FARM–LEVEL OPTIMIZATION OF BMP PLACEMENT FOR COST–EFFECTIVE POLLUTION REDUCTION

M. W. Gitau, T. L. Veith, W. J. Gburek

ABSTRACT. *With best management practices (BMPs) being used increasingly to control agricultural pollutant losses to surface waters, establishing the environmental effectiveness of these practices has become important. Additionally, cost implications of establishing and maintaining environmentally effective BMPs are often a crucial factor in selecting and adopting BMPs. This article considers both water quality and economic concerns and presents a methodology developed for determining cost-effective farm- or watershed-level scenarios through optimization. This optimization technique uniquely incorporates three existing tools: a genetic algorithm (GA), a watershed-level nonpoint-source model (Soil and Water Assessment Tool, SWAT), and a BMP tool. The GA combines initial pollutant loadings from SWAT with literature-based pollution reduction efficiencies from the BMP tool and with BMP costs to determine cost-effective watershed scenarios. The methodology was successfully applied to a 300 ha farm within the Cannonsville Reservoir watershed, a phosphorus (P) restricted reservoir within New York City's water supply system. An average reduction in dissolved P of 60% over the lifetime of the BMPs was set as the pollutant target. A baseline scenario was established to represent practices on the farm before BMP implementation. The most cost-effective scenario for the farm, under the presented methodology, achieved a cost-effectiveness of 0.6 kg dissolved P reduction per dollar spent per year. Additionally, the methodology determined alternative scenarios for the farm, which met the pollution reduction criterion cost-effectively. The methodology, as developed, is extendable to multi-farm or watershed-level evaluations.*

Keywords. *Agricultural nonpoint-source pollution, BMP, Genetic algorithm, SWAT.*

Improving water quality by reducing pollution from agricultural lands has become an issue of increasing interest. A wide range of structural and management−based practices, collectively known as best management practices (BMPs), are used to control pollutant losses. However, BMPs are increasingly being used without a sufficient research base to establish overall effectiveness of BMP combinations applied at the farm or watershed scale and to suggest the most effective placement of the BMPs (Dillaha, 1990; NRCS, 2004).

Cost implications of establishing and maintaining environmentally effective BMPs are a crucial factor in selecting and adopting BMPs. Costs are typically borne by farmers, who may not be willing to implement expensive BMPs. Additionally, economic interests between the private and public sector may differ. The farmer who is interested in increasing profit margins through increased yields will tend to focus on profitability when making management decisions. Society, on the other hand, may be primarily interested in improved water quality and may have little concern for costs unless pollution reduction costs are reflected in increased taxation, consumer−related costs, or public dollars invested with no return in improved water quality.

Pollutant losses from a site with one or more BMPs can often be measured satisfactorily over time after BMPs are implemented. However, pre-determination of the impact of a BMP on a specific site and of interaction effects among BMPs becomes much more complex. Likewise, BMP implementation and maintenance costs can be established through records kept by those implementing the BMPs, but assessing trade-offs between cost increase and pollution reduction across multiple fields or farms is more complex. The solution to identifying feasible, cost-effective BMP combinations, then, lies in optimizing selection and placement of the BMPs in order to determine combinations of high pollutant reduction at low cost.

Because there can be several workable and acceptable solutions to BMP placement for any farm or watershed, an optimization algorithm that efficiently provides a number of near-optimal solutions is desirable. One such technique is the genetic algorithm (GA; Goldberg, 1989). By sampling broadly across the response surface, GAs have the ability to provide a number of near-optimal solutions from different areas of the surface. The GA has previously been used by Chatterjee (1997), Srivastava et al. (2002), and Veith et al. (2003) in BMP optimization studies.

The objective of the presented study was to develop a methodology for determining optimal selection and placement of BMPs, with a view to identifying cost-effective solutions for nonpoint-source pollution reduction, with a focus on dissolved phosphorus (P). The study's objective was addressed by combining the Soil and Water Assessment Tool

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(SWAT; Arnold et al., 1998), a BMP tool (Gitau et al., 2002, Gitau, 2003), site-specific BMP costs, and an upgraded version of the GA presented in Veith et al. (2003). SWAT is a watershed-level, nonpoint-source model from which baseline pollutant loadings can be obtained. The BMP tool includes literature-based P reduction efficiencies for both management and structural BMPs. Optimization was carried out using the GA, a robust search algorithm for problems with a large number of variables and possible solutions.

