Development of a multiobjective optimization tool for the selection and placement of best management practices for nonpoint source pollution control

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[1] Best management practices (BMPs) are effective in reducing the transport of agricultural nonpoint source pollutants to receiving water bodies. However, selection of BMPs for placement in a watershed requires optimization of the available resources to obtain maximum possible pollution reduction. In this study, an optimization methodology is developed to select and place BMPs in a watershed to provide solutions that are both economically and ecologically effective. This novel approach develops and utilizes a BMP tool, a database that stores the pollution reduction and cost information of different BMPs under consideration. The BMP tool replaces the dynamic linkage of the distributed parameter watershed model during optimization and therefore reduces the computation time considerably. Total pollutant load from the watershed, and net cost increase from the baseline, were the two objective functions minimized during the optimization process. The optimization model, consisting of a multiobjective genetic algorithm (NSGA-II) in combination with a watershed simulation tool (Soil Water and Assessment Tool (SWAT)), was developed and tested for nonpoint source pollution control in the L'Anguille River watershed located in eastern Arkansas. The optimized solutions provided a trade-off between the two objective functions for sediment, phosphorus, and nitrogen reduction. The results indicated that buffer strips were very effective in controlling the nonpoint source pollutants from leaving the croplands. The optimized BMP plans resulted in potential reductions of 33%, 32%, and 13% in sediment, phosphorus, and nitrogen loads, respectively, from the watershed.

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1. Introduction

[2] Nonpoint source (NPS) pollution from agricultural areas has become one of the biggest challenges in maintaining surface water and groundwater quality. Agricultural activities such as tillage practices and land application of fertilizer and animal manure are significant factors contributing to NPS pollution, leading to excess runoff losses of sediment, nutrients, and pesticides. NPS pollutants are a major source of water quality impairment in many parts of the globe [*Novotny*, 1999; *U.S. Environmental Protection Agency* (*USEPA*), 2003]. Excess sediment loading is one of the most pressing NPS pollution challenges. More than 50% of the excess sediment loadings in many water bodies is contributed by the erosion of agricultural areas [*Ritter and Shirmohammadi*, 2001], affecting more than 10% of the impaired rivers and streams in the United States [*USEPA*, 2006]. The other important NPS pollutants of concern are the nutrients such as nitrogen (N) and phosphorus (P), affecting approximately 9% of the impaired rivers and streams [*USEPA*, 2006]. Sediment loading in the streams causes increased silting, therefore decreasing the stream flow, and also acts as a carrier for transportation of nutrients. Nutrients when present in increased concentrations result in accelerated eutrophication of the water bodies.

[3] Water quality affected by excess runoff, sediment, and nutrient losses from agricultural areas can be improved by implementing best management practices (BMPs) that control the movement of NPS pollutant loads. The BMPs can be implemented at a field or farm scale to control NPS loads at the source or to control the transport of pollutants once they have left the source areas [*Ritter and Shirmohammadi*, 2001]. Over the past 2 decades, numerous studies have been conducted to quantify BMP effectiveness at a field or farm scale. However, considering the resource constraints, it is not possible to implement BMPs at every farm in a watershed. Similarly, BMP placement at every agricultural field may not be needed because only a few "critical" areas in the watershed may potentially contribute disproportionately large amounts of pollutant loads in the watershed. BMPs when selected for implementation in these critical regions would achieve maximum pollution reduction.

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[4] Another important constraint in designing a watershed management strategy is the implementation and maintenance cost of BMPs. It is always desirable to implement a BMP that costs the least and gives the most reduction in pollutant load. Thus a balance has to be achieved between the ecological and economic implications of BMP implementation. For a given watershed with many farms and multiple BMP options in each farm, there can be many different ways of targeting BMPs that give a cost-effective pollution reduction. Finding such a solution through on-site evaluation of different targeting plans in a watershed is neither practical nor economically feasible. For example, a watershed with 500 farms and four different BMPs possible for every farm would require 4^{500} ($\sim 10^{300}$) evaluations. Another alternative can be random placement of BMPs in the watershed. However, such a solution does not have a directional effect to find an optimal solution. Therefore an efficient development of a watershed management plan requires a BMP optimization technique. The optimization technique searches for the best solution from all the possible solutions to achieve maximum pollutant reduction and minimum net cost increase for BMP placement.

[5] The BMP optimization problem usually contains a large search domain for the objectives and variables that needs to be solved to find an optimal solution. Genetic algorithm (GA) [*Holland*, 1975; *Goldberg*, 1989] is a heuristic global search algorithm, based on the idea of Darwin's evolutionary process. It searches the decision space based on the principles of "natural selection" and "survival of the fittest" to reach the optimal solution. Genetic algorithm has been used to optimize BMP selection and placement in a watershed [*Chatterjee*, 1997; *Srivastava et al.*, 2002; *Veith et al.*, 2003; *Gitau et al.*, 2004; *Arabi et al.*, 2006]. However, most of the previous work has focused on using a single objective function for optimization that combines BMP effectiveness and cost for optimization [*Chatterjee*, 1997; *Srivastava et al.*, 2002] or sequential optimization of effectiveness and cost as separate objective functions [*Gitau et al.*, 2004; *Veith et al.*, 2003], thus putting constraint on one objective function during optimization of the other. Some optimal solutions might be lost if the two conflicting objectives are considered separately. One exception to this approach was a study by *Bekele and Nicklow* [2005a] in which the authors used a multiobjective optimization tool for the selection and placement of BMPs in a watershed. However, the BMPs considered were crop management practices and did not include any structural or nutrient management BMPs. Sensitivity analysis of GA operational parameter estimation was also not provided in the model.

[6] Another major limitation with most of the optimization schemes [*Srivastava et al.*, 2002; *Bekele and Nicklow*, 2005a; *Arabi et al.*, 2006] was the large computation time needed to run the dynamically linked watershed model after each different BMP placement in the watershed, during the optimization, to estimate the pollutant loads in the watershed. The computation time for the optimization process was typically in days, which restricted the researchers to test their models on relatively small watersheds ranging in size from 3 to 133 km^2. It should be noted that the large computation time needed to find the optimal solution was not intrinsic to the optimization scheme; it was due to a large run time needed to simulate watershed processes using a distributed parameter watershed model.

[7] The motivation for the research was to develop a model that would solve for BMP placements at any watershed size of concern with a decreased computation time (which is typically in days with most of the models). In this paper we present a novel method to develop a multiobjective optimization model by establishing and incorporating a BMP tool that replaces the requirement of dynamic linkage with a hydrologic model in the BMP optimization architecture. A hydrologic model dynamically linked with an optimization engine to estimate the total pollutant loads from the watershed under various BMP solutions has been replaced with the BMP tool. The BMP tool is a database that contains the quantitative information regarding the effectiveness of a BMP to reduce a particular pollutant from a given land use. The method is tested for implementation on a large eight-digit hydrologic unit code watershed (with areas typically in the range of 1400–3000 km^2) to effectively search a large solution space for finding optimal watershed management plans that meet the multiple objective functions of being economically feasible and ecologically effective in controlling NPS pollutants in the watershed. The removal of dynamic linkage also accelerates the progress of the optimization algorithm and makes it possible to perform the optimization for relatively large number of iterations with less computation time. The increased iterations create a possibility to look into a greater horizon to find a near-optimal solution for the BMP selection and placement problem.

[8] The model is designed to provide a trade-off (Pareto-optimal front) between the two conflicting objective functions. The Pareto-optimal fronts generated can be used by the decision makers to select a solution from an ensemble of solutions that will meet the economical constraint while generating the best possible ecologically effective solution in the watershed. We hypothesize that the pollution reductions obtained by the optimization tool are achieved at lower costs when compared with a random placement of BMPs in the watershed. The following tasks are completed to accomplish the study goal: (1) development of a BMP tool that contains estimation of the BMP pollution effectiveness using the Soil and Water Assessment Tool (SWAT), a watershed scale NPS model; (2) formulation and development of a genetic algorithm based multiobjective optimization tool that addresses the multiple objective functions and incorporates land use constraints during the search process; (3) simultaneous estimation and sensitivity analysis of GA operational parameters using a novel approach; (4) application of the optimization tool on a watershed for phosphorus (P), nitrogen (N), and sediment control; and (5) comparison of the results obtained from the optimization tool with those of the random selection and placement of BMPs. The Pareto-optimal front developed after the final generation of the GA, for each NPS pollutant, provides near-optimal solutions for the two objective functions. The SWAT model is used to simulate the solutions obtained during the optimization to test the applicability of the solutions obtained from the BMP tool when implemented using a watershed model that incorporates routing and in-stream processes.

