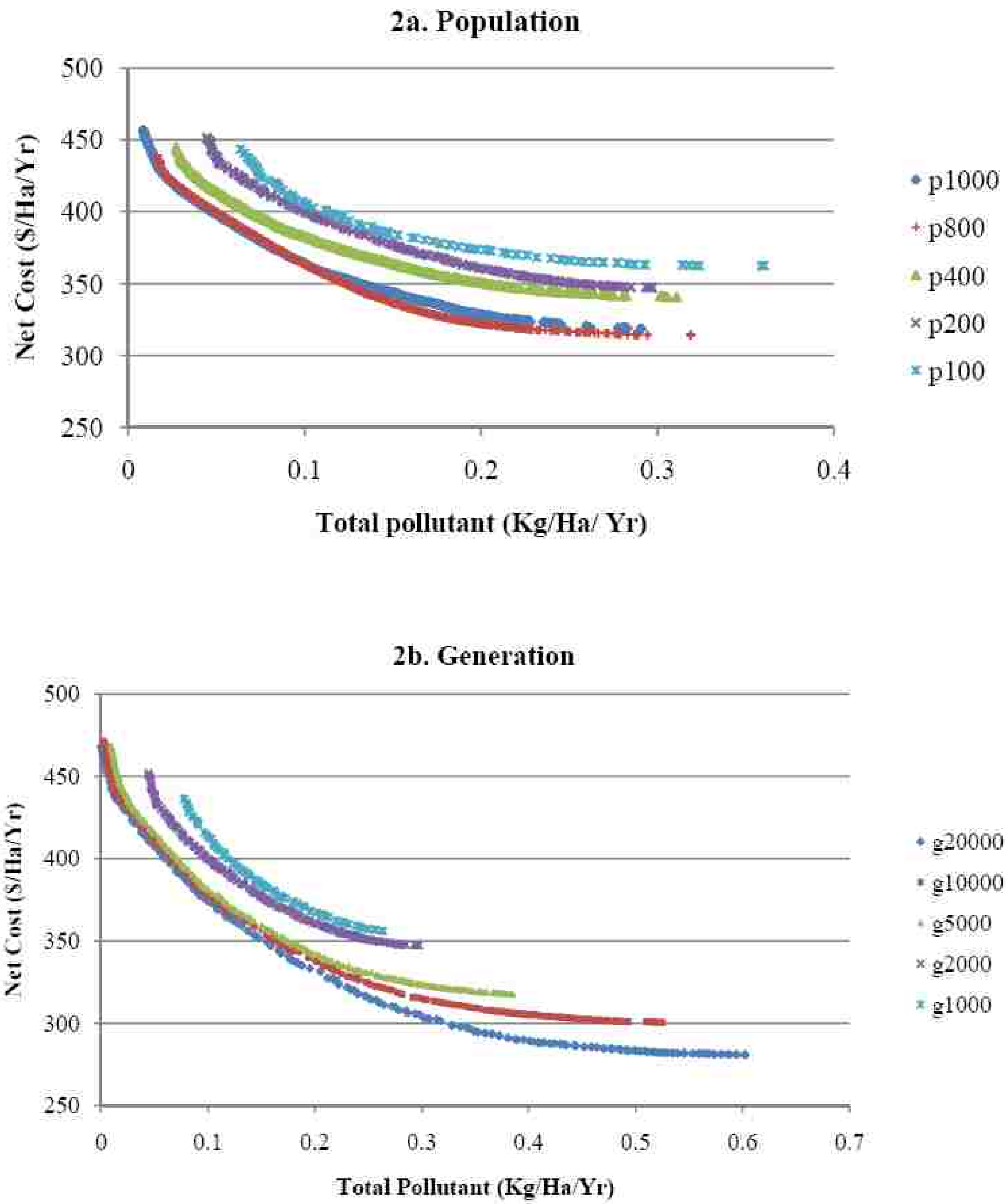
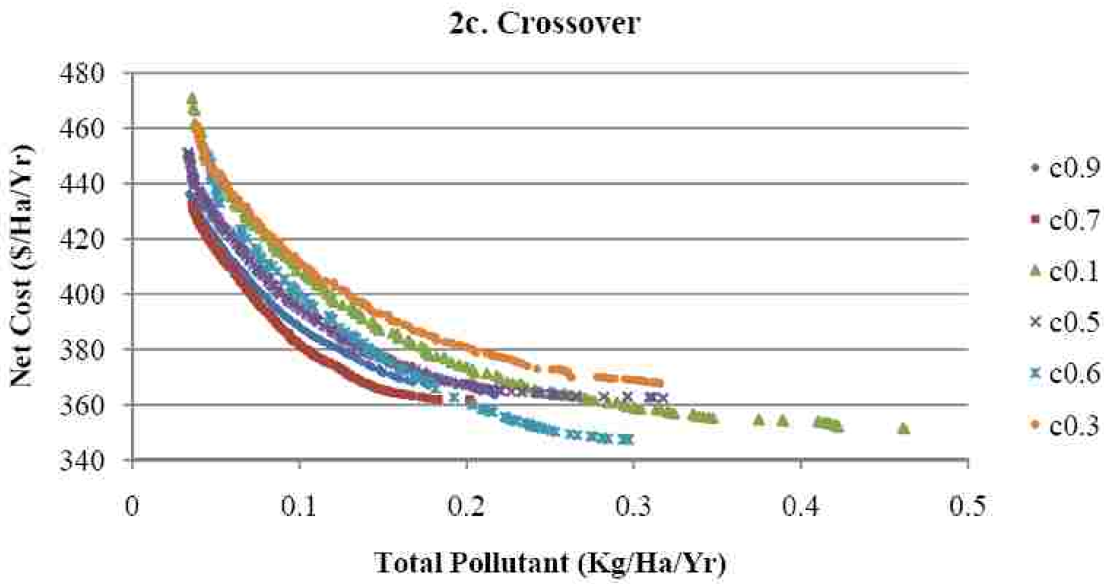


Figure 2. Sensitivity Analysis of Genetic Algorithm Parameters – Pareto-optimal Fronts