In the studies by Chatterjee (1997), Srivastava et al. (2002), and Veith et al. (2003), BMP effectiveness data were supplied through nonpoint-source model runs. Comparatively, use of the BMP tool is more time efficient with regard to optimization runs. The BMP tool also offers greater flexibility with regard to the types of BMPs that can be selected. Monitored data, when available in sufficient detail, can replace SWAT output in the presented methodology. However, by incorporating an accepted watershed-level model (SWAT) for initial estimation of pollutant loadings under a baseline scenario, the methodology extends to locations that have not been as fully sampled.

Materials and Methods

The developed methodology is comprised of four components: GA, SWAT, the BMP tool, and BMP costs. The GA combines average annual pollutant loads from SWAT with reduction efficiencies from the BMP tool and annualized BMP costs appropriate to the study area in an iterative process, in order to determine the cost-effectiveness of each BMP scenario. The components of the developed methodology and their interactions are shown in figure 1 and described further in this section.

Component Descriptions

Basic descriptions of the four components are presented in this subsection. Because the focus of this article is on the component interactions, which facilitate the optimization process, the descriptions explain more about model options selected within the components than history and theory of each component. References are given to allow the interested reader to quickly gather more specific information about a particular component.

Genetic Algorithm

A genetic algorithm (GA; Goldberg, 1989; Chambers, 1995) is used to optimize BMP placement with respect to cost and pollution reduction. The GA has been used since its inception in the 1960s, mainly in industrial engineering and business applications (Goldberg, 1989; Mitchell, 1999). In a basic GA, populations of individuals progress from generation to generation based on fitness scores that represent the optimization goal. Each individual of a population is modeled as a chromosome, with genes on the chromosome defining relevant traits of the individual. The possible values of each gene form an allele set for the gene. The value of each gene is selected from its allele set through crossover of existing individuals and through random mutation. Each individual is then assigned a fitness score based on how well the combined traits of the individual satisfy the objective of the optimization.

For example, each farm scenario is represented as an individual, or chromosome, within the GA. Each field within the farm is represented as a gene with the possible BMPs for that field forming the gene's allele set. The BMP scenario is then associated with a fitness score based on how well the scenario reduces costs and pollutant losses from the farm. The more the BMP scenario minimizes pollutant losses and costs, the more desirable (more fit) that scenario is and hence the higher its fitness score.

At each generation, new individuals are added to the population through crossover and mutation, while previous individuals with low fitness scores are dropped from the population. New individuals are typically more likely to be formed from highly fit existing individuals, which helps drive the GA toward improving solutions. The most fit chromosomes (i.e., the ones with the lowest pollutant losses and costs) from the previous generation are also often carried over into the new generation to ensure that the best-found solution is maintained. The process terminates when no further improvement in cost-effectiveness is being achieved.

The GA for this research uses a steady–state, tournament selection replacement scheme, in which a given percentage

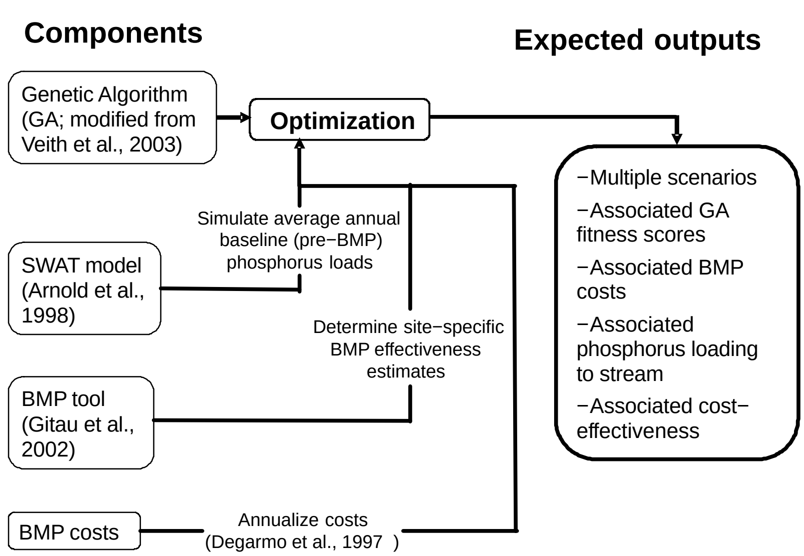

Figure 1. Flowchart of optimization methodology showing components and their interactions.

or a set number of the population is replaced at each generation (Mitchell, 1999). A tournament selection scheme probabilistically selects two members of the population based on the ratio of each individual's fitness to the sum of all fitness values. Of these two individuals, the one with the higher fitness score is chosen. The selection process is repeated, and the two chosen individuals are used to create two new individuals by reproduction, crossover, and mutation, based on the assigned probabilities of these operations. New members are created and added to the previous generation until the replacement percentage is met. Then the least fit members of the temporarily expanded population are removed from the generation, resulting in a constant population size with each successive generation.