2. Theoretical Background

[9] Genetic algorithm (GA) is a heuristic-based search technique used to find solutions for optimization problems.

GA is based on techniques inspired from evolutionary biology such as selection, inheritance, crossover, and mutation. A GA consists of a population of chromosomes (solutions) with variables coded in the form of genes. The initial population of chromosomes is randomly generated for the given population size. During the selection process at each successive generation (iteration) the existing solutions are picked and/or duplicated based on fitness of the individuals; the higher the fitness of the individual larger the chances of it being selected into the mating pool. The individuals in the mating pool then undergo genetic operations: crossover and mutation. Crossover, also called as recombination or reproduction, produces child solutions from the parent solutions present in the mating pool. Crossover is necessary to generate population for the next generation that shares many of the positive characteristics of the parent. During mutation, a bit in the chromosome sequence of population is selected randomly and is altered from its original state. Mutation is used to maintain genetic diversity from one generation of solutions to the next. *Goldberg* [1989] introduced the "mutation clock" operator to identify the net bit to be mutated by skipping $\eta = -p_m \ln(1 - r)$ bits from the present bit for any random number r and mutation probability p_m, therefore reducing the number of random numbers to be generated by $O(1/p_m)$.

2.1. Multiobjective Optimization Algorithm

[10] Most of the real-world hydrologic/water quality problems that require optimization of multiple, often competing, objectives are solved by combining them into a single objective function. However, if an expression for single objective function is not well known prior to the optimization, the process needs to be formulated as a multiobjective (MO) optimization problem with conflicting objective functions. Single-objective optimization yields a single optimal point, whereas the MO optimization produces a family of near-optimal points known as Pareto-optimal set, which provides decision makers with insight into different characteristics of the problem before a final solution is chosen.

[11] *Deb et al.* [2002] tested the performance of the two popular evolutionary based multiobjective optimization techniques: nondominated sorted genetic algorithm (NSGA-II) [*Deb*, 1999, 2001; *Deb et al.*, 2002]; and strength Pareto evolutionary algorithm (SPEA-2) [*Zitzler and Thiele*, 2000], on nine test functions and concluded that NSGA-II gave a better spread of the solutions and better convergence than SPEA-2 in eight of the nine test functions. Nondominated sorted genetic algorithm (NSGA-II) [*Deb*, 1999, 2001; *Deb et al.*, 2002] is a multiobjective optimization algorithm (MOOA) that can search a large number of variables and objective function space to find an optimal solution. The overall computation complexity of the algorithm is $O(MN^2)$, which usually is $O(MN^3)$ for most of the evolutionary techniques [*Deb et al.*, 2002]: where O is "order of," M is the number of objective functions, and N is the population size. Nondominated sorting and elitism are utilized to maintain diversity in the solutions and to produce Pareto-optimal set of solutions in NSGA-II.

2.2. Domination and Nondomination

[12] In a multiobjective optimization problem, if g_i, $\{i = 1, \ldots, M\}$ are the objective functions that need to be minimized,

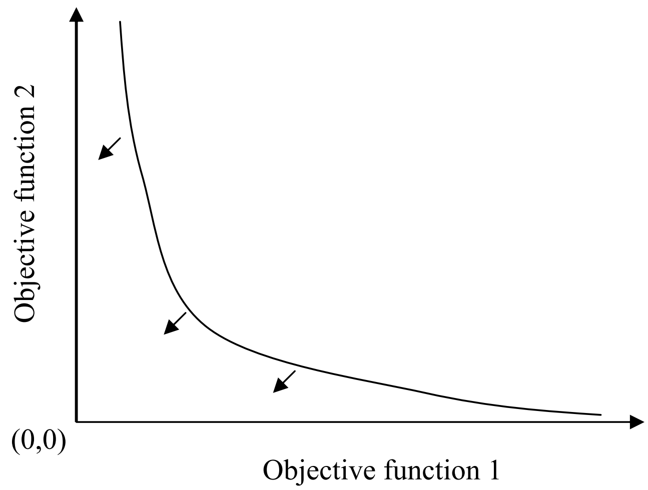

Figure 1. A conceptual Pareto-optimum front progress during multiobjective optimization.

a solution $x^{(1)}$ is said to dominate $x^{(2)}$ if both the following conditions are true [*Zitzler and Thiele*, 2000]:

$$\begin{aligned} &\forall i \in \{1, \ldots.., M\} : \; g_i\left(x^{(1)}\right) \le g_i\left(x^{(2)}\right) \wedge \\ &\exists j \in \{1, \ldots.., M\} : \; g_j\left(x^{(1)}\right) < g_j\left(x^{(2)}\right) \end{aligned}, \qquad (1)$$

i.e., $x^{(2)}$ is dominated by $x^{(1)}$ or in other words $x^{(1)}$ is nondominated by $x^{(2)}$.

[13] If each individual in a population of size N has solutions that are nondominated, then the representative of the solutions in the objective space determines the Pareto-optimal front. The objective of multiobjective optimization is to search for solutions in the global Pareto-optimal region (i.e., optimal for all the objective functions) and to achieve solutions that are separate from one another to the maximum possible extent in the nondominant front (Figure 1). This also helps in checking the premature convergence of the optimization process [*Deb et al.*, 2002].

2.3. Elitism and Crowding Distance

[14] There always exists a set of best solutions at each generation, which can be comparable to the population size N that can go along to the next generation. Such solutions that are nondominated among all the individual generations are called as elite solutions and are stored in an external set called the elite set. After every generation a percentage of population is replaced by individuals from the elite set.

[15] The crowding distance is defined as the sum of the side lengths of the cuboid that touches the neighboring solutions in case of the nonextreme solutions and is infinite for the extreme solutions [*Coello et al.*, 2005]. It is used by the NSGA-II to ensure that the solutions generated at each generation are well spread along the Pareto-optimal front and are far apart in the solution space.

2.4. Description of the Watershed Model

[16] The watershed model used in this study was the Soil and Water Assessment Tool (SWAT) model. SWAT is a process-based distributed-parameter watershed-scale model designed to simulate long-term effects of various watershed

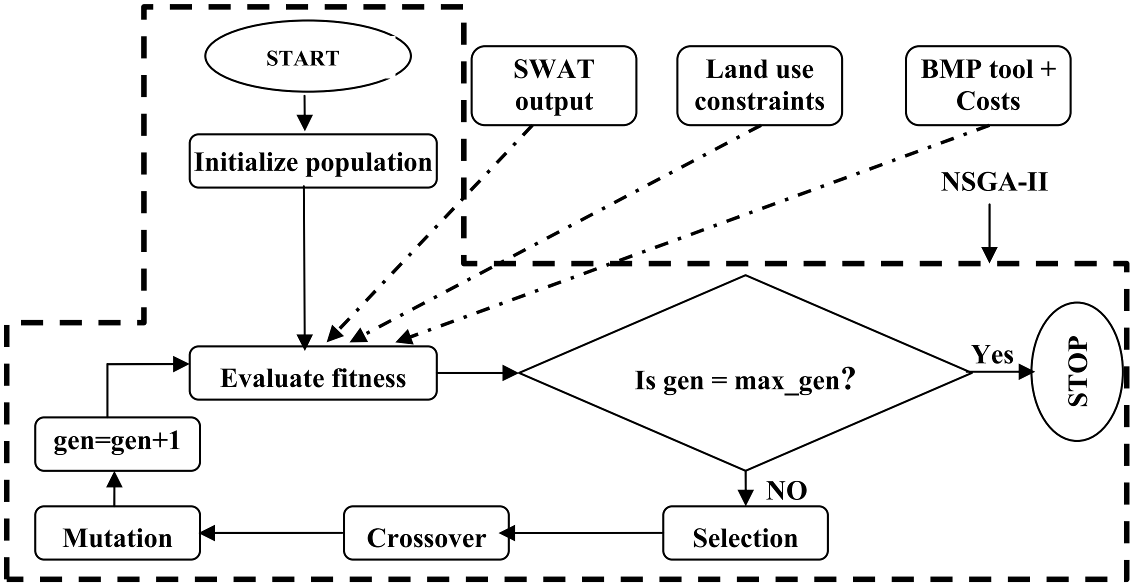

Figure 2. Flowchart for the different processes during the multiobjective optimization. The area within the dashed line denotes the optimization algorithm.