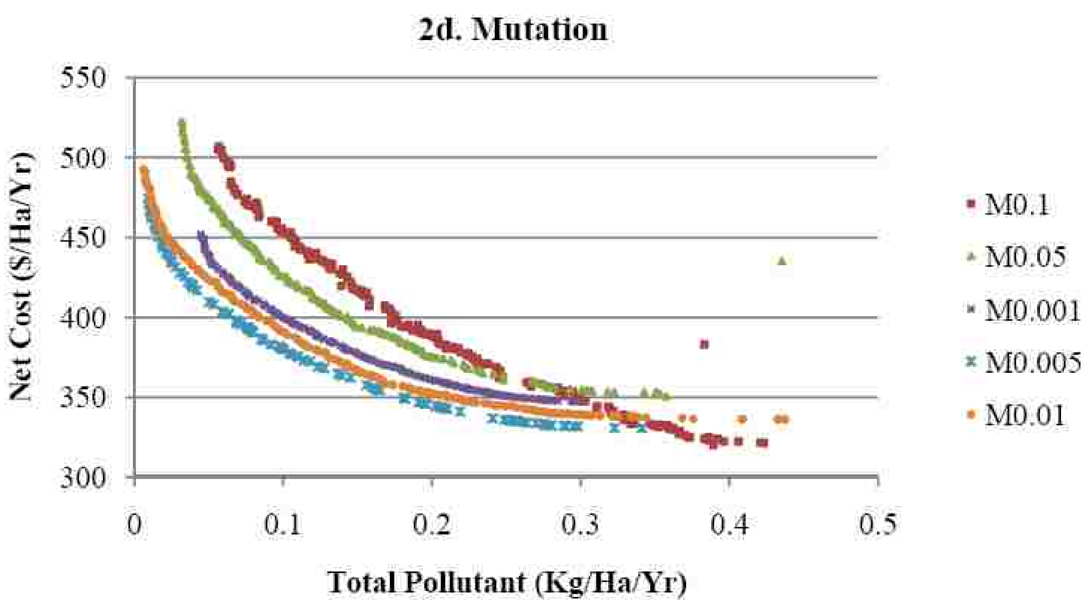


Figure 2. Sensitivity Analysis of Genetic Algorithm Parameters – Pareto-optimal Fronts

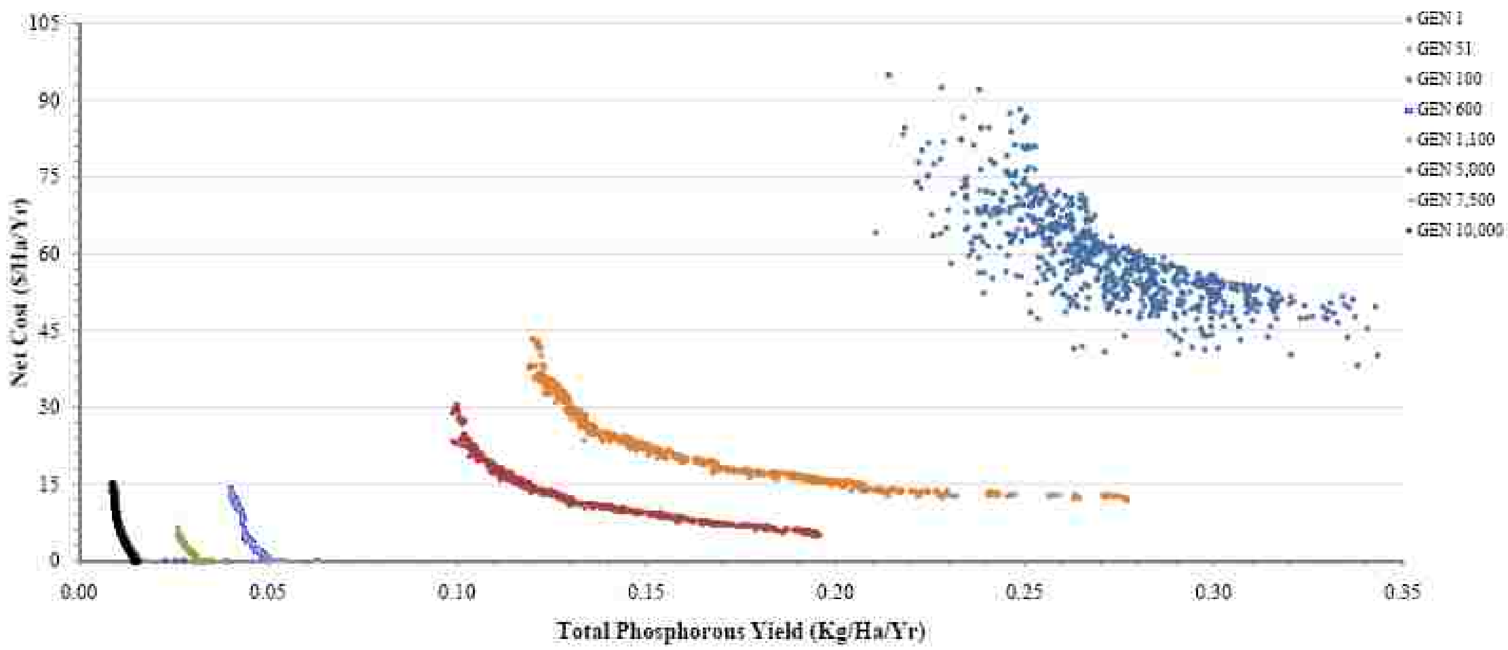


Figure 3a. Progress of the Pareto-optimal front for total phosphorous and net cost

