Selection and placement of best management practices used to reduce water quality degradation in Lincoln Lake watershed

Hector German Rodriguez,[1] Jennie Popp,[1] Chetan Maringanti,[2] and Indrajeet Chaubey[2]

Received 21 August 2009; revised 27 September 2010; accepted 3 November 2010; published 20 January 2011.

[1] 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 nondominated sorting genetic algorithm (NSGA-II). This multiobjective algorithm selects and locates BMPs that minimize nutrients pollution cost-effectively by providing trade-off curves (optimal fronts) between pollutant reduction and total 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 35 BMPs (combinations of pasture management, buffer zones, and poultry litter application practices). Selection and placement of BMPs were analyzed under various cost solutions. The NSGA-II provides multiple solutions that could fit the water management plan for the watershed. For instance, by implementing all the BMP combinations recommended in the lowest-cost solution, total phosphorous (TP) could be reduced by at least 76% while increasing cost by less than 2% in the entire watershed. This value represents an increase in cost of \$5.49 ha^{-1} when compared to the baseline. Implementing all the BMP combinations proposed with the medium- and the highest-cost solutions could decrease TP drastically but will increase cost by \$24,282 (7%) and \$82,306 (25%), respectively.

Citation: Rodriguez, H. G., J. Popp, C. Maringanti, and I. Chaubey (2011), Selection and placement of best management practices used to reduce water quality degradation in Lincoln Lake watershed, *Water Resour. Res.*, *47*, W01507, doi:10.1029/2009WR008549.

1. Introduction

[2] Arkansas is a state rich in water resources. These water resources have been fundamental for the development of the manufacturing, recreation, navigation, construction, and agriculture sectors. Among these waters is the Illinois River, which flows from northwest Arkansas into northeast Oklahoma and back to Arkansas again. The Arkansas side of the Illinois River watershed covers areas of both Washington and Benton counties. These counties have experienced a 27% population growth between 2000 and 2008 (Benton and Washington counties data are available at http://www.census.gov/), as well as road, industrial, commercial, and residential infrastructure development to support this growth. Agriculture, and in particular cattle and poultry activities, maintains a strong presence in these counties. Benton and Washington counties produced almost 200 thousand head of cattle and calves and almost 41 million broilers and other meat-type chickens a year (Benton and Washington counties data are available at http://www.agcensus.usda.gov/Publications/2007/index.asp). The poultry industry alone generated over 40,000 jobs, \$1.29 billion in income, and \$1.69 billion in value added to the region in 2008 [*Popp et al.*, 2010].

[3] The Illinois River watershed is currently on the 303(d) Impaired Water List because of excessive in-stream phosphorous (P) concentrations [*Arkansas Department of Environmental Quality*, 2008] sourced on the Arkansas side of the watershed, which eventually flows into Oklahoma (section 303(d) of the U.S. Clean Water Act (CWA) establishes that states are to list (the 303(d) list) waters for which technology-based limits alone do not ensure attainment of applicable water quality standards). This has triggered an interstate water quality dispute between Oklahoma and Arkansas regarding the role that animal agriculture, particularly poultry, contributes to the existence of excess P concentrations. Animal waste is linked to some environmental problems, especially high P concentrations in the watershed water [*Sharpley et al.*, 2007]. Other nutrient sources, such as from wastewater treatment plants, industry, and construction, are acknowledged [*Haggard and Soerens*, 2006; *Popp et al.*, 2007] as contributors as well, but most attention remains focused on animal agriculture. More information regarding the lawsuit is given by *Haggard and Soerens* [2006] and *Sharpley et al.* [2007].

[4] While there is a need to reduce excess P from all potential sources, this paper focuses on addressing P runoff

[1]Department of Agricultural Economics and Agribusiness, University of Arkansas, Fayetteville, Arkansas, USA.
[2]Department of Agricultural and Biological Engineering, Purdue University, West Lafayette, Indiana, USA.

0043-1397/11/2009WR008549

from cattle and poultry operations in the watershed. Although several studies have analyzed P concentration in the watershed [e.g., *Haggard et al.*, 2003; *Haggard and Soerens*, 2006; *Massey et al.*, 2009], none have analyzed the combined effect that pastureland, buffer zone, and poultry litter management could have as a P or nitrogen (N) concentration reduction strategy. Therefore, the purpose of this study is to estimate the water quality benefit and cost tradeoffs associated with different watershed management strategies to optimize best management practice (BMP) implementation and water quality improvement at the watershed level. Specifically, the objective of this study is to apply a genetic algorithm (GA) to find near-optimal sets of BMPs that minimize total P (TP) or total N (TN) concentration and total cost (TC) increases simultaneously in the Lincoln Lake watershed (described in section 1.1) on the Arkansas side of the Illinois River watershed. A watershed management expert can use the results of this analysis to make his least cost decision by determining which set of BMP combinations could reduce nutrients to a specific target level.

[5] It is hypothesized that TP (or TN) concentration at the watershed outlet could be reduced without considerable increase in TC, as compared with current concentrations and costs, by optimizing selection and placement of sets of BMP combinations across the watershed. This study used a nondominated sorting GA (NSGA-II) to evaluate the optimal fitness of each BMP combination on the basis of subfield pollutant loads estimated with the Soil and Water Assessment Tool (SWAT) [*Arnold and Fohrer*, 2005; *Gassman et al.*, 2007], percent reductions of BMPs estimated by comparing to those concentrations generated under current management practices, and BMP costs.

1.1. Lincoln Lake Watershed

[6] This study was conducted in the Lincoln Lake watershed (35°58′29″N, 94°25′5″W), a subbasin within the Illinois River watershed. The Lincoln Lake watershed is a small agricultural watershed with a total contributing area of 32 km^2. Moores Creek and Beatty Branch are two major tributaries that flow into Lincoln Lake (Figure 1). Moores Creek and Beatty Branch drain 21 and 11 km^2, respectively [*Gitau et al.*, 2010].

[7] The Lincoln Lake watershed has an average 6% of slope, with the elevation approximately ranging from 365 to 487 m. The major soil series in the watershed are Enders gravelly loam, Hector-Mountainburg gravelly fine sandy loam, and Captina silt loam and Linker loam. These soil series account for 23%, 21%, and 13% of the entire area, respectively. An average annual precipitation (1230.5 mm) was observed during 1990–2002, with the lowest average precipitation (74 mm) in January and the highest average precipitation (158.3 mm) in April. The average minimum and maximum temperatures during 1990–2002 were 8.7°C and 20.1°C, respectively.

[8] The watershed has mixed land use, with agricultural, forest, urban residential, urban commercial, and water representing 36%, 48%, 12%, 2%, and 2% of the watershed area, respectively. Pasturelands (Bermuda grass fields) used for haying and/or grazing are the primary agricultural land use in the watershed. Urbanization in the watershed has been increasing during the last 2 decades, where urban areas have increased from 3% in 1992 to almost 12% in 2004. Concurrently, pastureland in the watershed has decreased from 43% to 36% during the same time period [*Gitau et al.*, 2010]. Animal manure, including land application of poultry litter, is the primary means of fertilizing pasture areas in the watershed.

[9] Flow and water quality data have been collected at three different sites in the watershed since 1991. *Chaubey et al.* [2010] and *Gitau et al.* [2010] provide a detailed description of the water quality data monitored in this watershed. Continuous streamflow was monitored using a pressure transducer to measure stream depth, which was subsequently converted to streamflow using site-specific depth-discharge rating curves. Concentrations of sediment and various forms of P (orthophosphate and TP) and N (nitrate, ammonia, and TN) were measured separately during base flow and stormflow conditions. An autosampler was used to collect flow-weighted storm samples. Similarly, grab samples at biweekly intervals were collected to quantify water quality during base flow conditions. Details of laboratory analyses are provided by *Vendrell et al.* [1997] and M. A. Nelson et al. (Water quality monitoring of Moores Creek above Lincoln Lake 2006 and 2007 unpublished manuscript, 2008).

[10] In 2005, the U.S. Department of Agriculture (USDA) funded a conservation effectiveness assessment project (CEAP) to quantify how different BMPs in the watershed impacted water quality [*Duriancik et al.*, 2008]. This watershed was selected because the agricultural production, BMPs, and water quality issues are representative of the political, economic, and ecological challenges facing resource managers across the region.

1.2. Description of the Soil and Water Assessment Tool Model

[11] Hydrological models are powerful tools for assessing nonpoint sources (NPS) of pollution and evaluating effectiveness of BMPs on large watersheds [*Srivastava et al.*, 2007; *Borah et al.*, 2006]. In this study, the SWAT model was used to quantify the impacts of BMP options on P and N transport. 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 NPS of pollution in complex watersheds [*Arnold and Fohrer*, 2005; *Neitsch et al.*, 2005a]. The SWAT model was selected because it is one of the most commonly used models to evaluate the implementation impacts of various BMPs on watershed response in the USDA CEAP studies [*Duriancik et al.*, 2008]. In addition, more than 650 peer-reviewed journal articles have been published demonstrating the utility of the SWAT model in evaluating impacts of land use, land cover, watershed management, and climate change on watershed hydrology and pollutant transport [*Gassman et al.*, 2007].

[12] SWAT has eight main components: hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, pesticides, and agricultural management. 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.