management decisions on hydrology and water quality response [*Arnold et al.*, 1998]. The SWAT model is designed to be applicable not only in gauged basins but also in ungauged basins [*Arnold et al.*, 1998]. It performs well for long-term continuous simulations at both monthly and annual scales [*Borah and Bera*, 2004; *Gassman et al.*, 2007]. The SWAT model divides the watershed into subwatersheds or subbasins based on the outlets selected within the watershed by the user. It further divides subbasins into land areas, called hydrologic response units (HRUs), based on land use, management, and soil properties. All the model calculations are done at the HRU level. Flow and water quality response generated from each HRU is routed at subwatershed scale. The model generates daily, monthly, and annual simulation outputs at HRU, subwatershed, and watershed scales.

[17] The input data needed by the model are related to watershed physical characteristics, climate, plant growth, reservoir data (if any), and management practices at HRU level. The geographic information system (GIS) interface in the model simplifies the preparation of input files [*Di Luzio et al.*, 2004]. The typical GIS data needed by the model are digital elevation model (DEM), soil, and land use maps. The climatic input data required by SWAT are precipitation, temperature on a daily or subdaily basis from multiple climatic gauge locations, solar radiation, relative humidity, and wind speed. Agricultural activities can be given as input to the model by modifying the management files. SWAT simulates the flow, nutrients, sediment, and chemicals at the subbasin or HRU level. Surface runoff is computed using a modification of the SCS curve number technique [*Soil Conservation Service* (*SCS*), 1972], or modified Green-Ampt infiltration method. Modified universal soil loss equation (MUSLE) [*Williams*, 1975] is used by the SWAT model to estimate the soil erosion and sediment yield in the watershed. Nitrogen and phosphorus are applied through fertilizer, manure, or residue application, which can be modeled as inputs in SWAT for each HRU in the watershed. The important feature in SWAT is that it aids in modeling the various BMPs (structural and management based) by changing appropriate parameters in the input files of the model. This feature is utilized in the development of the BMP tool, which estimates the effectiveness of BMPs for a particular NPS pollutant reduction.

3. Methodology

[18] Figure 2 describes the methodology followed during the multiobjective optimization for selection and placement of BMPs in a watershed. The variables (equal to the number of HRUs) are initiated randomly for a given population size. The following are required as inputs into the optimization model to evaluate the objective functions of the population: (1) the baseline sediment and nutrient loading at a HRU level in the watershed estimated using a SWAT model run without any BMPs implemented in the watershed, (2) an allele set that provides land use constraints for the placement of BMPs, and (3) a BMP tool that provides pollutant reduction efficiency and corresponding costs for implementation. The population then undergoes selection and genetic operations (mutation and crossover) to create population for the next generation. After every generation a check is performed to see if the generation number has exceeded the maximum generations fixed. The model terminates if this condition is true to give a range of optimized solutions for the two objective functions at the final generation of the optimization.

3.1. Study Watershed

[19] The L'Anguille River watershed (LRW) is located in the Mississippi delta region in eastern Arkansas (Figure 3). The watershed covers an area of 2520 km^2 and drains the entire stretch (157 km) of the L'Anguille River. The main crops grown in the watershed are rice (26%) and soybeans (46%) and represent most (~72%) of the agricultural land (~95%) in the watershed (Table 1). The L'Anguille River is included in the list of impaired water bodies by the *Arkansas Department of Environmental Quality* (*ADEQ*) [2002]. Excessive sediment and nutrients originating from

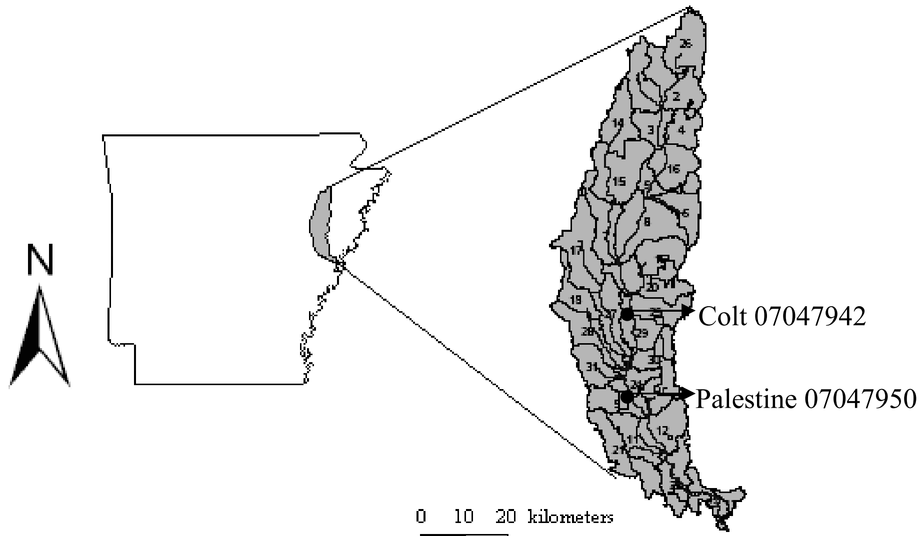

Figure 3. Location of L'Anguille River watershed in Arkansas, location of U.S. Geological Survey stream gauging stations in the watershed, and subwatershed delineation used in Soil Water and Assessment Tool (SWAT) modeling.

nonpoint sources are identified as the principal causes for impairment.

3.2. SWAT Model Development

[20] The inputs that go into the setup of SWAT model, such as digital elevation model (DEM), soil, and land use GIS maps, were obtained from Center for Advanced Spatial Technologies (CAST) at the University of Arkansas, Fayetteville. A sensitivity analysis was performed, using the built-in Latin hypercube one-at-a-time (LH-OAT) technique, to determine the parameters that were sensitive in the SWAT model for flow, sediment, and nutrients. A curve number technique developed by the *SCS* [1986] was used by SWAT to estimate the runoff. Curve number parameter (CN2), which is a function of soil's permeability, land use, and antecedent soil moisture conditions, was the most sensitive parameter for flow and sediment. The most sensitive parameters for N and P were the initial organic N concentration in the soil layer (SOL_ORGN) and the initial organic P concentration in the soil layer (SOL_ORGP), respectively. The flow information for the watershed was obtained from two U.S. Geological Survey (USGS) gauging stations. The upstream gauge is located near Colt, Arkansas (USGS gauge 07047942), and the downstream gauge is located near Palestine, Arkansas (USGS gauge 07047950) (Figure 3). The SWAT model was calibrated for flow at these two gauging stations. However, continuous sediment and nutrients (N and P) data were only available for the Palestine gauging station; consequently calibration for sediment and nutrients were performed only at this station. The SWAT model was calibrated for 15 years (January 1990 to December 2004). An autocalibration tool in SWAT 2005 was used for calibration of the model. Performance indices R^2 (R^2_{NS}) for monthly streamflow at Colt gauge station are 0.42 (0.58) and 0.68 (0.70) for calibration and validation periods, respectively. Monthly calibrated streamflow and sediment performance indices R^2 (R^2_{NS}) for Palestine gauge station are 0.41 (0.43) and 0.17 (0.23), respectively. Measured data for phosphorus and nitrogen at the gauging stations were very sparse and therefore could not be used for model calibration using these objective functions. Model outputs for nitrogen and phosphorus were compared with the quarterly measurements done in the watershed to make sure that the calibrated outputs were within the range of the values measured quarterly in the watershed. Detailed procedures about the SWAT model calibration can be obtained from *Schaffer* [2007]. The watershed was divided into 32 subbasins and 433 HRUs. The SWAT model was used to get the estimates of the pollutant loading at the HRU level for the watershed for 15 years of the calibration period (1990–2004). Average annual pollutant load from each HRU was considered in the study.