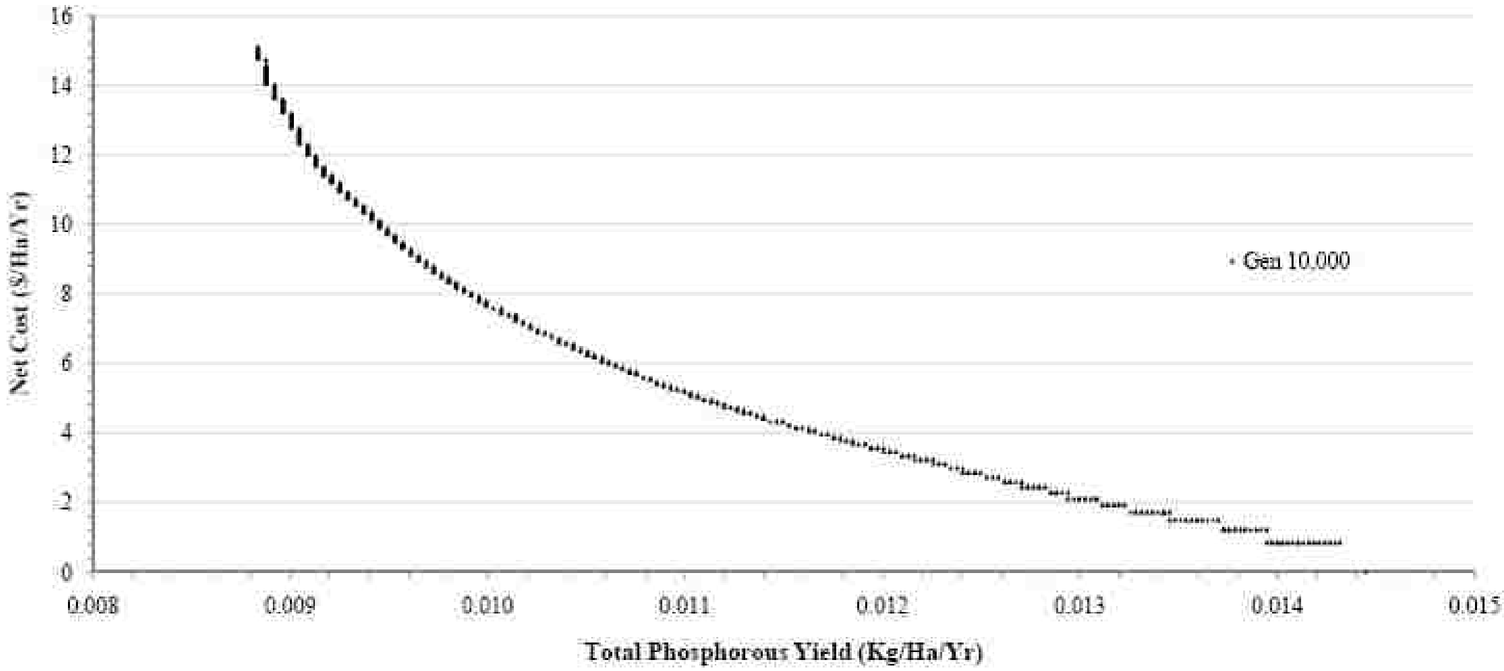
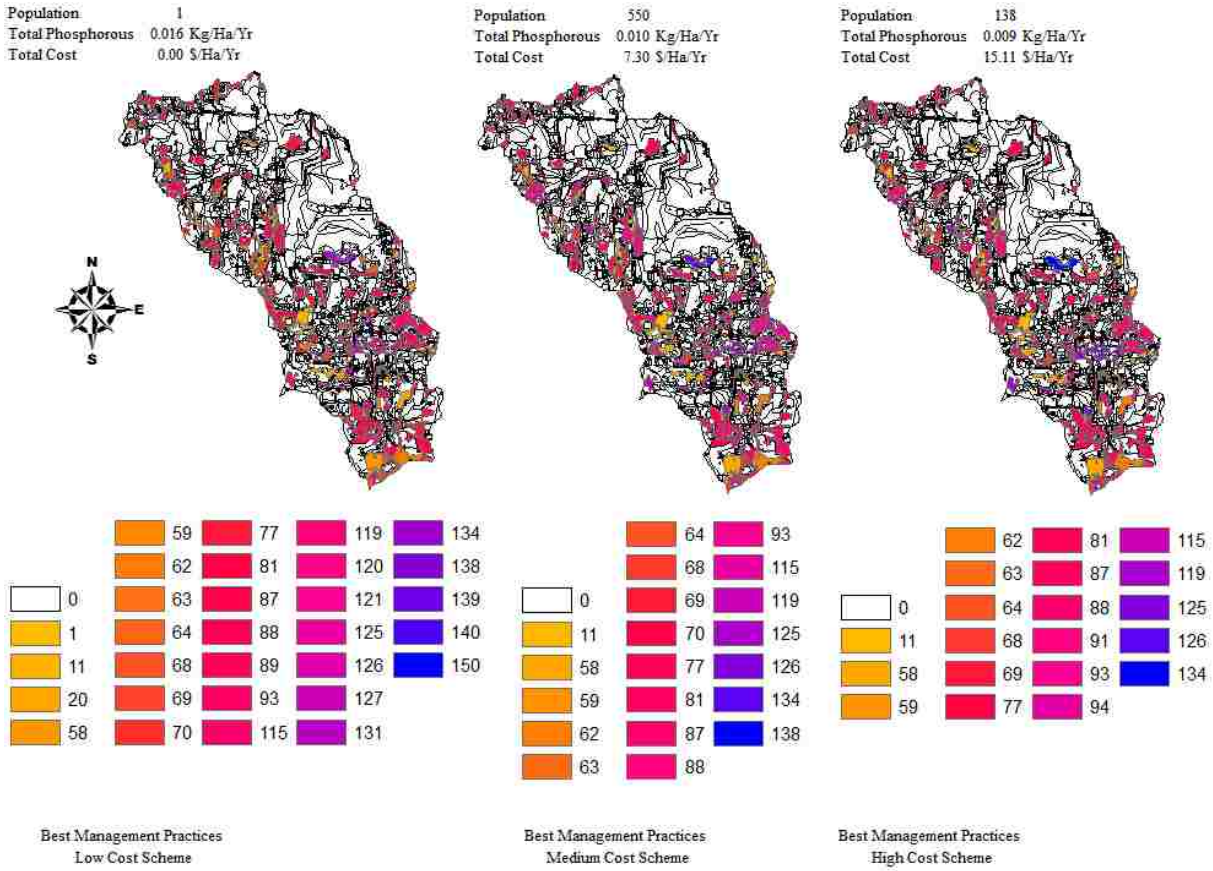


Figure 3b. Pareto-optimal front for total phosphorous and net cost – Generation 10,000



This map was created by Chetan Maringanti.

Figure 4. Selection and Location of Best Management Practices to Control Total Phosphorous under Three Cost Schemes for Generation 10,000