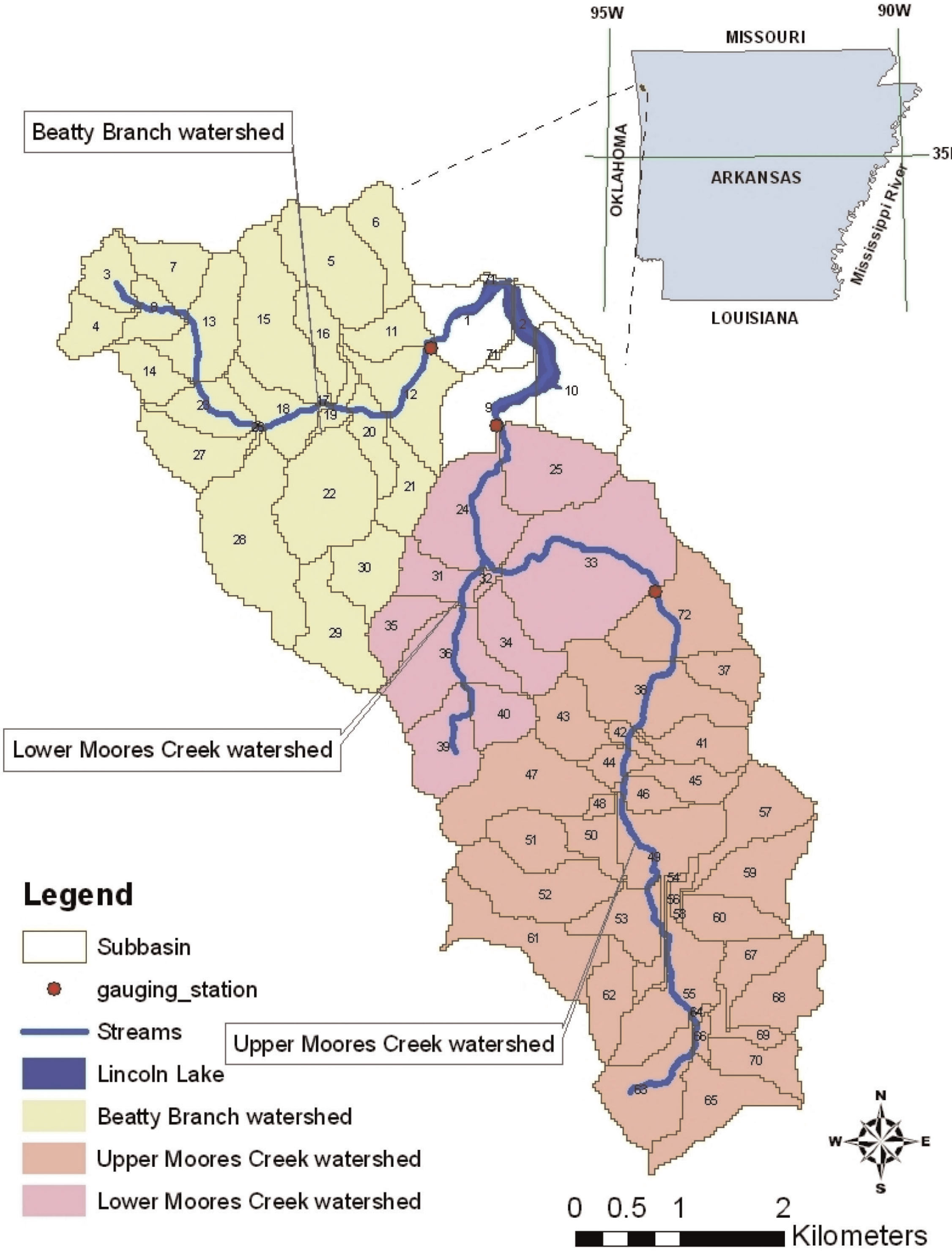

Figure 1. Lincoln Lake watershed and subbasins. The inset map on the top right shows the location of Lincoln Lake watershed in Arkansas and the neighboring states.

[13] The overall hydrologic balance is simulated for each HRU. Primary inputs 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 NPS pollutant loads. See *Gassman et al.* [2007] and *Neitsch et al.* [2005b] for further description of SWAT.

1.3. Genetic Algorithm

[14] A GA is a technique based on evolutionary principles of reproduction, recombination, and mutation that

seeks optimal solutions to solve a search problem [*Goldberg*, 1989; *Holland*, 1975]. It models individuals of a population as chromosomes (solutions) with genes on the chromosome encoding a specific trait of an individual. Alleles are the possible settings for a trait. Fitness of each chromosome is evaluated with objective functions that use the genetic information as the variables. More fit chromosomes are the most likely ones to survive into the next generation (iteration).

[15] This process occurs in generations starting with a random set of solutions. The fitness (i.e., the value of the objective function) of each individual in the population is evaluated; multiple individuals are randomly reproduced on the basis of their fitness and then randomly recombined and randomly mutated to form a new population [*Koza*, 1992]. This occurs in each generation (iteration). The new population is then used in the next iteration of the algorithm. The algorithm stops either when an adequate fitness level has been achieved for the population or when a maximum number of generations have been produced [*Koza*, 1992].

[16] Genetic algorithms have been applied to complicated 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. The literature is rich in examples of the use of GAs to find combinations of BMPs to reduce sediment runoff, nutrient runoff, or both at the watershed level. Several studies [*Arabi et al.*, 2006; *Gitau et al.*, 2006; *Veith et al.*, 2004] linked at least three components (a NPS 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 across the United States. This kind of optimization is functional. However, some of the studies concluded that a single objective function is not always the best alternative and that a more sophisticated and robust objective function should maximize pollutant reduction and minimize costs simultaneously.

[17] In contrast, other studies [*Bekele and Nicklow*, 2005; *Maringanti et al.*, 2009; *Muleta and Nicklow*, 2005] used multiobjective functions with conflicting objectives. As a result, these studies did not find a single optimal solution; rather, they provided trade-off curves between different objectives and alternative solutions. Agricultural water quality degradation is a multiobjective 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.

1.4. Multiobjective Optimization

[18] In this study NSGA-II was employed. This GA is a fast and efficient multiobjective evolutionary algorithm that finds multiple near-optimal solutions (Pareto-optimal solutions) in a single model execution [*Deb et al.*, 2002]. Finding Pareto-optimal solutions assure that none of the solutions dominate the other solutions. Consequently, every Pareto-optimal solution is better than the rest in at least one objective function. According to *Zitzler and Thiele* [1999], in a multiobjective optimization problem, if g_i, $\{i = 1,\ldots,M\}$, are the objective functions that need to be minimized, a solution $x^{(1)}$ is said to dominate $x^{(2)}$ if both of the following conditions are true:

$$\forall i \in \{1, \ldots, M\} : g_i(x^{(1)}) \le g_i(x^{(2)}),$$

$$\exists j \in \{1, \ldots, M\} : g_j(x^{(1)}) < g_j(x^{(2)}). \qquad (1)$$

[19] That is, $x^{(2)}$ is dominated by $x^{(1)}$, or in other words, $x^{(1)}$ is nondominated by $x^{(2)}$. Nondominance assures that the solutions are spread along a smooth curve when projected on a two-dimensional space. *Maringanti et al.* [2009] describe in more detail the nondominance property of a NSGA-II algorithm, and *Deb* [2001], *Deb et al.* [2002], and *Maringanti et al.* [2009] provide a detailed mathematical description of this algorithm.

2. Materials and Methods

[20] The approach proposed in this study linked three components as inputs into the NSGA-II multiobjective optimization model to evaluate the objective functions of a given chromosome (i.e., solution). The three components were (1) nutrient loading (i.e., TP or TN) at the HRU level generated in SWAT, (2) an allele set that provides all allowable BMP combinations to be implemented, and (3) nutrient reduction efficiency and implementation cost for each BMP combination. A C^{++} programming language implementation of NSGA-II was used to link these various components to evaluate the objective functions (equations (3) and (4)). As mentioned, this process occurs in generations starting from a random population. Individuals in the population reproduce, recombine, and mutate to create a new population for the next generation. The algorithm stops either when an adequate fitness level has been achieved or a maximum number of generations has been reached.

2.1. Best Management Practices Characterization

[21] Agricultural BMPs suggested by a collaborative dialogue among northwest Arkansas stakeholders [*Pennington et al.*, 2008; *Popp et al.*, 2007], practices used in the development of the Arkansas P index [*DeLaune et al.*, 2004], and previous BMP studies in the region [*Chaubey et al.*, 1995; *Srivastava et al.*, 1996; *Moore and Edwards*, 2007] served as the basis for the initial choice of BMP factors for inclusion in this analysis. The factors were grouped into three general categories: pastureland, buffer zone, and poultry litter management.

[22] Pastureland management contained one factor at three levels (no grazing, optimum grazing, and overgrazing). Grazing operations started on 30 September of each year. The number of days animals grazed in any given field varied for both overgrazing and optimum grazing. The overgrazing lasted for 213 days until 30 April of each year. The animals were rotated through various HRUs for optimum grazing such that a minimum biomass of 200 kg ha^{-1} was maintained in the field.

[23] Buffer zones contained one factor: buffer zone width at three levels (0, 15, and 30 m). Buffer zones were simulated to be placed at the edge of the pasture fields. The buffer widths (15 and 30 m) were based on previous studies evaluated in the pasture areas [*Chaubey et al.*, 1995] and

on research reported in the literature on recommended buffer widths for nutrient reductions [*Schmitt et al.*, 1999; *Mayer et al.*, 2005]. The SWAT model calculates trapping efficiency (trap) for sediment, nutrients, and pesticides as trap $= 0.367(\mathrm{FILTERW})^{0.2967}$ [*Neitsch et al.*, 2005a]. The trapping efficiency in the form of an exponential equation represents a significantly greater pollutant reduction for longer buffer lengths similar to the values measured by *Chaubey et al.* [1995] and *Srivastava et al.* [1996]. Recently, this process in the SWAT model has been improved with consideration of both sheet and concentrated overland flow conditions and evaluation of buffer zone performance separately for sediment-attached and soluble water quality parameters [*White and Arnold*, 2009]. However, this updated version was not available during our study.