3.3. Allele Set Preparation

[21] The BMPs are land use and land cover specific; that is, every land use has a unique set of BMPs that can be applied for NPS pollution control. These sets of BMPs applicable to each HRU are called allele sets and serve as an input in the optimization model by narrowing the search space for a given land use to a definite set of BMPs. Table 2 shows the allele set for rice and soybean, the two crops that constitute major agricultural land use in the LRW. For rice, three nutrient management plans (NMP) were the only BMPs considered for placement, as it is not feasible to have buffer strips in rice

Table 1. Distribution of Land Use/Land Cover in the L'Anguille River Watershed

	Percent Distribution in the Watershed
Rice	25.7
Soybean	45.8
Cotton	4.5
Forest	16.8
Pasture	2.9
Urban	1.7
Other	2.6

Table 2. Allele Set of Best Management Practices in L'Anguille River Watershed

Crop	Allele Set
Rice	type 1; NMP 1, NMP 2, NMP 3[a]
Soybean	type 1; NMP 1, NMP 2, NMP 3
	type 2; buffer 0 m, 5 m, 10 m
	type 3; conservative till, no till

[a]NMP 1, 2, and 3 represent 25% below optimal, optimal, and 50% above optimal application of P fertilizer, respectively.

fields. Selection of BMPs directly stemmed from our discussion with the stakeholders, such as famers and county extension agents. Rice fields in the southeastern United States typically have ponded water that stay in fields for an extended period of time. This allows the sediment to settle in rice fields. Prior to harvesting, the fields are drained into drainage ditches as concentrated flow. Because of low sediment concentration in effluent discharge from rice fields and concentrated flow discharge, buffer strips are not a feasible option and are not practiced in this and other watersheds. Also, a no-till option was not considered for rice because it is not practical to cultivate rice without tillage. However, buffer strips and no-till BMPs can be selected for soybean crops.

3.4. BMP Tool

[22] BMP tool provides an estimate for the costs and pollution effectiveness for each BMP that can be implemented at a HRU scale in the watershed. To develop the BMP tool (Figure 4), all the HRUs in the watershed that have a common land use are selected. The allele set is used to choose BMPs to be placed in the selected HRUs. One BMP at a time is allotted from the allele set corresponding to the chosen land use and placed in all the selected HRUs. There were 54 different BMP placements possible after combing the various combinations of individual and set of BMPs that can go into a particular land use. The SWAT model was run for these 54 different scenarios to generate input data for the BMP tool. The pollutant load in the watershed is estimated by evaluating the SWAT model for the given BMP scenario. BMP pollution efficiency is estimated by calculating the percentage reduction in the pollution load for the BMP scenario when compared with the baseline pollutant load. The cost information is used to estimate the total costs for the placement of BMPs. This process is repeated for all the possible BMPs in the allele set to develop the database that constitutes the BMP pollution reduction and corresponding BMP implementation costs. This database, termed the BMP tool, was used to estimate the BMP pollution reductions, thus removing the need of a dynamic linkage with the SWAT model during the optimization process.

[23] The following are the assumptions/limitations of the BMP tool developed in this study:

[24] 1. The goal of the BMP optimization is to minimize pollution reduction at the HRU level. It is assumed that when the impact of in-stream processes is minimal in pollutant transport, HRU level optimization will produce efficient solution. Routing and in stream processes are not considered when the tool is applied at an HRU level. However, in a watershed where in-stream processes are highly critical, the full dynamically linked optimization model needs to be used.

[25] 2. Meteorological factors are the only dominant processes affecting temporal variability in BMP performance from one year to another.

[26] 3. The pollution reductions established for various BMPs are specific for the watershed under consideration.

[27] The BMP costs that were used in the model were annual net costs per unit area of the watershed. These costs included the establishment, maintenance, and opportunity costs. The cost information for the various BMPs for year 2007 were obtained from University of Arkansas Cooperative Extension Service (CES) [*CES*, 2007] rice and soybean production budgets and *Natural Resources Conservation Service* [2006]. The cost information included the costs of production (fertilizers, fungicides, herbicides, irrigation, labor, fuel, seed, etc.) for different tillage systems [*Rodriguez et al.*, 2007] as shown in Table 3. Some of the BMPs considered resulted in increased crop yields, which was also added into the cost component. All the cost estimates were made per unit area ($/ha).

3.5. Multiobjective Genetic Algorithm Model Development

[28] As already mentioned, the watershed was delineated into 32 subbasins, which were further divided into 433 HRUs. These 433 HRUs are the variables for which the BMPs are to be searched to meet the two objective functions: (1) minimization of pollutant loading and (2) minimization of the net cost increase at the watershed because of the placement of

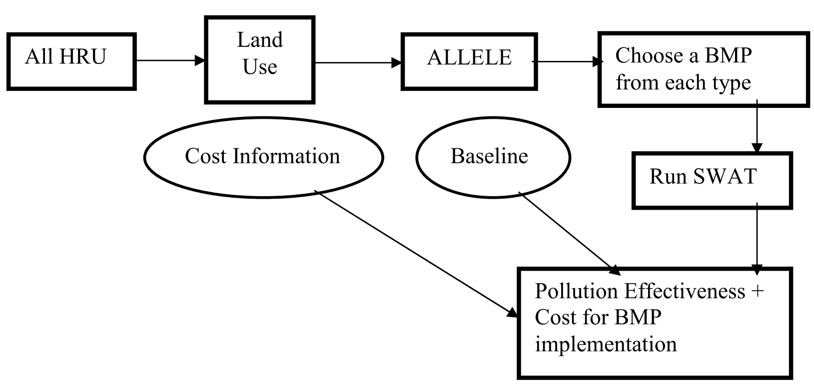

Figure 4. Best management practices (BMP) tool implementation in a watershed. The allele set contains the variables (BMPs) that need to be chosen for placement. Baseline indicates the calibrated SWAT model against which costs and pollution effectiveness of BMPs are evaluated.

Table 3. Cost Estimates for Rice and Soybean Production, 2007 Prices

	Tillage System ($ ha^{-1})		
	Rice	Soybean	
Cost Distribution	Conservation	Conservation	No-Till
Variable expenses			
Custom work	255.61	80.00	78.00
Diesel fuel	36.02	36.02	36.02
Fertilizer			
Nitrogen	104.37	NA	NA
Phosphorus	68.54	60.61	60.61
Phosphorus (+50%)	102.82	90.92	90.92
Phosphorus (−25%)	51.41	45.46	45.46
Filter strips			
Five-meter width	NA	14.79	14.67
Ten-meter width	NA	29.57	29.35
Fungicide and seed treatment	33.01		
Herbicides and 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 and maintenance	32.50	18.13	12.15
Seed	35.76	92.58	92.58
Fixed expenses: Machinery and equipment	147.75	83.18	53.31

BMPs at the farm (HRU) level. The chromosome string corresponding to the optimization problem consists of 433 genes (Figure 5).

[29] The two objective functions that need to be optimized are mathematically expressed as

$$\min[(f(\mathbf{X})) \wedge (g(\mathbf{X}))] \forall f \in [P, N, Sed]. \tag{2}$$

Total reduction in the pollution load is expressed as weighted average of the HRUs in the watershed $f(\mathbf{X})$:

$$f(\mathbf{X}) = \frac{\sum_{x \in \mathbf{X}} (\mathbf{P}(x) \times \mathbf{A}(x))(1 - \mathbf{R}(x))}{\sum_{x \in \mathbf{X}} \mathbf{A}(x)}. \tag{3}$$

The net cost of the placement of BMPs in the watershed is estimated as $g(\mathbf{X})$:

$$g(\mathbf{X}) = \frac{\sum_{x \in \mathbf{X}} \mathbf{C}(x)\mathbf{A}(x)}{\sum_{x \in \mathbf{X}} \mathbf{A}(x)}, \tag{4}$$

where $\mathbf{X}$ represents the HRUs in the watershed, $\mathbf{P}$ is the unit pollutant load from a HRU, $\mathbf{R}$ is the pollutant reduction efficiency of BMP, $\mathbf{A}$ is the area of HRU, and $\mathbf{C}$ is the unit cost of the BMP.