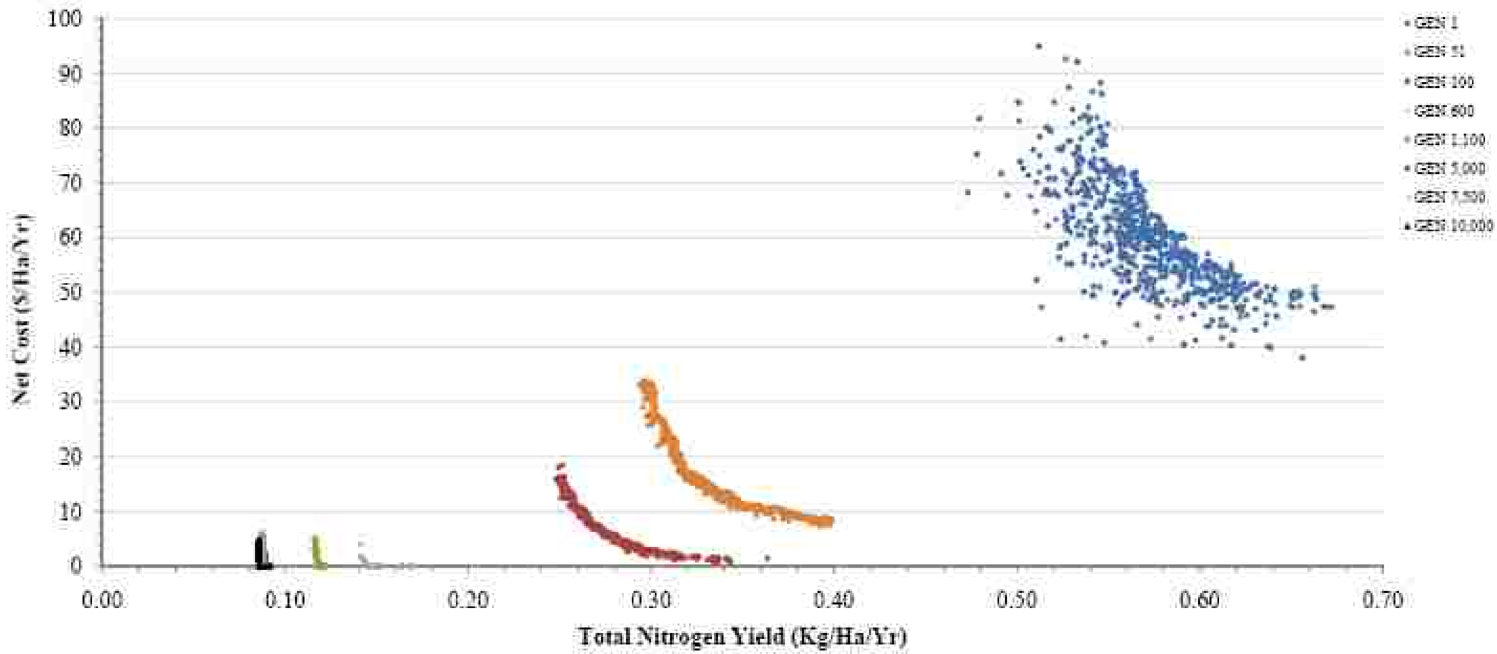


Figure 5a. Progress of the Pareto-optimal front for total nitrogen and net cost

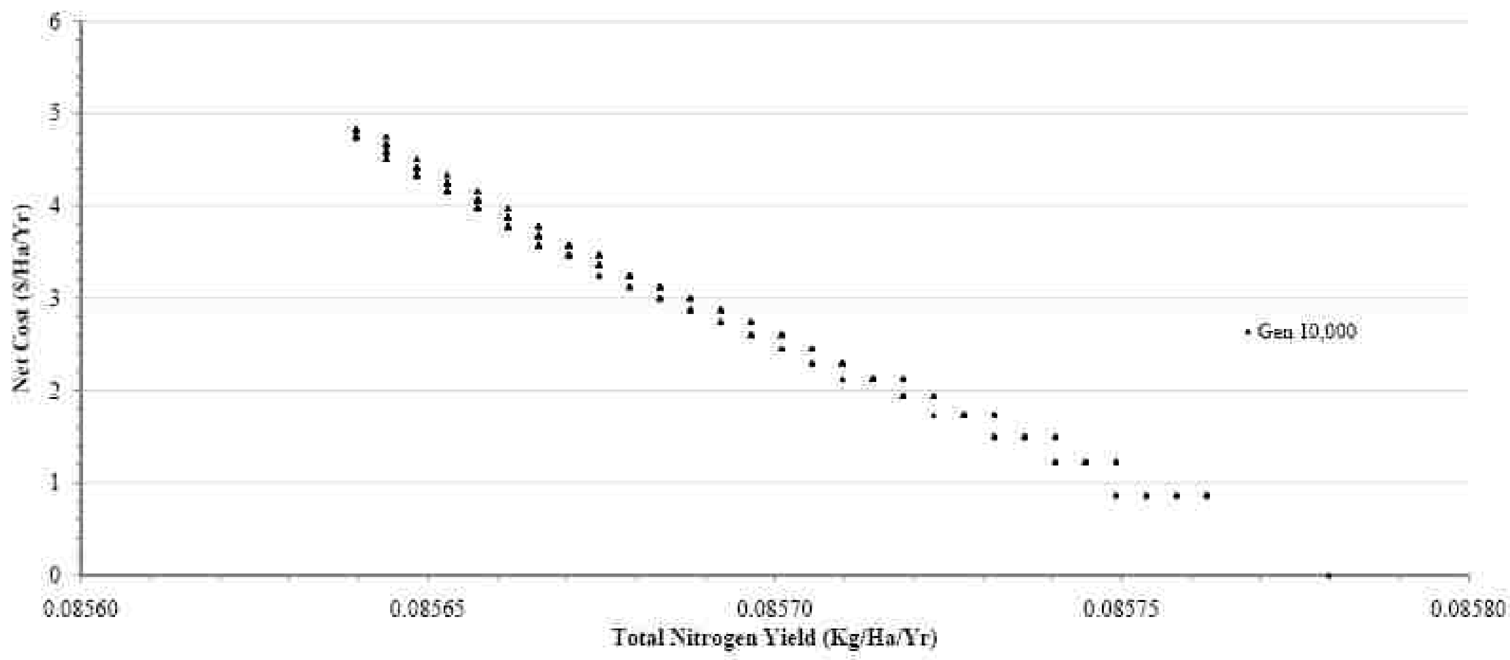
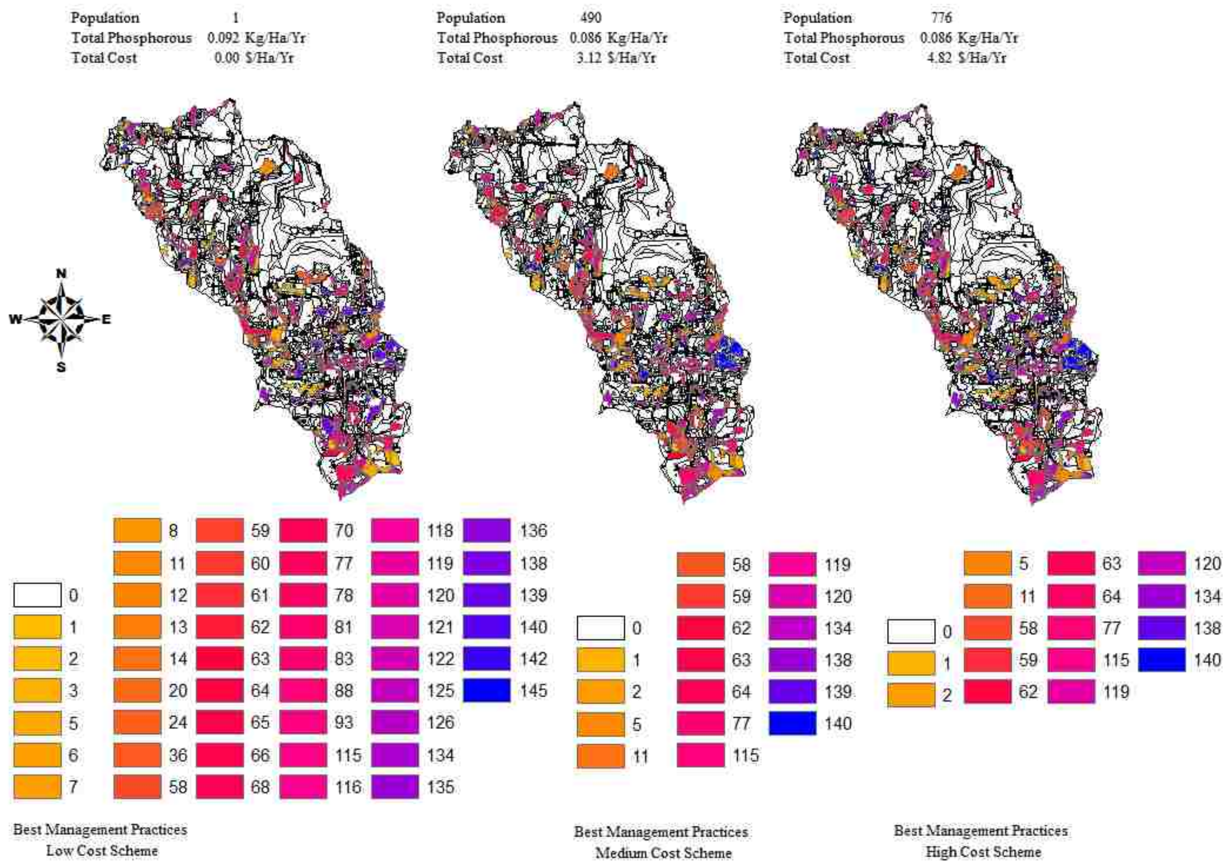