[24] Poultry litter contained three factors: six poultry litter application rates (0, 2.5, 3.7, 4.9, 6.2, 7.4 t ha^{-1}), two litter characteristics (nonamended litter and alum-amended litter), and three application timings (spring, summer, and fall). Alum was applied at a rate of 10% by weight of the litter (i.e., 20,000 broilers produce approximately 20 t of moist litter per flock) to precipitate soluble P and consequently reduce P runoff [*Moore et al.*, 2004].

[25] The above categories lead to 171 different BMP combinations. Because all the BMPs were related to pasture management in the watershed, it was assumed that all BMPs were applicable to all pastureland in the watershed. This approach will not preclude any of the areas from being considered for any particular BMP. For comparison purposes, a baseline (optimal grazing, no buffer, 4.9 t ha^{-1} of poultry litter spread during the fall season, without alum) that represented the common practices that producers performed in the Lincoln Lake watershed was used.

[26] The number of BMP combinations analyzed was reduced to 35 on the basis of five rules. First, the baseline was excluded because it served as the basis for comparison. Second, all the BMP combinations that included overgrazing practices were excluded (57 BMP combinations) because overgrazing is not a sustainable agricultural practice and a preliminary analysis showed in every pasture HRU that overgrazing creates more pollution. Third, any other nonovergrazing BMP combination with pollution values greater than the baseline was also excluded because the goal of this study is to reduce pollutant loads. Fourth, nonpoultry litter applications were excluded because they are an unrealistic option for this watershed. Finally, poultry litter applications of 3.7 and 6.2 t ha^{-1} were excluded because a preliminary analysis showed that they were not chosen, except in a few instances, in the final solution. Table 1 displays the 35 BMP combinations and the baseline analyzed in this study.

2.2. SWAT Input Data

[27] Land use and land cover at 28.5 m resolution, elevation data at 30 m resolution, and SSURGO soil data were the primary geographic information system (GIS) input files needed for the SWAT model. The watershed was divided into 72 different subbasins on the basis of watershed topography and stream network using the SWAT ArcView (AVSWAT) interface [*Di Luzio et al.*, 2004]. The subbasins were further partitioned into HRUs on the basis of soil and land use characteristics.

[28] Highly detailed farm- and field-scale management data, including litter and nutrient management, animal grazing, and location of various BMPs in the watershed, were available from *Chaubey et al.* [2010]. A soil/land use threshold of 0%/0% was used in AVSWAT to delineate HRUs and to capture the detailed land management data that were available for the watershed. The 0%/0% threshold values for soils and land use is the most detailed representation of HRUs in the SWAT model, as it does not lump any soil or land use type into another category. Subsequently, for each subbasin, different combinations of land use and soils were mapped with the HRU codes generated by the SWAT model to give spatial representation of the HRUs. This also enabled us to differentiate the practical impacts of various BMP locations using the optimization program described in section 2.4.

[29] The primary SWAT outputs of interest were TP and TN. Although TP is the limiting nutrient in this watershed, TN was also evaluated since data for this nutrient were also available. Model-simulated and measured values of streamflow, sediment, TN, mineral P, and TP values were compared to validate the ability of the SWAT model to accurately simulate catchment responses. *Chaubey et al.* [2010] presented a detailed overview of the model performance for this watershed where they reported statistically similar values of TN, TP, sediment, and streamflow between simulated and measured data.

[30] Uncertainty in future weather conditions was captured by generating 250 different realizations of weather data from 2001 to 2028. The WXGEN [*Sharpley and Williams*, 1990] weather generator program generated the weather data using measured historical weather data from 1990 to 2003. The SWAT simulations for 2001–2003 were used as the model warm-up years. Data from 2004–2028 were used to optimize the BMPs in the watershed. Weather data used for all SWAT simulations and BMP combinations were the same. The SWAT model was run for 28 years (2001–2028) for each of the 36 BMP combinations. The 250 different weather realizations represent hypothetical uncertainty in future weather conditions; that is, these are not climate change projections. Averages of the 250 outputs, for each BMP combination, at the HRU level were used in the BMP optimization to generate TP and TN pollutant loads.

[31] Because poultry litter is only used to fertilize pastureland (i.e., Bermuda grass fields), only pasture areas (461 HRUs, or 35% of the overall land area) were considered for implementation of BMP combinations within the watershed. Average HRU weighted (by area) pollutant loads were estimated for all considered HRUs within the watershed to develop a single pollution value (i.e., TP or TN) for a particular BMP combination. This value was then compared to the baseline to obtain a percentage pollutant reduction value for each BMP combination. A preliminary analysis showed that TP and TN reductions were very similar over time. Because of the time involved in consolidating and analyzing results, only information from the first 5 years (i.e., an average from 2004 to 2008) for each pollutant was analyzed.

2.3. Total Cost of Production (Including BMP Costs)

[32] Standard costs of production for all BMP combinations included herbicides, implements, repair and maintenance, fuel

Table 1. BMP Combinations and Associated Total Cost

			Poultry Litter Management			
BMP Set	Grazing	Buffer Width (m)	Quantity (t ha^{-1})	Application Time	Alum	Total Cost[a] (\$ ha^{-1})
24	Optimal	0	2.47	Spring	No	288.33
36[b]	Optimal	0	4.94	Fall	No	314.01
78	Optimal	30	2.47	Spring	Yes	437.42
80	Optimal	30	4.94	Spring	Yes	577.25
81	Optimal	30	2.47	Spring	No	334.68
83	Optimal	30	4.94	Spring	No	371.76
84	Optimal	30	2.47	Summer	Yes	437.42
86	Optimal	30	4.94	Summer	Yes	577.25
87	Optimal	30	2.47	Summer	No	334.68
89	Optimal	30	4.94	Summer	No	371.76
90	Optimal	30	4.94	Fall	Yes	577.25
92	Optimal	30	7.41	Fall	Yes	717.07
93	Optimal	30	4.94	Fall	No	371.76
116	No	15	2.47	Spring	Yes	414.25
118	No	15	4.94	Spring	Yes	548.38
119	No	15	2.47	Spring	No	311.50
121	No	15	4.94	Spring	No	342.88
122	No	15	2.47	Summer	Yes	414.25
124	No	15	4.94	Summer	Yes	548.38
125	No	15	2.47	Summer	No	311.50
127	No	15	4.94	Summer	No	342.88
128	No	15	4.94	Fall	Yes	548.38
130	No	15	7.41	Fall	Yes	682.50
131	No	15	4.94	Fall	No	342.88
133	No	15	7.41	Fall	No	374.27
135	Optimal	15	2.47	Spring	Yes	414.25
137	Optimal	15	4.94	Spring	Yes	548.38
138	Optimal	15	2.47	Spring	No	311.50
140	Optimal	15	4.94	Spring	No	342.88
141	Optimal	15	2.47	Summer	Yes	414.25
143	Optimal	15	4.94	Summer	Yes	548.38
144	Optimal	15	2.47	Summer	No	311.50
146	Optimal	15	4.94	Summer	No	342.88
147	Optimal	15	4.94	Fall	Yes	548.38
149	Optimal	15	7.41	Fall	Yes	682.50
150	Optimal	15	4.94	Fall	No	342.88

[a]Five year average (2004–2008); total costs were estimated in 2004 dollars.
[b]Baseline.

diesel, interest on capital, and labor. Predetermined standard costs of production and costs of BMPs were estimated using information obtained for 2007. These were the most recent data available at the time of the calculation. A fixed rate of inflation was used to account for inflation effects each year. Total costs for each BMP combination were calculated with inflation from 2005 to 2028 and then annualized to 2004 (i.e., deflated to 2004 dollars).

[33] The costs for each BMP combination were calculated on the basis of the different practices used. Buffer zone costs were estimated following the Natural Resources Conservation Service (Riparian forest buffer (Ac.) code 391, Conservation practice standard, in Field Office Technical Guide Section IV, available at http://efotg.sc.egov.usda.gov/references/public/AR/391.pdf). Buffer zone costs were calculated assuming a predetermined buffer area. The area was estimated by multiplying the width (15 and 30 m) with a constant length of 30 m provided by Natural Resources Conservation Service (Filter strip (acre) code 393, Conservation practice specifications, in Field Office Technical Guide Section IV, available at http://efotg.sc.egov.usda.gov/references/public/AR/393spec.pdf). This length was chosen on the basis of the most predominant slope (>6%) in the watershed. Costs included establishment of the buffer every 10 years and maintaining the buffer 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 t^{-1}. This cost was provided by H. L. Goodwin (personal communication, 2008). Total costs for each BMP combination were calculated by adding the standard costs of production and the respective costs for each BMP combination. These costs can be expressed as follows:

$$TC_{j,k,l} = CP + CBMP_{j,k,l}, \quad (2)$$

where TC represents total cost of production, CP represents cost of production, CBMP represents BMP cost, j is buffer, k is poultry litter, and l is alum. BMP combination cost-effectiveness was estimated by calculating the percentage change in cost when compared to the cost of the baseline. Table 1 displays TC per hectare including BMP cost associated with each BMP combination.