[30] During the optimization process, the algorithm searches first for a particular management practice from the given allele set for a particular land use. The subsequent estimation of the pollution loading and cost estimates for the placement of this particular BMP in the selected HRU are obtained from the BMP tool. A weighted average of the pollutant loading and the net costs at HRU level are calculated to get an estimate at the watershed level.

[31] The SWAT output (baseline scenario) for the pollutant loading at HRU level, BMP effectiveness estimated from various SWAT runs, economic data, and allele sets form the inputs for the optimization model. One pollutant (P, or N, or sediment) is considered at a time during the optimization; that is, three different optimization models were developed for each of the pollutants of concern in the watershed.

[32] The various parameters of a GA are population size, number of generations, crossover rate, and mutation probability. Population size determines the number of individuals considered for the evolutionary process. The members of this

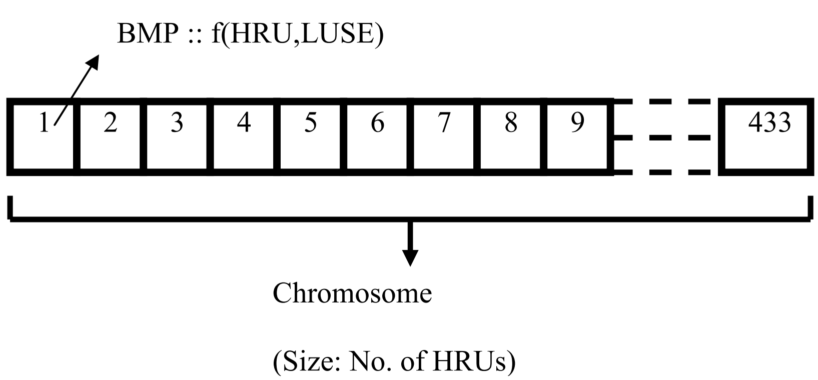

Figure 5. Gene string for BMP representation in a watershed.

Table 4. Default and Optimal Parameters Chosen for Genetic Algorithm From Sensitivity Analysis

Parameter	Default	Optimal
Population	100	200
Number of generations	1000	40000
Crossover probability	0.9	0.9
Mutation probability	0.0001	0.001

population undergo genetic modifications through the process of mutation and crossover to obtain a new set of individuals that might be stronger than the parent. The weaker individuals from the pool are eliminated during this process so that the number of individuals in the population remains the same but the population is more fit than before. This process is continued for a given number of iterations known as generations.

[33] Usually the performance of GA is improved by increasing the population size and number of generations, but that also increases the computation time to reach a near-optimal solution. Crossover and mutation probability are the parameters that create the offspring, and hence are critical in driving the algorithm toward an optimal solution.

3.6. Sensitivity Analysis and Estimation of GA Parameters

[34] A sensitivity analysis was performed on GA parameters to determine the influence of these parameters on the Pareto-optimal front. The various GA parameters (population size, generations, mutation, and crossover probability) were changed, one at a time, to evaluate the effects of each parameter on the Pareto-front. Estimating the goodness of the Pareto-optimal front is subjective. The closer the front gets to the origin, the better the solution is to minimize the two objective functions (Figure 1). The parameter value for which the Pareto-front was closest to the origin in sensitivity analysis was taken as the parameter estimate for the optimization process.

[35] Default genetic algorithm operational parameters were considered as shown in Table 4. Sensitivity analysis was performed by changing a particular operational parameter while keeping the other three parameters fixed. Bounded parameters such as crossover (0 to 1) and mutation probability were varied such that it covered a range of values between the bounds. Pareto-optimal fronts were plotted after every run and the progress in the front was observed.

[36] The total pollutant load and net cost for the placement of BMPs in the watershed were estimated from equations (3) and (4). All the estimates were based on an annual average per unit area in the watershed. These two objective functions are plotted against each other during the sensitivity analysis to get a subjective estimate of the GA operational parameter sensitivity and simultaneously obtain an optimal value for these parameters.

4. Results and Discussion

[37] The baseline watershed response consisted of conservative tillage for both rice and soybean with no buffer strips and nutrient management plans (NMP) implemented. The annual average HRU area weighted baseline loadings from the watershed for sediment, phosphorus, and nitrogen yield were 1.8 t ha^{-1} a^{-1}, 1.5 kg ha^{-1} a^{-1}, and 17.4 kg ha^{-1} a^{-1}, respectively.

4.1. Sensitivity and Estimation of GA Operational Parameters

[38] The closer the Pareto-optimal front gets to the origin the better the solution is for the two objective functions considered in this study. Figure 6 shows the sensitivity of GA parameters, namely, population size, number of generations,

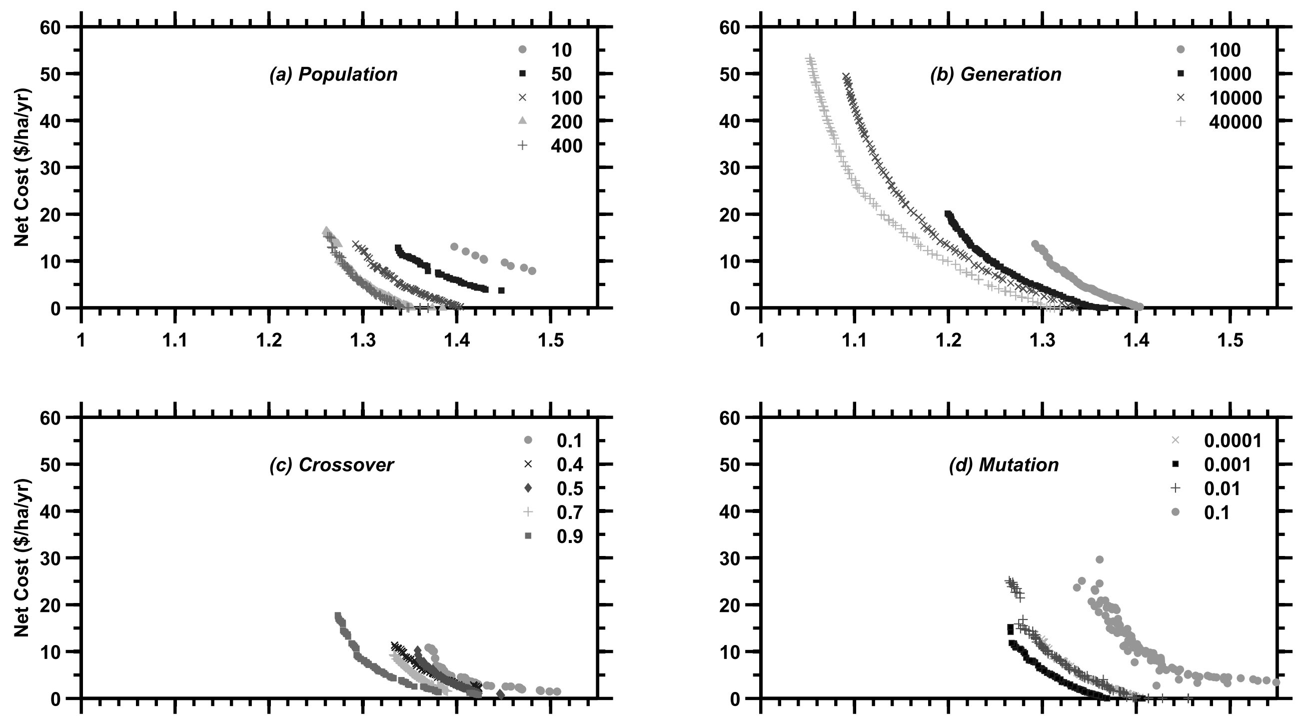

Figure 6. Pareto-optimal front for the sensitivity analysis of genetic algorithm (GA) parameters.

crossover probability, and mutation probability. Increases in the population size provided more freedom for the individuals in the solution space as more individuals were present during each evolution and there was therefore a higher probability of obtaining a better offspring. Improvement in the Pareto-optimal front was observed in the beginning when the population was increased from 10 to 200. However, when the population was further increased to 400, considerable change was not observed in the front. This can be explained by the increased freedom of the solution space that the population of 400 has, which requires more generations for the individuals to show a considerable change in the objective functions. Additionally, as all the runs were made for a fixed number of generations, some of the individuals in the population did not get enough chance to converge. The results could be improved if a population of 400 was chosen and the model was run for a larger number of generations, but that would considerably increase the computation time.