Figure 5b. Pareto-optimal front for total nitrogen and net cost – Generation 10,000



This map was created by Chetan Maringanti.

Figure 6. Selection and Location of Best Management Practices to Control Total Nitrogen under Three Cost Schemes for Generation 10,000

CHAPTER VI

Projects Overview

This study results from two projects. The combined goal of those projects was to quantify the environmental benefits of best management practices (BMPs) for two types of agricultural production systems in two Arkansas watersheds. The first project was conducted in the L'Anguille River watershed, a Section 319 priority watershed. The objective was to perform cost-benefit analyses of land management and water conservation practices on water quality. The crops of interest were rice and soybeans.

The second project was conducted in the Lincoln Lake watershed, a sub-basin of the Illinois River watershed. The Illinois River watershed is also a Section 319 priority watershed. The objective was to quantify how implementation, timing and spatial distribution of a variety of BMPs within the watershed decrease nutrient runoff. Comprehensive economic analyses were performed to optimize BMPs selection by minimizing water quality negative impacts and BMPs implementation costs including bermudagrass producers' risk attitudes.

Research Findings

Findings from the stochastic dominance (SD) and genetic algorithm (GA) provide a wide range of solutions when trade-offs between environmental and economic conditions must be analyzed simultaneously. The SD analysis reveals the environmentally and economically preferred best management practices (BMPs) and their trade-offs relative to each other. There appear to be options to improve nutrients runoff and net returns upon current BMPs being implemented. In general, producer's risk aversion level matters. Slightly risk averse producers will prefer different BMPs than extremely risk averse producers regardless of crop analyzed. The GA optimization finds specific combinations of BMPs to reduce nutrients runoff in a cost-effective way. More specific findings show that:

- Conservation tillage in rice and no tillage in soybeans are the most effective BMPs to reduce total phosphorous (TP) runoff regardless of the subbasin analyzed in the L'Anguille River watershed;
- Nongrazing management pasture systems are preferred in terms of TP runoff and total nitrogen (TN) runoff reduction in the Lincoln Lake watershed;
- Optimal grazing management pasture systems are preferred when TP runoff and net cost were optimized simultaneously;
- Buffer zones are very effective in reducing TP runoff. It was reduced by at least 90%; and
- Low poultry litter application rates (i.e., less than 2 tons per acre) are preferred in terms of TP runoff and TN runoff reductions but poultry litter treated with alum did not reduce TP runoff as expected.

From the findings of this research some overall conclusions can be made.

Research Conclusions

The overall research goal was to evaluate how implementation, timing and spatial distribution of agricultural BMPs can be used within two watersheds in Arkansas to reduce nutrient runoff while minimizing producers' exposure to additional risk. This goal was achieved, leading to three conclusions:

1. Best management practices have the potential for reducing nutrient pollutant losses from agricultural land areas;
2. Producers will be reluctant to adopt BMPs that increase their costs or reduce their net returns drastically regardless of their water quality benefits; and
3. Cost-savings from selecting BMPs become evident when critical factors for reducing TP runoff are analyzed using an environmental-economic model.

Conclusions resulting from the evaluation of cost and net return risk were:

4. Ranking BMPs solely in terms of their effectiveness to reduce nutrient runoff can lead to cost-prohibited recommendations since producer's risk aversion level matters; and
5. Producers would have to receive a risk premium to adopt any of the BMPs analyzed in this study. This is true for both row crop and forage producers.

Conclusions resulting from the optimization model were:

6. Timing, implementation costs and spatial distribution of BMPs within a watershed affect BMP selection; and
7. Several solutions provide different BMP combinations to be placed in different locations within a watershed to obtain similar results at different costs.

Additional general conclusions drawn from this research were as follows:

8. There are some BMPs that can reduce nutrient runoff, maintain agricultural production and improve water quality without affecting producers' cost or net returns dramatically; and

9. Decision makers need to weight trade-offs between nutrient runoff reduction and net cost increase when selecting BMPs.