2.4. NSGA-II Multiobjective Optimization Model Development

[34] Pollution loading output data from SWAT and cost data were the inputs used in the NSGA-II optimization

model. Output from SWAT provided pollutant (i.e., TP and TN) loads at the HRU level for each of the 35 BMP combinations analyzed in this study. Cost data for each BMP combination were used to calculate the percentage cost change from the baseline. This information was used to estimate each BMP combination effectiveness (percentage change from the baseline) to reduce TP or TN. Pollutant loadings (kg ha^{-1}) were averaged with area as a weight to estimate a load at the watershed level. Similarly, the unit cost for implementation of BMP (\$ ha^{-1}) was averaged to obtain a single cost estimate for BMP implementation at the watershed level. A weighted average of the pollutant loading per hectare (i.e., TP or TN) and the TC for each BMP combination at the HRU level was estimated at the watershed level.

[35] The objective was to minimize two objective functions: (1) percentage change in total pollutant runoff and (2) total cost increases at the watershed level. The following were the two objective functions that needed to be minimized during the optimization process:

$$f(X) = \left(\frac{\sum_{\mathrm{hru}=1}^{n\mathrm{HRU}} \left[P_{\mathrm{pol,hru}} (1 - R_{\mathrm{pol,bmp}}) A_{\mathrm{hru}} \right]}{\sum_{\mathrm{hru}=1}^{\mathrm{nHRU}} (P_{\mathrm{pol,hru}} A_{\mathrm{hru}})} \right) \tag{3}$$

$$g(X) = \left(\frac{\sum_{\mathrm{hru}=1}^{n\mathrm{HRU}} (C_{\mathrm{hru}} A_{\mathrm{hru}})}{\sum_{\mathrm{hru}=1}^{n\mathrm{HRU}} A_{\mathrm{hru}}} \right), \tag{4}$$

where HRU represents the hydrologic response unit in the watershed, *P* is the unit pollutant load from a HRU (i.e., TP or TN), *R* is the pollutant reduction efficiency of BMP, *A* is the area of each HRU, and *C* is the unit cost of each BMP combination.

[36] Placement of BMP combinations was planned for the HRU level. Thus, the searching space consisted of 35^{461} possible combinations (i.e., any BMP combination of the 35 available can be placed in any of the 461 pasture HRUs). NSGA-II simulates individuals of a population as chromosomes (solutions), which in turn contain genes (HRUs) as the building blocks (in this case each chromosome consists of 461 genes), and each of these genes represents a particular set of BMPs (BMP combination) on the chromosome encoding a specific trait.

[37] The NSGA-II results are very sensitive to the operational parameters that define the search algorithm. In order to search effectively for near-optimal solutions, the optimal NSGA-II operational parameters, such as population size, number of generations, crossover, and mutation rates, need to be estimated. This task was performed by using a nonlinear sensitivity analysis in which different values of the NSGA-II operational parameters were incremented one at a time at the end of the final generation using different population sizes, numbers of generations, mutations, and crossover probabilities. *Maringanti et al.* [2009] provide more details of how to conduct sensitivity analyses to estimate GA parameters.

[38] Table 2 describes the parameters that were used during the sensitivity analyses. The final optimization model ran for 10,000 generations and 800 populations. The crossover and mutation probabilities generated the offspring. Crossover and mutation probabilities of 0.700 and 0.005, respectively, were identified as the most efficient parameter values. These parameter values were used for optimizing the selection and the placement of BMP combinations per the TP and TN models developed in this study. These optimization models (with 10,000 generations and 800 populations for generation) were completed in less than 1 h using a SiCortex 5832 supercomputer that consists of 812 Dell PowerEdge 1950 Dual Quad-Core computer nodes.

Table 2. Genetic Algorithm Parameters and the Values That Were Modified During the Sensitivity Analysis

Parameter	Values
Number of generations	1,000; 2,000; 5,000; 10,000; 20,000
Population size	100; 200; 400; 800; 1,000
Mutation rate	0.0005; 0.0001; 0.005; 0.001; 0.01
Crossover rate	0.1; 0.3; 0.5; 0.6; 0.7

[39] The final solution is represented by generation 10,000. This generation contained 800 solution sets (sets of BMP combinations) corresponding to each of the chromosomes. Each population represents a final near-optimal solution with a nutrient concentration load and its corresponding TC. Each solution provides a set of 461 BMP combinations to be placed in each of the pasture HRUs (461 HRUs) across the watershed.

3. Results and Discussion

[40] The NSGA-II optimally selected and placed BMP combinations (alleles) according to their pollutant load reduction and TC change in each of the 461 pasture HRUs. The results are divided in three sections: TP and TC, TN and TC, and an analysis of the joint optimization problems.

3.1. Total Phosphorous and Total Cost

[41] This optimization problem evaluated the cost-effectiveness of selecting and placing BMP combinations to reduce TP while simultaneously minimizing TC. The baseline 5 year weighted average TP loading estimated at the watershed outlet was 0.505 kg ha^{-1}. The spread of the solution was improved significantly during the optimization process (Figure 2).

[42] As expected, the NSGA-II generated a number of near-optimal solutions by selecting and placing BMP combinations (alleles) that minimized both TP runoff and TC increases for Bermuda grass producers at the watershed level. The final Pareto-optimal solution displays a range of chromosomes that when compared to the baseline, reduces TP considerably.

[43] The final generation was widespread without solutions being concentrated either in the lower or in the higher TC, giving decision makers a broader set of options from which to select. It is important to highlight that each dot in Figure 2 represents a chromosome (solution) and each chromosome has 461 genes (each gene has a specific BMP combination, or allele), one for each pasture HRU. To illustrate this process, from generation 10,000, three solutions of the 800 available were chosen: the lowest cost (chromosome 459), the medium cost (chromosome 191), and the highest cost (chromosome 606).

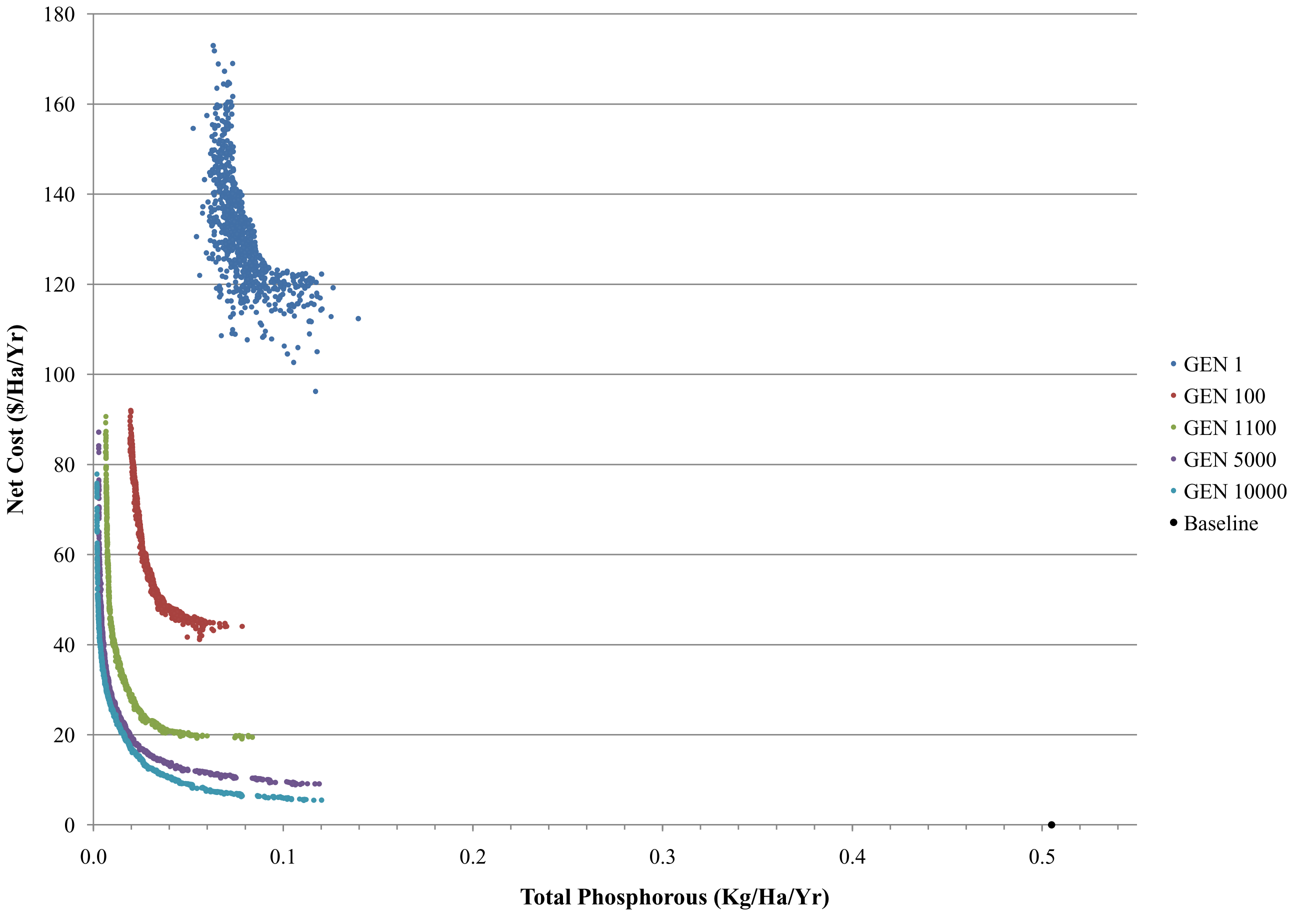

Figure 2. Progress of the Pareto-optimal front for total phosphorous and total cost.

[44] Table 3 shows the frequency distributions (in percent) of the BMP combinations selected for each of the cost solutions analyzed in this example. Table 4 exhibits the frequency distributions (%) of the factors that create each BMP combination. Figure 3 exhibits the selection and spatial placement of BMP combinations within the watershed (at the HRU level). TP loads were reduced by at least 76% under all cost implementation solutions.