[39] The number of generations had a significant influence on the shift of the Pareto-optimal front toward the origin, i.e., in finding a better optimal solution. The more the number of generations, the more the changes obtained in a gene string resulting in the survival of the fittest. Initially during the sensitivity analysis the model was run for 40,000 generations. It was noticed that there was a definite improvement in the front as the number of generations increased. A total of 80,000 generations were used in the final BMP optimization model.

[40] No consistent pattern in the shift of Pareto-optimal front was noticed for the crossover probabilities. The solution improved when it was increased from 0.1 to 0.4, but when it increased to 0.5 the front moved away from the origin. However, when the crossover probability was increased further (>0.5) the front again shifted toward the origin, suggesting faster convergence for high crossover probability.

[41] The mutation probability range suggested by NSGA-II was between 0 and 0.0004 (the maximum suggested limit value was calculated based on the chromosome length), but it was noticed that for a slightly higher mutation probability (= 0.001) the Pareto-optimal front moved toward the origin. However, further increase in the mutation probability (= 0.1) had a drastic deterioration in the performance. This can be explained by the decrease in convergence of the population due to excessive mutation rates.

[42] Although increasing the population size yielded a better solution, considering the increased computation time and delayed convergence for higher population values, an average value of 100 was chosen for the model. The crossover probability and mutation probability, following the assessment, were 0.9 and 0.001, respectively, which showed a faster convergence during the sensitivity analysis. As previously mentioned, the number of generations was set at 80,000, which was large enough to allow the model to reach a near-optimal solution. The various parameters that were used for the development of the model are shown in Table 4. The optimization model runs made for each pollutant (sediment, phosphorus, and nitrogen yield) with a population size of 100 for 80,000 generations took 2 h to complete on a Centrino Duo@2.16GHz computer.

[43] An interesting observation made was that the pollutant reduction was noticed without an increase in the total net cost (Figure 7). This can be explained as the increase in the crop yield because the placement of a certain BMP nullifies the increase in cost because of implementation and maintenance of the BMPs at a watershed scale. Such a reduction can be termed as "zero net cost BMP scenario."

[44] Figure 7a shows that sediment yield (SYLD) was observed to decrease right from the first generation because most of the BMPs applied were effective in reducing the sediment loads from the HRUs. However, the sediment yield range tends to narrow toward the final generations where the solutions begin to reach saturation with respect to sediment yield reduction and only increase in net cost was observed. As the convergence of the solution space was achieved with respect to the sediment yield objective function, the Pareto-optimal front still followed a smooth pattern with a good spread of solutions in the variable space; that is, the solutions were not concentrated toward either the higher-cost or the lower-cost scenarios. It is noticed in Figure 7b that the range of solutions after the final generation would lead to a reduction in sediment yield by 31–33% for a net cost increase of \$0–55 ha^{-1} a^{-1}, respectively. Population during the initial generations had no solution for zero-dollar sediment reduction, but as the optimization progressed the algorithm could search for some zero net cost BMPs that were effective. A smooth Pareto-optimal front with a good spread illustrated the effectiveness of the multiobjective optimization algorithm to search nondominant solutions. It was observed that the front started to get saturated as the number of generations was increased.

[45] Figure 7c demonstrates the progress in the Pareto-optimal front during the optimization of the phosphorus model. The starting population was spread around the baseline phosphorus load considering the presence of some management practices, such as NMP (+50% above normal P application) that would increase the P loading from the baseline, if selected. This pattern was noticed only during the early stages of the optimization where the individuals are selected randomly. However, as the optimization progressed the algorithm could search for sets of solutions that would lead to reduction in total phosphorus loads in the watershed. Zero net cost phosphorus reduction was observed with a few solution sets. The optimized solution in the last generation (Figure 7d) has solutions in range of 17–32% reduction in total phosphorus for a net cost of \$0–58 ha^{-1} a^{-1}, respectively. It was noticed that the solutions at the final generation followed a very good spread and the solution space had populations distributed far from each other, which would give a broader option to be chosen when making a watershed management decision.

[46] Figures 7e and 7f show the progress in the nitrogen optimization model and the solution at the final generation of the BMP optimization process, respectively. It was noticed that nitrogen generally had a higher initial loading than the phosphorus. The reduction in the nitrogen yield was noticeable from the first generation as there were no management practices, unlike phosphorus, that would increase the nitrogen losses from the farms. The Pareto-optimal front got closer to the origin as the number of generations was increased. After 30,000 generations it followed a vertical trend with very little variation in the nitrogen yield observed. However, a significant change in the net cost was observed. The optimized solution in the last generation has solutions in the range of 11–13% reduction of nitrogen for a net cost increase

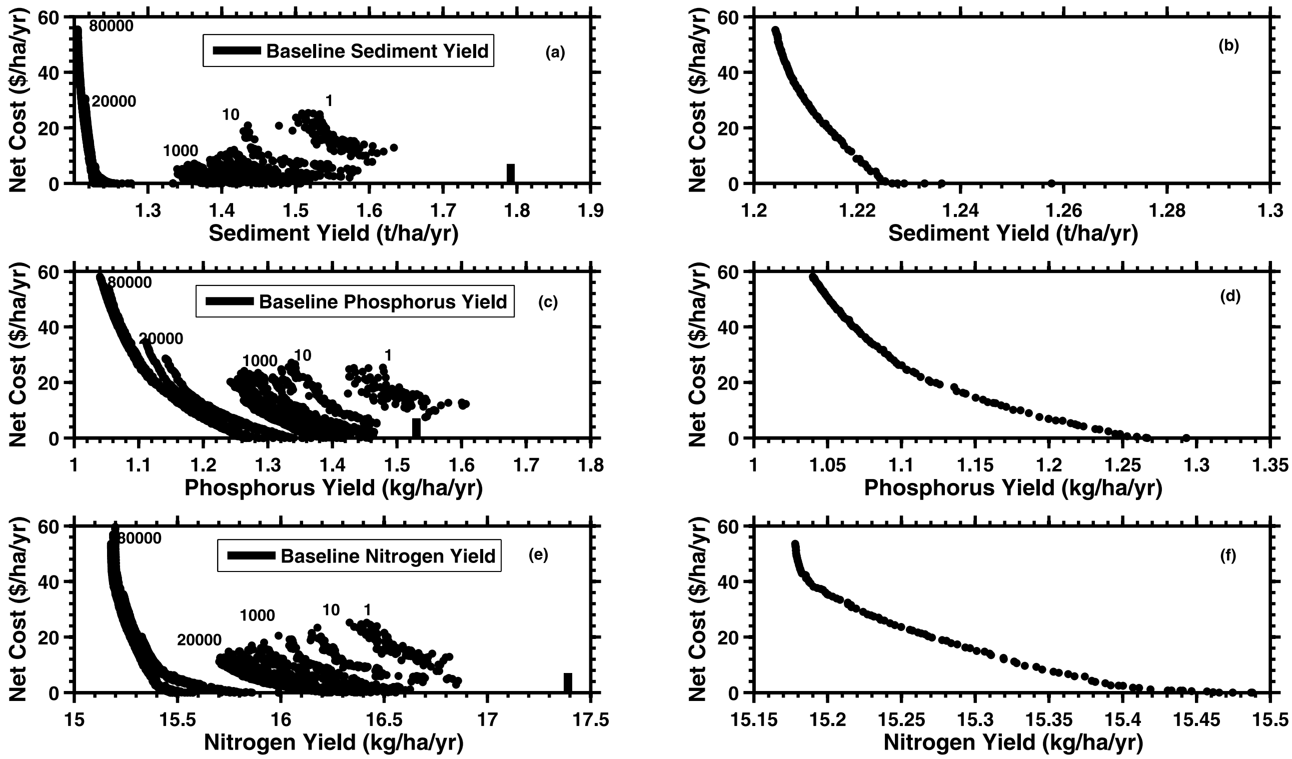

Figure 7. Pareto-optimal fronts (a, c, e) during the optimization and (b, d, f) after the final generation for sediment, phosphorus, and nitrogen reduction.

of \$0–53 ha^{-1} a^{-1}, respectively. It should be noted that almost all the models converged much before (~30,000) the maximum number of generations (80,000) selected for the optimization. The additional generations served to validate that the optimization algorithm had reached the global optimal solution.