Some of the conclusions derived from this research are very watershed specific, because the BMP alternatives were simulated through specific soil and weather conditions. However, the methodologies used can be extended rather readily to other watersheds within the state and the nation, as well as to other management alternatives, for evaluating their impacts in water quality improvement and implementation cost minimization.

Hypotheses Testing

Based on findings of this study, the two hypotheses are rejected. That is, the SD analysis showed that cost and net risk cannot be ignored when selecting BMPs. Risk neutral; slightly risk averse and extreme risk averse producers would prefer different BMPs. In addition, the evidence generated with the optimization model (GA) showed that selection, timing and placement of BMPs within the watershed impact the cost of implementing BMPs to comply with water quality goals. Producers can choose among different BMPs associated with low, medium and high cost schemes.

The Complexity of the Policy Process

Many authors define environmental issues as "wicked problems" that are difficult to pin down because they are influenced by numberless complex social, economical, technical and political factors [Kreuter et al., 2004; Vinzant and Crothers, 2002; Kickert et al., 1997]. There are many potential barriers to sustainable water quality management; Bulkley [1992] and Huang and Xia [2001] list at least 14 challenges. Among the most important challenges are: 1) how the outputs from numerous water pollution research projects can be effectively linked to policy formulation, 2) how the formulated policies can be interpreted into practical and workable activities and 3) how the suggested activities can be implemented at the local level.

Ideally, public policy should solve problems without creating new ones. However, a successful policy outcome requires success in a set of processes that include the setting of the agenda, specification of alternative policy choices, an authoritative choice among those specified alternatives and the implementation of the decision [Kingdon 1995]. Policy is expected to involve a logical sequential process that begins with the identification of a problem, selection of the optimal alternative, implementation, evaluation and redesign as needed.

Science and technology play a critical part in all of these steps by setting priorities and action agendas. For example, water research can inform us of: 1) when nutrients levels become a significant problem (i.e., water quality modeling/monitoring) or 2) provide strategies that would reduce nutrients to specific levels and at what costs (i.e., evaluations of BMPs).

Unfortunately, the policy process is complex both in terms of the nature of the problems presenting themselves and also complex in terms of the competing, confusing and conflicting political aspects of the world in which the problem exits. There exist many environmental and socio-economic objectives related to different stakeholder groups that may conflict with each other [Lakeshminarayan et al., 1994]. The government has to deal with numerous actors in developing and implementing water quality policy.

Indeed, water quality policy requires the concerted efforts of multiple actors, all possessing significant capabilities but each dependent on multiple others to solidify policy intention and convert it into action. Unfortunately, the complexity of water quality problems requires technical and scientific analyses, which by their nature excludes the majority of the stakeholders in the given problem [Mostashari and Sussman, 2005].

Although it is well known that the success of policy lies in how well it is implemented, policy success rests not only on the cooperation and collaboration among the stakeholders involved in the policy process but also on the congruence of policy goals, agency priorities and operative goals [Meyers et al., 2001]. Since policies emerge from challenges in which people and interest have something to gain or to lose, water policies that appear to be effective and efficient might affect the environment (and future generations) or impact several social groups.

It is clear that political and technical forces have pressured significantly water policy in recent years in Arkansas, an example of this is the current TP standard imposed by Oklahoma [Smith, 2002]. Two regulatory water quality programs target agricultural production: the Concentrated Animal Feeding Operations (CAFOs) and the Total Maximum Daily Load (TMDL). The CAFOs are a category of point source (PS) under the National Pollution Discharge Elimination System (NPDES) program [EPA, 2007]. Under Section 301 of the Clean Water Act (Title 33, Chapter 26, § 1311, USC), discharges of pollutants from CAFOs to waters of the United States are prohibited unless authorized by a NPDES permit [EPA, 2007]. The TMDL requirements specify the maximum amount of a pollutant that a river, stream or lake can receive without seriously harming its drinking or swimming or aquatic life uses [EPA, 2008a]. These specific regulations mandate producers to take certain corrective measures; some of which were analyzed in this study (i.e., poultry litter application rates; poultry litter amendments, pasture management systems, etc).

One of the most limiting problems is getting stakeholders to agree on the right indicators or outcome measures. All stakeholders have different ideas about what constitutes the appropriate suite of indicators to measure progress toward water quality. The environmental protection agency (EPA) is the main organization charged with the implementation of environmental control legislation. The Arkansas Department of Environmental Quality (ADEQ) follows EPA mandates. However, there are more than twenty organizations with responsibility for preserving the state's water quantity, quality and public health. Consequently, water quality policy goals and institutional goals might be viewed differently depending on the perspectives and biases of those involve in the formulation and implementation processes [Kreuter et al, 2004].

Additionally, the relationship of the implementing agency to its immediate target group is very important. The needs of the target group cannot be ignored when designing water quality policies. Therefore, a critical component of good water quality policy decision making is the idea and reality of inclusion. Inclusion ensures that all people with a stake in decisions that affect their lives can contribute to and influence the decision-making process [Scheberle, 2004]. The EPA is beginning to realize that and has efforts to move away from its traditional top-down regulatory approach [EPA, 2008b].

Policy Options and Implementation Strategies

There is usually a negative relationship between the appropriateness of a policy option (e.g., goal congruence, to which extent the policy outcome is congruent with its goal) and the level of resources and commitment needed from those in charge of policy formulation and implementation. There are numerous groups with an interest in addressing water quality issues in Arkansas. However, stakeholders' interests vary, among other things, based on the benefits they can obtain from a policy change and its direct and indirect effects. Water pollution has received and still attracts a great deal of attention. Since several studies have shown the effectiveness of BMPs in improving water quality, several institutions promote their use. Consequently, agricultural producers might benefit greatly and directly from a change towards better participation in the services provided by agencies such as the Natural Resources Conservation Service (NRCS) or the University of Arkansas Cooperative Extension Service (UACES).

Economic pressures create disincentives for producers to include water conservation practices in their management plans. As mentioned before, water conservation practices can be prohibitively expensive. Without technical and financial assistance in developing and executing water conservation plans, producers are often not able to afford to both produce commodities (often with poor economic returns) and preserve water resources. In addition, some regulatory demands place an economic burden on producers that makes it difficult for them to invest in a comprehensive water conservation plan. The goal of this research would be to find the most appropriate option feasible of being implemented in both watersheds. Following is a discussion of the set of policy options and implementation strategies considered feasible.