[45] The NSGA-II assigned mainly BMP combinations that included optimal grazing practices, a buffer zone, and 2.5 t ha^{-1} of poultry litter, with no alum and spread during the summer (Table 4). Optimal grazing practices were placed on 64%, 66%, and 84% of the HRUs for the lowest-, the medium-, and the highest-cost populations, respectively. The optimal grazing management practices are preferred because producers need to maintain a minimum biomass per hectare during grazing [*Neitsch et al.*, 2005b]. In other words, this practice offers permanent ground cover while reducing runoff.

[46] The most common optimal grazing BMP combinations were 81 and 87 (see Tables 1, 3, and 4). These two BMP combinations were placed on 31% of the pasture HRUs in the medium-cost population, on 26% in the high-cost population, and on 15% in the lowest-cost population. The most common nongrazing BMP combination was 125 (see Tables 1, 3, and 4). This BMP combination was most preferred in the lowest- and the medium-cost solutions covering at least 10% of all pasture HRUs.

[47] Not surprisingly, high TP loading reductions were obtained when buffer zones were used. Buffer zones were placed on at least 86% of the pasture HRUs for all three levels of costs (Table 4). Under the lowest- and the medium-cost solutions, 15 m wide buffers were preferred over 30 m wide buffers. The highest-cost population placed a buffer zone in almost all of the pasture HRUs. However, 30 m wide buffers were preferred. This explains, in part, the high TP reduction and high cost of this population, as shown in Tables 3 and 4.

[48] BMP combinations that include applications of 4.9 t ha^{-1} or less of poultry litter were placed in at least 94% of the HRUs for the three cost solutions analyzed. However, BMP combinations that recommend applications of 2.5 t ha^{-1} of poultry litter were preferred (Table 3). Low poultry litter applications (2.5 t ha^{-1}) may be preferred for two reasons: (1) they are less expensive, and (2) P concentration in soil may be decreased since less P is available for runoff.

[49] Even though studies have proved that alum reduces TP [*Moore and Edwards*, 2007; *Shreve et al.*, 1995], poultry litter treated with alum was not selected frequently by the GA. In fact, this practice was not used in at least 86% of the pasture HRUs for the lowest- and the medium-cost

Table 3. BMP Combination Frequency Distributions (%) for the Lowest-, the Medium-, and the Highest-Cost Solutions for Total Phosphorous (TP) and Total Nitrogen (TN) for Generation 10,000

	Lowest Cost		Medium Cost		Highest Cost	
BMP Set	TP	TN	TP	TN	TP	TN
0	3.3	2.0	0.4	2.8	0.0	1.1
24	7.2	0.9	1.1	5.4	0.4	2.4
36	3.5	1.3	0.7	3.5	0.0	1.7
78	1.1	1.1	1.1	1.3	4.1	1.1
80	0.4	0.9	0.7	0.4	3.7	0.4
81	8.2	15.6	16.1	8.9	14.1	14.8
83	3.3	4.1	4.8	3.0	8.9	2.8
84	0.9	1.7	1.5	0.9	6.9	1.5
86	0.2	0.4	0.9	0.0	5.4	0.0
87	7.2	10.4	14.5	8.0	12.1	9.8
89	2.0	2.2	2.6	3.3	6.7	2.2
90	0.4	0.0	0.4	0.0	1.7	0.0
92	0.4	0.7	0.2	0.0	3.9	0.7
93	2.8	2.6	4.8	3.0	9.1	4.1
116	1.5	0.7	1.7	1.3	0.7	1.3
118	0.4	0.2	0.0	0.0	0.7	0.7
119	9.3	10.0	7.8	9.8	1.1	8.0
121	2.8	3.0	3.0	2.8	1.1	3.9
122	0.4	0.9	0.9	0.7	0.7	1.3
124	0.2	0.2	0.4	0.4	0.9	0.4
125	10.4	10.8	10.2	11.7	6.3	10.0
127	2.4	3.3	4.1	2.4	2.2	3.5
128	0.2	0.2	0.7	0.0	0.7	0.4
130	0.0	0.0	0.0	0.2	0.7	0.0
131	3.0	3.7	2.6	3.9	1.1	3.0
133	1.7	0.7	2.4	2.6	0.0	1.3
135	1.5	1.3	0.7	0.9	0.9	1.3
137	0.0	0.2	0.4	0.7	0.7	0.0
138	7.6	6.5	3.7	7.6	0.7	7.8
140	1.7	2.0	1.1	1.5	1.1	2.8
141	1.3	1.5	0.7	0.2	0.2	0.9
143	0.7	0.7	0.4	1.1	0.4	0.4
144	8.3	6.7	5.4	6.7	0.7	5.4
146	2.6	1.7	2.2	2.6	0.9	1.7
147	0.2	0.4	0.4	0.4	0.7	1.1
149	0.4	0.0	0.2	0.0	0.4	0.0
150	2.4	1.5	1.3	2.0	0.4	2.2

Table 4. BMP Combination Frequency Distributions (%) by Factor for the Lowest-, the Medium-, and the Highest-Cost Solutions for Total Phosphorous (TP) and Total Nitrogen (TN) for Generation 10,000

	Lowest Cost		Medium Cost		Highest Cost	
	TP	TN	TP	TN	TP	TN
Grazing						
No	32.5	33.6	33.8	35.8	15.8	33.8
Optimal	64.2	64.4	65.7	61.2	84.2	65.1
Buffer zone						
0 m	10.6	2.2	1.7	8.9	0.4	4.1
15 m	59.2	56.2	50.3	59.4	22.8	57.5
30 m	26.9	39.7	47.5	28.6	76.8	37.3
Poultry litter quantity						
0.0 t ha^{-1}	3.3	2.0	0.4	2.8	0.0	1.1
2.5 t ha^{-1}	64.9	68.1	65.3	63.1	48.8	65.5
4.9 t ha^{-1}	29.3	28.6	31.5	31.0	46.2	31.5
7.4 t ha^{-1}	2.6	1.3	2.8	2.8	5.0	2.0
Alum						
No	86.3	87.0	88.3	88.5	66.8	87.4
Yes	10.4	11.1	11.3	8.5	33.2	11.5
Timing						
Spring	45.1	46.4	42.1	43.4	38.0	47.3
Summer	36.4	40.6	43.8	38.0	43.4	37.1
Fall	15.2	11.1	13.7	15.6	18.7	14.5

solutions. However, alum was placed in one third of the HRUs for the highest-cost population. This factor also explains the high TP reduction and high TC (Table 3).

[50] Timing of litter application seems to be important. BMP combinations that recommend spring and summer litter applications were placed on at least 81% of the HRUs for all three populations, but there is a slight preference for summer applications. However, fall application, which is the common practice in the watershed, was less preferred.

[51] BMP combinations that recommend optimal grazing, a small buffer (15 m), and a spring application of 2.5 t ha^{-1} of poultry litter (without being amended with alum) were recommended for the lowest-cost solution. However, by implementing all the BMP combinations recommended in population 459 (461 BMP combinations, one for each pasture HRU), TP could be reduced by at least 76% while increasing TC by no more than $5804, or less than 2%, for the entire watershed. This value represents an increase in TC of $5.49 ha^{-1} when compared to the baseline (see Table 3). Implementing all the BMP combinations proposed with the medium- and the highest-cost solutions will decrease TP drastically but will increase TC in the entire watershed by $24,282 (7%) and $82,306 (25%), respectively.

3.2. Total Nitrogen and Total Cost

[52] This optimization problem evaluated the cost-effectiveness of selecting and placing BMP combinations to reduce TN while simultaneously minimizing TC increase from the baseline. The baseline 5 year weighted average for TN loading estimated at the watershed outlet was 0.952 kg ha^{-1}. Figure 4 displays the improvement of the solution during the optimization process. As with the previous optimization problem, the NSGA-II generated a number of near-optimal solutions by selecting and placing BMP combinations that minimized TN runoff and minimized TC increases for Bermuda grass producers at the watershed level.

[53] It is expected that decision makers will select solutions that do not increase TC, as the TN reduction benefits are marginal when selecting more expensive solutions (Figure 5). As with the previous optimization problem, three chromosomes were chosen from generation 10,000; the lowest cost (chromosome 530), the medium cost (chromosome 406) and the highest cost (chromosome 355). Table 4 displays the value of the objective functions for each of the solutions analyzed in this example.

[54] For all cost implementation solutions, TN loads were reduced by at least 98.9%. Table 4 shows that optimal grazing practices were placed on 64%, 61%, and 65% of the HRUs for the lowest-, the medium- and the highest-cost solutions, respectively. As with the previous optimization problem, the most common optimal grazing BMP combinations were 81 and 87 (see Tables 1 and 3).