[47] The GIS maps shown in Figures 8, 9, and 10 represent the spatial allocation of BMPs in the watershed for sediment, phosphorus, and nitrogen reduction, respectively. As HRUs are defined in the SWAT model based on the land use and soil distribution within a subbasin, the location of HRUs cannot be explicitly described. In order to represent the optimization solutions that were obtained at HRU level for 433 HRUs present in the watershed, the subbasins were divided manually into a number of HRUs present in each subbasin. It should be noted that the spatial representation of HRUs could also be obtained by subdividing the watershed into approximately 433 subbasins, and then using the option of dominant land use and soils for HRU distribution, resulting in a single HRU per subbasin. Figures 8, 9, and 10 present three different BMP scenarios for a given pollutant. The three scenarios represent the solution for the BMP selection and placement corresponding to (1) the solution that has a high net cost, and the best ecologically effective solution, (2) the solution that is median of the range of net cost and pollution reduction, and (3) the solution that has the least net cost. All the scenarios had the similar placement of BMPs for rice, as there were not many choices (three NMPs) for the placement of BMPs in rice. For soybean fields, scenario 1 typically had BMPs that would reduce the pollutant to the fullest extent possible, therefore representing larger buffer strips (10 m) and nutrient management plans that would result in least pollutant load (mostly NMP 1 or NMP 2). It was observed that scenario 3 had a large number of BMPs that contributed to the reduction in the pollutant load without an increase in the net cost primarily because the increase in crop yield revenue nullified the increase in cost because of the placement of BMPs in the watershed. It was also observed that there were many more sets of BMPs selected for scenario 3 when compared with scenario 1 and scenario 2.

[48] It was hypothesized that the optimal selection and placement of BMPs in a watershed would yield higher pollution reductions at much lesser costs when compared with a random BMP selection approach. In order to test the hypothesis, BMPs were selected randomly to be placed in the watershed. Figure 11 shows that the random placements of BMPs were all clustered in a fixed region and the optimized results are proven to be superior in minimizing the two objective criterion of total pollutant load and total cost increase because of the placement of BMPs in the watershed. It should be noted that placement of BMPs in agricultural watersheds is largely random. Many state agencies administering cost-share programs for BMPs do not prioritize BMP selection or placement, resulting in random selection and placement of BMPs in the watershed. The results from this study indicate that an optimal BMP placement can be performed very efficiently using the BMP tool developed in this study. When implemented, the optimal BMP selection and placement will result in significantly greater reduction in NPS pollution in agricultural watersheds compared with the random BMP placement.

4.2. Applicability of the Optimization Solutions When In-Stream Processes Are Considered

[49] The objective function used with the BMP tool optimized BMP placement to minimize pollutant losses at field

Figure 8. Type and location of BMPs selected in L'Anguille River watershed for sediment reduction.

scale. This approximation helps in reducing the model complexity by using an area-weighted average for pollutant reduction in the watershed as the objective function. However, when the in-stream processes are considered, the dynamic linkage of the optimization model with the watershed model may be necessary; however, a dynamic linkage will result in large computation time required to find near-optimal solutions. The dynamic linkage with the watershed model may not be necessary if the solutions are able to perform similar when the in-stream processes are considered or if in-stream processes do not alter the magnitude of pollutant transported from the watershed. *Migliaccio et al.* [2007] reported that SWAT-simulated nitrogen and phosphorus losses were not significantly affected by in-stream processes at an annual timescale. In order to test the applicability, solutions were sorted according to the cost and picked at regular intervals starting from the lowest-cost to the highest-cost solutions with a 10% increment each time. This process was repeated after 10, 40, 100, 1000, and 5000 generations. All of these selected solutions were used to simulate the SWAT model by changing the input files accordingly. Figure 12 provides the Pareto front when the SWAT model is used to simulate the annual pollutant loadings (sediment, P, and N) at the Palestine gaging station (Figure 3) considering the in-stream processes in the watershed. The estimates provided on the *x* axis of Figure 12 are different (in magnitude) from the estimates provided on the *x* axis of Figure 7; the former represent the total loading of the pollutant passing through the particular gauge location (Palestine) in the watershed and the latter represents the total average area-weighted loading at a HRU scale in the entire watershed. It is observed that the optimized solutions obtained using the BMP tool are able to capture the behavior of the trend in the objective functions when the in-stream process are considered. The Pareto front moved closer to the origin with increase in the number of generations. Also, the optimized solutions resulted in smaller loadings of sediment, P, and N compared with baseline load at the gauging station. The loading reductions due to BMP placement were also very similar with the in-stream process and the BMP tool, indicating that the BMP tool could be used to efficiently optimize BMP placement in large agricultural watersheds.

5. Summary and Conclusions

[50] Watershed level placement of BMPs to achieve maximum NPS pollutant reduction with minimal increase in BMP implementation costs is an active area of research. This requires finding an optimal solution from many millions of feasible alternatives for the selection and placement of BMPs. The BMP optimization problem requires searching a large variable space to get an optimal solution. Genetic

Figure 9. Type and location of BMPs selected in L'Anguille River watershed for phosphorus reduction.

algorithms (GA) are search techniques that search the solution space globally and hence perform better than the local search techniques (for example, back propagation, SIMPLEX, etc.) to solve problems with large variable space. Most of the previous work done in developing models for this problem has used GA for optimization by considering the two objectives of cost increase and pollution reduction individually by placing a constraint on one objective while optimizing the other. The drawback with this approach is that some solutions might be lost because the two objectives are considered separately. We have addressed this problem with the development of a multiobjective optimization algorithm framework that considers both objectives simultaneously. Also, the previous models developed were confined to either field scale or small watersheds (area < 13 km^2), as most of these models used a dynamic linkage between the optimization model and the watershed simulation model, which increased the computation time considerably. In this study we have developed a BMP tool that replaces the dynamic linkage in the model architecture. The BMP tool required running the watershed simulation model for all 54 different combinations of BMPs possible in the watershed. BMP pollution efficiency was computed for each of the combination of BMPs by comparing the pollutant load for the particular BMP placement scenario with the baseline scenario when there was no BMP implemented. BMP implementation costs were estimated based on the unit cost information and considering a fixed interest rate. The replacement of the dynamic link with the BMP tool considerably improved the computation time (10^{-9} s per evaluation per unit area (in hectares) of the watershed size when compared with 0.02 s [*Arabi et al.*, 2006] and 0.07 s [*Bekele and Nicklow*, 2005a] per evaluation per unit area (in hectares) of the watershed size) and therefore was extended for BMP placement in a larger USGS eight-digit HUC watershed (LRW).

[51] The multiobjective optimization of the two objective functions was performed using the genetic algorithm NSGA-II. The inputs for the optimization algorithm included initial pollutant yield from a calibrated SWAT model, allele set with various options for BMP selection in a particular land use, BMP tool which consisted of pollutant reduction efficiencies, and cost estimates for each BMP. The SWAT model was used to simulate various BMP scenarios for the watershed; these scenarios were then used in the development of pollution reduction effectiveness for the various BMPs. A sensitivity analysis of the parameters of NSGA-II was performed to find the parameters that had significant influence on the solution. This process also estimated the parameters for NSGA-II. The final optimized result gave a trade-off between the two objective functions. Overall the nutrient and sediment optimization models performed well in reducing the pollutant loads from the watershed. This trade-off can be used

Figure 10. Type and location of BMPs selected in L'Anguille River watershed for nitrogen reduction.