Option 1. Do Nothing

This would assume that water pollution is not an issue which is clearly an erroneous assumption, as the water degradation in these two watersheds is real. The nutrients runoff effects on water quality from agricultural land are measurable, and have been monitored for decades. Few people disagree with the need of protecting Arkansas' water quality. Therefore, doing nothing is not a valid option, as it misrepresents pollution impacts of agriculture and fails to recognize scientific evidence. This would also go against growing scientific evidence that has drawn attention to the extent of NPS pollution and its negative environmental impacts.

Decision makers can argue that the current resources in terms of research (including scientific knowledge), technical assistance and cost-share programs are not enough to tackle the problem at the moment. As a result, the local government, research, public and private institutions have to develop both the economic and hydrological information needed for decision makers to make informed decisions regarding water quality improvement plans in these watersheds. This option advocates for continuing with the same managements practices the producers are currently using.

Option 2. Identification of Producers in both Watersheds

It is evident that the first step should be the identification of producers; in this case the row crop producers and hay producers with stakes in the L'Anguille River and Lincoln Lake watersheds. In both of the watersheds analyzed in this study, identification of producers should be somehow easy to do. The reason is that both watersheds have created a coalition or a partnership to protect water resources. The L'Anguille River Watershed Coalition and the Illinois River Watershed Partnership have specific goals of how improve water quality in these two watersheds and some producers are already members of them.

Identification of producers is important since they are the ones that implement BMPs. The UACES and the NRCS could partner to provide technical assistance regarding the water conservation practices. The NRCS could inform producers about the cost-share program available to them. In this way, understanding which BMPs work best for producers and knowing that financial assistant is available, producers will be more willing to implement the BMPs proposed in this study. It is highly likely that not all producers will participate in educational activities or enroll in financial assistance programs. In fact, it is expected that some of them completely ignore the technical and financial assistance available to them. It is expected some producers will not be interested in the initiative, but would likely become involved after some success with other producers has been achieved.

Creating a sense of group belonging is important. The integration of producers would be beneficial to identify potential leaders. The organization of a social gathering could be a good opportunity for producers (and likely their families) to interact among themselves and with representatives from relevant public agencies, and also to get a sense of the services available to them through short presentations, demonstrations and written materials. Enough economic and human resources should be devoted for an event like this. The director of the respective partnership or coalition should be present to encourage producers that are not members of these organizations to get involved.

A desirable outcome to be expected from this option would be: 1) a detailed list of producers in the L'Anguille River watershed and in the Lincoln Lake watershed, 2) the organization of a meeting with the objective of introducing them to the agencies and services available and 3) an invitation to become members of the partnership or coalition in their respective watersheds if they are not already members. It would also be desirable if call rounds could also be conducted periodically. This periodic contact would be helpful in keeping track of producer members and avoiding producer's apathy.

There are a number of potential sources for financial support for outreach. An example is funding from USDA's Cooperative State Research, Education, and Extension Service (CSREES). Grants are available through the Integrated Research, Education, and Extension Competitive Program: National Integrated Water Quality Program. Applications are accepted in an annual basis. Applications for 2009 were accepted until July 15th. A large number of institutions are eligible, including land grant universities, private institutions and state controlled institutions of higher education. The percent of applications funded last fiscal year was 22 percent.

The most important advantage of this option is its applicability. Assuming the funds are sufficient; UACES extension agents could identify producers and other stakeholders living in these two watersheds. Achieving the second goal will demand seeking the cooperation of public agencies and private businesses towards the organization of a meeting. Agencies need to provide the relevant information regarding the benefits of implementing BMPs to control water pollution. These two objectives can be successfully achieved with some degree of involvement and cooperation from the community. The third goal stresses the need of inviting producers to become members of the partnership or coalition in their respective watersheds if they are not already members.

On the downside, this option addresses the problem only partially. This option only ensures that producers will have a first-time contact with the public agencies, but does not address longer-term issues such as further coordination among producers to voice their demands or continuing involvement of agencies in providing producers with water conservation education. However, it is expected that the directors from the partnership or coalition from these two watersheds be present and encourage producers to become members of these organizations emphasizing the missions and visions that they have for their respective watersheds. This is a good approach since members of these organizations include people from agriculture, business, conservation, construction, government and education backgrounds. So producers will feel that they are not alone in controlling water pollution.

Option 3. Encourage Producers to Enroll in Cost-Share Programs to Implement BMPs

This option complements and strengthen the second option and, combined, would likely lead to a better outcome. Identifying producers is a critical task since they are the ones that implement BMPs. There are programs that set up multiyear contracts with landowners to implement new conservation practices that improve water quality. In their stewardship efforts, producers can share the implementation cost of land and manure management practices. Since the NRCS has already a cost-share program available, producers could have access to funds to implement some of the BMPs suggested in this study.

The cost-share program promotes among others the reduction of pollution from animal wastes, nutrients and sediments and improvement of the management of grazing lands. Cost share rates for practices range from 40 percent to 75 percent. There is a specific funding category for the L'Anguille River watershed. Practices are focused on erosion control and sediment reduction. Additionally, producers who own or operate no more than 100 acres of grassland or pasture are also eligible. It is expected that several of the producers in the Lincoln Lake watershed fall in the previous category. Producers can enroll in this program in their local USDA field service center by completing an application.

On the downside, this option does not guarantee that producers can enroll in the program. First, producers need to fulfill the requirements of the program. Second, these kinds of programs deal with funding limitations or program caps and third, it is expected that some producers will be discouraged to participate since they need to enter in a contract agreement and comply with programs goals.

Option 4. Tax Currently Management Practices Used by Producers in both Watersheds

The use of practices that decrease runoff of nutrients should be encouraged. In this study scenarios include combinations of BMPs. When BMPs were compared to the current practices used by producers in their farm operations, some BMPs proved to be both environmentally and economically superior to current practices. Since the amount of pollution per field is not easily measured, the risk premiums estimated in this study could be used to calculate taxes for the current practices being used.

It is assumed that producers who are risk averse might be willing to pay a tax (i.e., risk premium) to avoid changes in their management systems. Those taxes should be equal to the risk premium. In this study, several BMPs reduced nutrients runoff considerably when compared to the current practices used by producers. Consequently, a watershed decision maker needs to identify the BMPs that are close to the practices currently used by producers but that reduce nutrient runoff to a target value that needs to be established at the watershed level. In this particular case, the idea of a tax aims to alter producers' behavior.

On the downside, this option will increase the cost of production for producers that prefer the current practices better. Watershed nutrients runoff reduction measurements will be different depending on the number of producers that prefer to pay the taxes or prefer to switch to one of the BMPs proposed. Paying a tax does not reduce the pollution associated with the current practice employed. In addition, tax rule changes are difficult and time consuming. Although, the use of risk premiums seems like a good alternative to estimate taxes for BMPs, effective and dependable pollution metering devices are needed. Currently, these devices do not exist.