[55] These two BMP combinations were most preferred in the lowest-cost solution, where they were placed on 26% of the HRUs, followed by the highest-cost solution (25%) and by the medium-cost solution (17%). Similarly, the

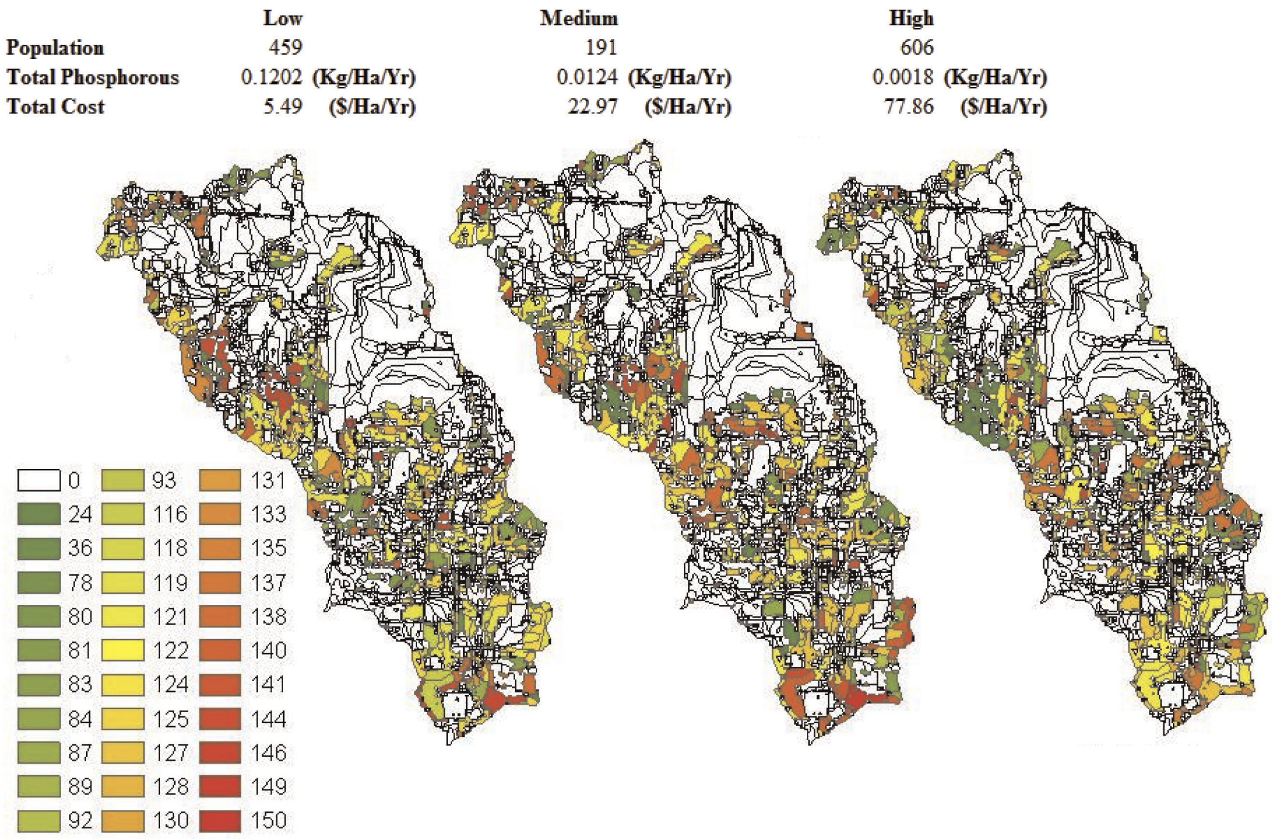

Figure 3. Selection and location of BMP combinations to control total phosphorous under three cost solutions for generation 10,000.

most common nongrazing BMP combination was 125. This BMP combination was implemented in at least 10% of all HRUs regarding the cost solution analyzed (Table 3).

[56] Buffer zones proved to be effective at reducing TN as well and were placed in all three cost solutions. A buffer zone was suggested for implementation in 96%, 88%, and 95% of the HRUs for the lowest-, the medium-, and the highest-cost solutions, respectively (Table 4). BMP combinations that include smaller buffer zones are less expensive than those with larger buffer zones (see Table 1). This could explain, in part, why smaller buffer zones were preferred in all cost solutions.

[57] BMP combinations that include poultry litter applications of 4.9 t ha^{-1} or less were placed in at least 94% of the HRUs for the three cost solutions analyzed. Still, BMP combinations that recommend poultry litter applications of 2.5 t ha^{-1} were preferred (Table 4). A low poultry litter application rate may be preferred for three reasons: (1) it is less expensive, (2) it contains less N than higher application rates, and (3) it is expected that Bermuda grass will increase N uptakes because lesser amounts of this element are available.

[58] Poultry litter treated with alum was not a very common practice to reduce TN. This practice was not recommended to be used in at least 87% of the HRUs. Conversely, timing of litter application seems to be important to reduce TN runoff. BMP combinations that recommend spring and summer litter applications were placed on at least 84% of the HRUs for all three cost solutions. However, spring applications of poultry litter were more popular. Preference for BMP combinations where poultry litter is applied during the spring could be explained by the ability of Bermuda grass to respond promptly (i.e., nutrient uptake) to applied fertilizer, especially nitrogen [*Slaton et al.*, 2006].

[59] The NSGA-II predominantly recommended assigning BMP combinations with optimal grazing practices, a buffer zone, and spring applications of 2.5 t ha^{-1} of poultry litter (without being amended with alum) for the three cost solutions analyzed. The analysis shows that TN runoff could be reduced substantially without increasing TC. Although this outcome was unexpected, it was noticed that five BMP combinations (24, 119, 125, 138, and 144) cost less than the baseline (see Table 1). These five BMP combinations were recommended to be implemented in 35%, 41%, and 34% of the pasture HRUs for the lowest-, the medium-, and the highest-cost solutions, respectively. This explains, in part, the low cost obtained with the three chromosomes analyzed.

[60] The high TN reductions could be explained by two major factors. First, four of the five BMP combinations mentioned above (119, 125, 138, and 144) recommend implementing a small buffer (15 m). Several studies conducted in northwest Arkansas [*Chaubey et al.*, 1995; *Srivastava et al.*, 1996] have shown the effectiveness of buffer zones to reduce runoff losses of nutrients from land areas treated with animal manure. Second, BMP combinations including poultry litter applications of 4.9 t ha^{-1} or

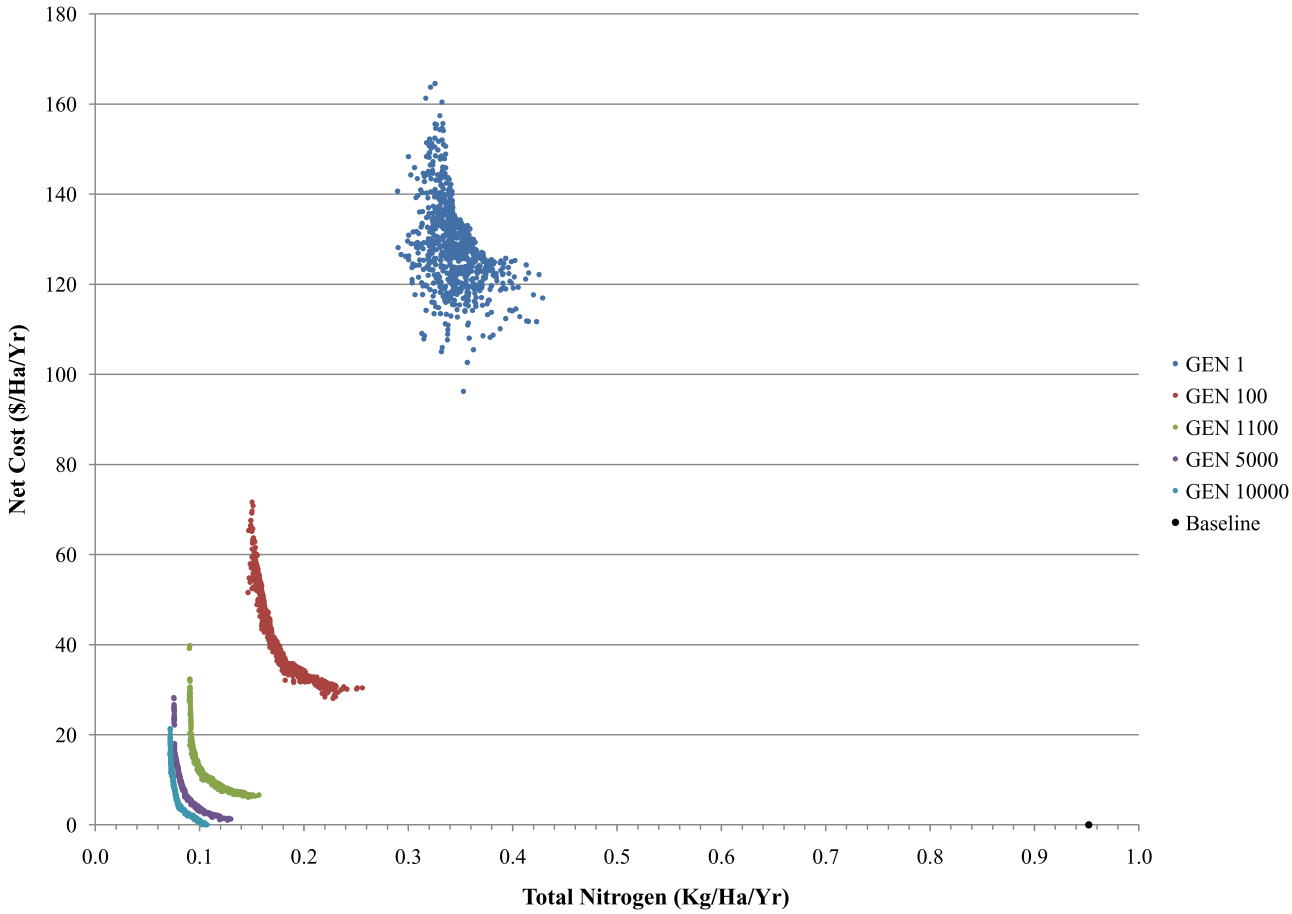

Figure 4. Progress of the Pareto-optimal front for total nitrogen and total cost.

less were recommended to be placed on 97%, 94%, and 97% of the pasture HRUs for the lowest-, the medium-, and the highest-cost solutions, respectively.