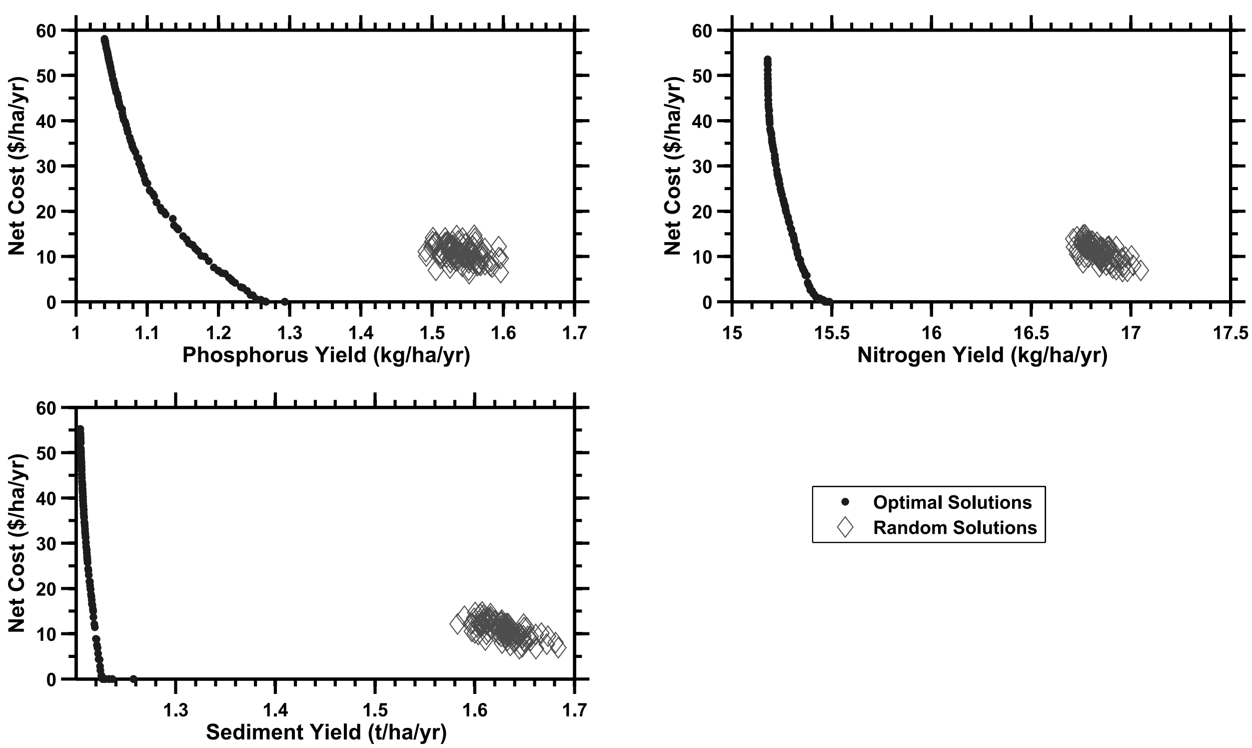

Figure 11. Random versus optimal selection and placement of BMPs in L'Anguille River watershed.

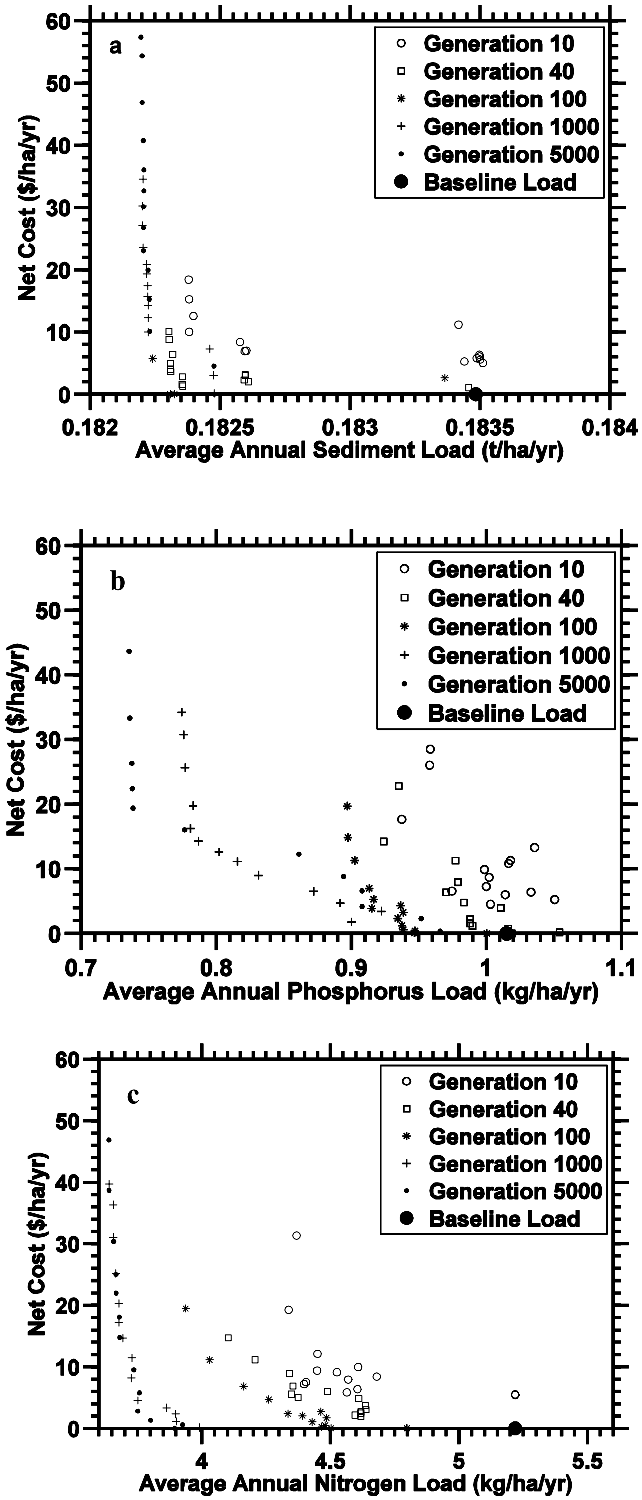

Figure 12. Simulation of the solutions obtained during optimization using the SWAT model for estimating the (a) sediment, (b) phosphorus, and (c) nitrogen loads at Palestine gage station in the watershed.

in the development of total maximum daily loads (TMDLs) in the watershed to meet the water quality goals by providing a cost-effective solution. In order to test the applicability of the solutions when implemented at a watershed scale, solutions were picked for selected generations and populations and modeled in the SWAT model to simulate the pollutant loads. It is observed that the amount of reductions obtained at the Palestine gauge station are similar to the reductions obtained when a spatially weighted value for pollutant load is used as an objective function with the aid of BMP tool in the optimization. The increased performance of the BMP tool was therefore innovative to extend the BMP solution and placement to larger watersheds.

[52] The optimization model developed is a general model and can be easily extended to any other watershed to develop the Pareto-optimal fronts. The model gives a range of options available for pollution reduction and their corresponding costs for the implementation of BMPs. This trade-off can aid the watershed modelers in TMDL development and to estimate the corresponding cost for the placement of BMPs to achieve TMDL goals.

[53] The global optimization techniques, genetic algorithms, are slow in convergence when compared with local search techniques such as back propagation, conjugate gradient method, and SIMPLEX. Hybrid search techniques that combine the advantages of global and local search techniques have been used to address some of the watershed level hydrologic problems [*Bekele and Nicklow*, 2005b]. Future developments in the model should try incorporating a local search technique into the search process of genetic algorithm. Three different BMP selection and placement optimization models were developed for the three NPS pollutants of concern, as no weightage was sought to be placed on these pollutants to develop the objective function. However, future work can consider the product of percentage reduction from baseline of each of the pollutants loads to develop the combined objective function to be maximized for the selection and placement of BMPs in the watershed.

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