In this particular case, authorities cannot operate an effective tax program because they cannot determine pollution levels of an individual producer (or location) and so cannot calculate the tax bill. Furthermore, even if the tax bill can be estimated it brings the complication of which government agency will be in charge of collecting taxes and the corresponding logistics in terms of personnel, forms, office space, watershed jurisdiction, etc. However, since this study showed that some BMPs could reduce nutrient runoff and increase net returns simultaneously, tax money could be used to demonstrate that environmental protection is not simply a necessity but smart business. Hopefully, producers that are not interested at the beginning will enroll in the program sometime in the near future.

Selection of Preferred Policy Option

The key to successful implementation of any water quality initiative is the acceptance by the stakeholders that it is necessary and that it will produce results worth the efforts and resources they must supply. This requires sound not only politically, but also economically feasible. The strategy suggested in this study to take to the local, state and federal government has to develop both the economic and hydrological information needed for water legislators and others to make informed decisions regarding water quality improvement plans in this watershed.

The selection of the preferred policy option emerges from the political and economic evaluation of the alternatives presented in the previous section. Based on the information about each option available from this study, it is suggested that producers be encouraged to enroll in cost-share programs to implement BMPs. Producers could implement some of the BMPs suggested in this study since there is a program already in place that provides producers with technical and financial assistance. Politically speaking, this alternative seems to raise less conflicting issues than the other alternatives analyzed. However, it requires a level of commitment and cooperation among members that might be difficult to achieve in the short run. It also adds a number of procedural complexities that might prove too costly for many relevant actors given the complexity and the number of stakeholders involve in water quality issues.

Research Contribution

Conclusions from this study can be effectively linked to water quality policy formulation. Results from this research can be seen as policy options that take into consideration environmental benefits and economic costs of various BMP alternatives. Since BMPs are already policy choices being recommended to solve water quality problems and water quality policymakers are very familiar with them, it is expected that these solutions have political acceptability.

In managing water quality, the EPA takes a holistic watershed approach. This approach: 1) builds partnerships among federal, state, local governments as well as other private agencies and interest groups, 2) characterizes the watershed to identify problems, 3) identifies solutions and 4) designs an implementation program [EPA, 2008b]. Results from this research can address the third point if a watershed plan is implemented either in the L'Anguille River watershed or in the Lincoln Lake watershed.

This research study contributes to the process because it has shown that:

- environmental and economic impacts of BMPs in reducing nutrients runoff from different agriculture cropping systems can be captured by integrating hydrological and economic modeling,
- significant cost savings could be achieved in reducing nutrient runoff by optimizing the selection and placement of BMPs within the Lincoln Lake watershed,
- producers farming on nutrients surplus areas (as identified by the EPA, ADEQ, the state extension service and other agencies), who switch from their current

practices to one of the optimal solutions proposed in this analysis, could substantially reduce TP and TN runoff loading potential,

- water quality management practices should be linked to net returns. Some BMPs could increase net returns and reduce nutrients runoff simultaneously,
- BMPs that producers select and implement greatly determine the quality of the water. For instance, a buffer zone can reduce TP considerably. However, when including a buffer zone in their management plan, producers have to deal with increasing cost of production by installing and maintaining the buffer, reduction of cropping area, reduction of yields and consequently returns,
- nongrazing pasture systems are preferred in terms of TP reduction and net returns increase in the Lincoln Lake watershed. However, implementing this pasture practice implies shifting the cropping systems representative of the production practices currently used in the watershed. Consequently, these findings highlight that some BMPs that improve water quality can be cost-prohibitive, and
- ignoring producers' risk preferences would lead to inappropriate policy choices since the model revealed that producers' risk preferences matter.

The research results could assist policy makers to identify implementation costs and to develop optimal allocation of proposed BMPs to achieve environmental goals. In particular, the variability of regional characteristics suggests a need for targeted policies that match local needs. For example, most acreage in the Delta region is under row crop cultivation. Combined with the region's unique soil types and topography, specific crop BMPs should be employed, based on the costs of achieving desired environmental goals. Thus, the present study could help assist policy makers within the region to implement the most effective farmland environmental policies.

This research also demonstrates the importance of geophysical conditions on the cost of a policy. Since the costs of pollution reduction vary significantly across regions to be efficient and effective, each region should adopt the policy that allows the optimal resource allocation and economic returns. Thus, the type of research conducted here presents one approach that may be useful in implementing BMPs, which will need to be addressed at local levels according to local conditions.

The author of this dissertation can present the results of this study to the partnership or coalition of each watershed, the local NRCS and the local UACES. Letting producers and other stakeholders know that this kind of research is available and that some BMPs have proved to reduce nutrients runoff without increasing cost might help change stakeholders' behavior. Results from this study should be presented to state agencies such as the ANRC and the ADEQ and federal agencies like the EPA. Since all these agencies advocate for the use of BMPs, studies like this one could support previous research or bring new alternatives to be considered in solving water quality issues in Arkansas.

Recommendations

Without underestimating the complexity of the policy process, some recommendations of how the findings of this research could be implemented at the local level follow.

- This research evaluated economically efficient BMPs with respect to their associated water effects. The hydrological simulations provided a predicted nutrient pollution range from current and alternative combinations of BMPs. This information could be evaluated by EPA, ANRC, ADEQ, NRCS and UACES and other state and local authorities for the establishment of efficient and effective nutrient pollution control plan.

- Agencies like the UACES and NRCS could provide technical assistance and the NRCS could provide financial assistance to implement BMPs that could help producers to reduce nutrient runoff.
- Producers could address nutrient pollution more effectively with more education and information about programs that assist them. Outreach efforts to reduce nutrients loads to water bodies from animal agriculture could be more effective and cost efficient if BMPs are implemented in critical areas within the watershed. Water quality programs should address the highest environmental priorities first.
- Agency budgets for giving incentives to producers to reduce TP and TN loading would be more cost-effective if targeted to producers in critical nutrient areas. A government cost-share program already exists. So, this program could be used to subsidize producers for adopting some of the BMPs proposed in this study. Producers would be provided incentives to voluntarily adopt environmentally efficient BMPs.
- Simulation of expected net returns may allow the identification of those producers who could most efficiently reduce TP runoff. Such producers could be persuaded more readily through incentives to include some of the BMPs proposed in this research in their management plans.

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