3.3. Joint Optimization Problems (TP and TN)

[61] Table 3 shows that of the 36 BMP combinations available, all of them have the potential to reduce TP. However, BMP combinations 90 and 149 were not recommended to reduce TN in any of the sample cost solutions analyzed. The cost of these BMP combinations could potentially affect their selection. Table 1 shows that these two BMP combinations are very expensive when compared to the baseline. Consequently, only two BMP combinations were not recommended to reduce TP and TN simultaneously.

[62] The variability in selecting BMP combinations to reduce both nutrients simultaneously can be seen from both Table 3 and Table 4. Across the lowest-, the medium-, and the highest-cost solutions, only six BMP combinations (81, 87, 119, 125, 138, and 144) were more frequently suggested (often ranked within the top five in terms of the frequency distribution) for implementation to reduce both TP and TN simultaneously than any other BMP combination. These six BMP combinations were recommended to be placed in at least 51%, 53%, and 35% of the HRUs for the lowest-, the medium-, and the highest-cost solutions, respectively. However, these BMP combinations overlapped in the same HRUs in only 31% of the lowest-cost solutions, 25% of the medium-cost solutions, and 10% of the highest-cost solutions. These results imply that selection and placement of BMP combinations are important factors to consider to achieve TP and TN reduction goals simultaneously in this watershed.

[63] Even though the majority of the BMP combinations analyzed were recommended to reduce both nutrients, their frequencies and placement distributions across the HRUs will determine their effectiveness. Consequently, policy makers should set nutrients reduction goals for the watershed. Once those nutrient reduction goals are established, a watershed management expert could make a decision by determining which set of BMP combinations could reduce nutrients to a specific target level at the lowest cost. Then, this information could be made available to the producers in the watershed.

4. Conclusions

[64] This study uses a NSGA-II, which allowed pollutant runoff and TC to be minimized simultaneously. This optimization technique determined the specific set of BMP combinations to reduce a pollutant of interest in a cost-effective way. The methodology used in this study linked HRU-level pollutant loadings for 35 BMP combinations and their TC with a NSGA-II. The methodology was

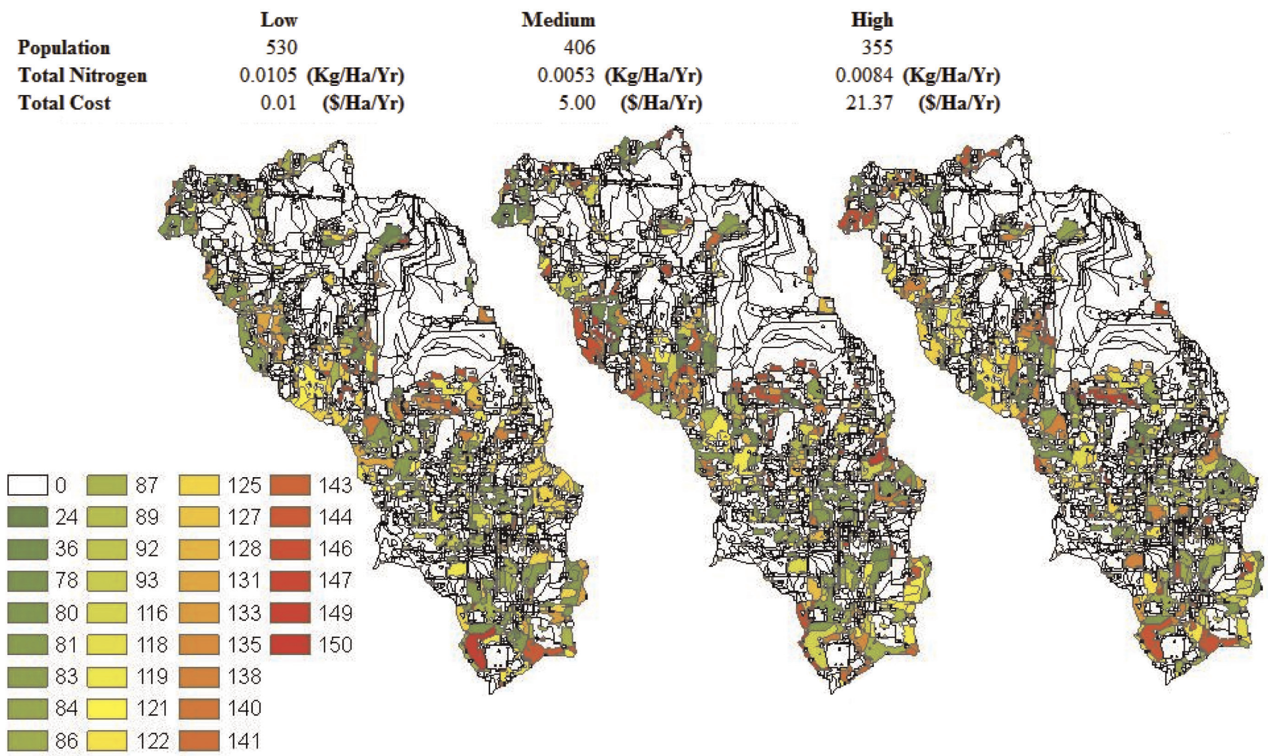

Figure 5. Selection and location of BMP combinations to control total nitrogen under three cost solutions for generation 10,000.

demonstrated in the Lincoln Lake watershed, where TP pollution has been a major concern.

[65] Results from this research offer policy options that take into consideration environmental benefits and economic costs of various BMP alternatives. These results provide watershed management experts with a wide range of near-optimal solutions when trade-offs between environmental and economic conditions must be analyzed simultaneously.

[66] Economic pressures create disincentives for producers to include water quality management practices in their management plans. In this regard, the near-optimal solutions not only offer economic savings predicted within the model, but also ensure that meaningful pollution reductions will occur for each nutrient. This contributes to a policy framework to maximize participation and benefits for all stakeholders involved in the process.

[67] The advantages and novelty of this methodology for policy makers and watershed management experts lie in two aspects: (1) the ability to identify and view the Pareto-optimal front of two objective functions simultaneously (i.e., TP/TC or TN/TC) and (2) the flexibility to select any set of BMP combinations (i.e., there are 800 nondominated sets of solutions for each pollutant) and still obtain an optimal solution that better fits the production and environmental goals of the watershed than the baseline solution.

[68] Although the methodology proved to be effective in finding near-optimal solutions for a single pollutant, the work of *Rabotyagov et al.* [2010] and *Whittaker et al.* [2009] could be the starting point to develop further modeling approaches that can optimize selection and placement of BMP combinations that reduce several pollutants (i.e., sediments, N, P, etc.) and reduce cost simultaneously. The approach proposed in those two studies will be useful to extend this analysis to include environmental policy instruments that help to address the interstate water quality dispute between Oklahoma and Arkansas. Challenges will exist, including data availability, data collection methodology specific to this multiobjective optimization process, and visualization of the results for higher-dimensional problems.

[69] Additionally, as currently modeled in SWAT, buffer zones drastically reduce pollutant losses. The BMP optimization should be conducted with the new algorithms [*White and Arnold*, 2009] to compare the reduction in pollutant losses due to buffer zones. This algorithm was not available at the time of our modeling efforts.

[70] **Acknowledgments.** Funding for this research was provided by the USDA CSREES under Conservation Effects Assessment Project Grant Program (award 2005-48619-03334). The authors thank Margaret Gitau and Li-Chi Chiang for their technical expertise on the SWAT simulation model.

References

Arabi, M., R. S. Govindaraju, and M. M. Hantush (2006), Cost-effective allocation of watershed management practices using a genetic algorithm, *Water Resour. Res.*, *42*, W10429, doi:10.1029/2006WR004931.

Arkansas Department of Environmental Quality (2008), 2008 list of impaired waterbodies (303(d) list), report, North Little Rock. (Available at http://www.adeq.state.ar.us/water/branch_planning/pdfs/303d_list_2008.pdf)

Arnold, J. G., and N. Fohrer (2005), SWAT 2000: Current capabilities and research opportunities in applied watershed modeling, *Hydrol. Processes*, *19*, 563–572, doi:10.1002/hyp.5611.

Bekele, E. G., and J. W. Nicklow (2005), Multiobjective management of ecosystem services by integrative watershed modeling and evolutionary algorithms, *Water Resour. Res.*, *41*, W10406, doi:10.1029/2005WR004090.

Borah, D. K., G. Yagow, A. Saleh, P. L. Barnes, W. Rosenthal, E. C. Krug, and L. M. Hauck (2006), Sediment and nutrient modeling for TMDL development and implementation, *Trans. ASABE*, *49*, 967–986.

Chambers, L. (2001), *The Practical Handbook of Genetic Algorithms: Applications*, 2nd ed., 501 pp., Chapman and Hall, Boca Raton, Fla.

Chaubey, I., D. R. Edwards, T. C. Daniel, P. A. Moore, and D. J. Nichols (1995), Effectiveness of vegetative filter strips in controlling losses of surface-applied poultry litter constituents, *Trans. ASAE*, *38*, 1687–1692.

Chaubey, I., L. Chiang, M. Gitau, and S. Mohamed (2010), Effectiveness of BMPs in improving water quality in a pasture dominated watershed, *J. Soil Water Conserv., 65*(6), 424–437, doi:10.2489/jswc.65.6.424.

Deb, K. (2001), *Multi-objective Optimization Using Evolutionary Algorithms*, John Wiley, New York.

Deb, K., A. Pratap, S. Agarwal, and T. Meyarivan (2002), A fast and elitist multiobjective genetic algorithm: NSGA-II, *IEEE Trans. Evol. Comput.*, *6*, 182–197.

DeLaune, P. B., P. A. Moore, D. K. C. Carman, A. N. Sharpley, B. E. Haggard, and T. C. Daniel (2004), Development of a phosphorus index for pastures fertilized with poultry litter—Factors affecting phosphorus runoff, *J Environ. Qual.*, *33*, 2183–2191, doi:10.2134/jeq2004.2183.

Di Luzio, M., R. Srinivasan, and J. G. Arnold (2004), A GIS-coupled hydrological model system for the watershed assessment of agricultural nonpoint and point sources of pollution, *Trans. GIS*, *8*, 113–136.

Duriancik, L. F., et al. (2008), The first five years of the Conservation Effects Assessment Project, *J. Soil Water Conserv.*, *63*, 185A–197A, doi:10.2489/jswc.63.6.185A.

Gassman, P. W., M. R. Reyes, C. H. Green, and J. G. Arnold (2007), The Soil Water Assessment Tool: Historical development, applications, and future research directions, *Trans. ASABE*, *50*, 1211–1250.

Gitau, M. W., T. L. Veith, W. J. Gburek, and A. R. Jarrett (2006), Watershed level best management practice selection and placement in the town Brook watershed, New York, *J. Am. Water Resour. Assoc.*, *42*, 1565–1581.

Gitau, M., I. Chaubey, E. Gbur, J. Pennington, and B. Gorham (2010), Impact of land use change and BMP implementation on water quality in a pastured northwest Arkansas watershed, *J. Soil Water Conserv.*, *65*(6), 353–368, doi:10.2489/jswc.65.6.353.

Goldberg, D. E. (1989), *Genetic Algorithms in Search, Optimization and Machine Learning*, Addison-Wesley, Boston, Mass.

Haggard, B. E., and T. S. Soerens (2006), Sediment phosphorous release at a small impoundment on the Illinois River, Arkansas and Oklahoma, USA, *Biol. Eng.*, *28*, 280–287, doi:10.1016/j.ecoleng.2006.07.013.

Haggard, B. E., T. Soerens, W. R. Green, and R. P. Richards (2003), Using regression methods to estimate stream phosphorous loads at the Illinois River, Arkansas, *Appl. Eng. Agric.*, *19*, 187–194.

Holland, J. H. (1975), *Adaptation in Natural and Artificial Systems: An Introductory Analysis With Applications to Biology, Control, and Artificial Intelligence*, 1st MIT Press ed., 211 pp., MIT Press, Cambridge, Mass.

Koza, J. R. (1992), *Genetic Programming: On the Programming of Computers by Means of Natural Selection*, 819 pp., MIT Press, Cambridge, Mass.

Maringanti, C., I. Chaubey, and J. Popp (2009), Development of a multiobjective optimization tool for the selection and placement of best management practices for nonpoint source pollution control, *Water Resour. Res.*, *45*, W06406, doi:10.1029/2008WR007094.

Massey, L. B., L. W. Cash, and B. E. Haggard (2009), Water quality sampling, analysis and annual load determinations for the Illinois River at Arkansas Highway 59 bridge, 2008, *Arkansas Soil Fertil. Stud., MSC 352*, 1–11.

Mayer, P. M., S. K. Reynolds, T. J. Canfield, and M. D. McCutchen (2005), Riparian buffer width, vegetative cover, and nitrogen removal effectiveness: A review of current science and regulations, *Rep. EPA/600/R-05/118*, U.S. Environ. Prot. Agency, Washington, D. C.

Moore, P. A., and D. R. Edwards (2007), Long-term effects of poultry litter, alum-treated litter, and ammonium nitrate on phosphorus availability in soils, *J. Environ. Qual.*, *36*, 163–174, doi:10.2134/jeq2004.0472.

Moore, P. A., S. Watkins, D. Carmen, and P. B. DeLaune (2004), Treating poultry litter with alum, *Rep. FSA8003-PD-1-04N*, Coop. Extension Serv., Div. of Agr., Univ. of Arkansas, Little Rock.

Muleta, M. K., and J. W. Nicklow (2005), Decision support for watershed management using evolutionary algorithms, *J. Water Resour. Plann. Manage.*, *131*, 35–44, doi:10.1061/(ASCE)0733-9496(2005)131:1(35).

Natural Resources Conservation Service Arkansas (2002), Buffer strip code 391, *Conserv. Pract. Stand. 1*, 1–5.

Neitsch, S. L., J. G. Arnold, J. R. Kiniry, and J. R. Williams (2005a), Soil and Water Assessment Tool theoretical documentation, version 2005, 494 pp., Grassland, Soil and Water Res. Lab., Agric. Res. Serv., Temple, Tex. (Available at http://swatmodel.tamu.edu/media/1292/SWAT2005theory.pdf)

Neitsch, S. L., J. G. Arnold, J. R. Kiniry, R. Srinivasan, and J. R. Williams (2005b), Soil and Water Assessment Tool: Input/output file documentation, version 2005, 541 pp., Grassland, Soil and Water Res. Lab., Agric. Res. Serv., Temple, Tex. (Available at http://swatmodel.tamu.edu/media/1291/SWAT2005io.pdf)

Pennington, J., M. A. Steele, K. A. Teague, B. Kurz, E. Gbur, J. Popp, G. Rodríguez, I. Chaubey, M. Gitau, and M. A. Nelson (2008), Breaking ground: A cooperative approach to data collection from an initially uncooperative population, *J. Soil Water Conserv.*, *63*, 208–211, doi:10.2489/jswc.63.6.208A.

Popp, J., H. G. Rodríguez, E. Gbur, and J. Pennington (2007), The role of stakeholders' perceptions in addressing water quality disputes in an embattled watershed, *J. Environ. Monit. Restor.*, *3*, 255–263, doi:10.4029/2007jemrest3no125.

Popp, J., N. Kemper, W. Miller, K. McGraw, and K. Karr (2010), Contribution of the agricultural sector to the Arkansas economy in 2007, *Res. Rep. 989*, Arkansas Agric. Exp. Stn., Div. of Agric., Univ. of Arkansas, Fayetteville.

Rabotyagov, S., T. Campbell, M. Jha, P.W. Gassman, J. Arnold, L. Kurkalova, S. Secchi, H. Feng and C. L. Kling (2010), Least cost control of agricultural nutrient contributions to the Gulf of Mexico hypoxic zone, *Ecol. Appl.*, *20*, 1542–1555, doi:10.1890/08-0680.1.

Schmitt, T. J., M. G. Dosskey, and K. D. Hoagland (1999), Filter strip performance and processes for different vegetation, widths, and contaminants, *J. Environ. Qual.*, *28*, 1479–1489, doi:10.2134/jeq1999.00472425002800050013x.

Sharpley, A. N., and J. R. Williams (1990), EPIC-erosion productivity impact calculator, 1. Model documentation, *Tech. Bull. 1768*, Agric. Res. Serv., U.S. Dep. of Agric., Washington, D. C.

Sharpley, A. N., S. Herron, and T. Daniel (2007), Overcoming the challenges of phosphorus-based management in poultry farming, *J. Soil Water Conserv.*, *62*, 375–389.

Shreve, B. R., P. A. Moore, T. C. Daniel, D. R. Edwards, and D. M. Miller (1995), Reduction of phosphorus in runoff from field-applied poultry litter using chemical amendments, *J. Environ. Qual.*, *24*, 106–111, doi:10.2134/jeq1995.00472425002400010015x.

Slaton, N. A., R. E. Delong, B. R. Golden, C. G. Massey, and T. L. Roberts (2006), Bermuda grass forage response to nitrogen, phosphorous and potassium fertilization rate, *Arkansas Soil Fertil. Stud.*, *548*, 52–57.

Srivastava, P., D. R. Edwards, T. C. Daniel, P. A. Moore, and T. A. Costello (1996), Performance of vegetative filter strips with varying pollutant source and filter strip lengths, *Trans. ASAE*, *39*, 2231–2239.

Srivastava, P., K. W. Migliaccio, and J. Simune (2007), Landscape models for simulating water quality at point, field, and watershed scales, *Trans. ASABE*, *50*, 1683–1693.

Veith, T. L., M. L. Wolfe, and C. D. Heatwole (2004), Cost-effective BMP placement: Optimization versus targeting, *Trans. ASAE*, *47*, 1585–1594.

Vendrell, P. F., M. A. Nelson, W. L. Cash, K. F. Steele, K. A. Teague, and D. R. Edwards (1997), Nutrient transport by streams in the Lincoln Lake basin, *Publ. MSC-210*, pp. 45–51, Arkansas Water Resour. Cent., Fayetteville.

White, K. L., and J. G. Arnold (2009), Development of a simplistic vegetative filter strip model for sediment and nutrient retention at the field scale, *Hydrol. Processes*, *23*, 1602–1616, doi:10.1002/hyp.7291.

Whittaker, G., R. Confesor, S. M. Griffith, R. Fare, S. Grosskopf, J. Steiner, G. Muller-Warrant, and G. M. Banowetz (2009), A hybrid genetic algorithm for multiobjective problems with activity analysis-based local search, *Eur. J. Oper. Res.*, *193*, 195–203, doi:10.1016/j.ejor.2007.10.050.

Zitzler, E., and L. Thiele (1999), Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach, *IEEE Trans. Evol. Comput.*, *3*, 257–271, doi:10.1162/106365600568202.

I. Chaubey and C. Maringanti, Department of Agricultural and Biological Engineering, Purdue University, West Lafayette, IN 47907, USA.

J. Popp and H. G. Rodriguez, Department of Agricultural Economics and Agribusiness, University of Arkansas, Fayetteville, AR 72701, USA. (hrodrig@uark.edu)