SWAT

The Soil and Water Assessment Tool (SWAT; Arnold et al., 1998) is a daily time step, continuous simulation, river basin or watershed scale model designed for use in gauged or ungauged basins. SWAT incorporates features of several models, including the Simulator for Water Resources in Rural Basins (SWRRB; Williams et al., 1985; Arnold et al., 1990); Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS; Knisel, 1980); Ground Water Loading Effects on Agricultural Management Systems (GLEAMS; Leonard et al., 1987); and Erosion Productivity Impact Calculator (EPIC; Williams et al., 1984). SWAT simulates water movement, sediment loss, and nutrient losses throughout the simulated region.

The model allows a flexible discretization of a watershed. The watershed is first partitioned into subwatersheds or subbasins. Each subbasin is then further subdivided into hydrologic response units (HRUs), which are land areas within a subbasin that have distinct land cover and soil. The degree of subdivision is based on land use and soil thresholds specified by the user. Any land use that occupies a percentage larger than the specified threshold is considered a unique land use. Soils occupying percentages larger than the specified soil threshold, within the land use area, are considered unique soils. Land use and soil areas not meeting these pre-determined thresholds are lumped within the larger areas. Lowering the thresholds lessens the lumping, and the model can be set to preclude any lumping by setting both thresholds to zero.

Base input data required to run SWAT includes climate (precipitation, temperature, relative humidity, solar radiation, and wind speed), land use, soils, and topography. The model will set defaults for most of the other input parameters, such as those pertaining to management, crop growth, and water quality. However, entering known or measured values for these inputs and calibrating unknown parameters to the extent possible improves the accuracy of the watershed representation and thus, theoretically, the overall model accuracy.

SWAT calculates slopes while building the input data files. However, SWAT performs slope computations on a subbasin basis, assigning the same slope value to all HRUs within a subbasin regardless of their position on the landscape. Slope affects both water flow and pollutant transport and is a key input for the BMP tool. Thus, the DEM was used to recalculate slopes on an HRU basis to obtain a representative slope for each HRU.

SWAT provides several levels of spatial and temporal output. The BMP placement methodology discussed in this article used HRU-level output as input for the GA. Average annual output from SWAT was used to correspond to effectiveness estimates from the BMP tool, which represent average BMP effects over time. SWAT also provides output on a variety of water quality parameters. Of interest to this study was dissolved P.

BMP Tool

Developed within Microsoft Access, the BMP tool (Gitau et al., 2002; Gitau, 2003) was based on effectiveness data obtained from published BMP monitoring studies. The underlying database contains data on particulate, dissolved, and total P effectiveness (defined as the percentage by which P is reduced), associated site and study characteristics, and complete literature citations for a variety of agricultural BMPs. It also contains information on nitrogen, sediment, and runoff reductions (not addressed in this article). The database currently contains 32 BMPs grouped into three broad categories: erosion control, nutrient management, and barnyard management. At present, the database contains data analyzed for eight classes of BMPs (table 1): animal waste systems, barnyard runoff management, conservation tillage, contour strip cropping, crop rotation, vegetated filter strips, field-level nutrient management plans, and riparian forest buffers. Analyses involve descriptive statistics (mean, range, and standard deviation) determined for each BMP, by individual soils or slopes, and by combinations of soils and slopes.

The BMP tool was designed to allow site-specific estimates of BMP effectiveness and to facilitate access to

Table 1. Eight classes of best management practices (BMPs) used in the BMP tool.

BMP	Description
Animal waste systems	Systems designed for proper collection, transport, and storage of livestock manure and other animal waste.
Barnyard runoff management	Exclusion of clean water runoff from barnyard and disposal of remaining barnyard runoff in a way that minimizes its pollution potential.
Conservation tillage	Any tillage and planting system that leaves a minimum of 30% of the soil surface covered with plant residue after the tillage or planting operation (i.e., reduced-tillage or no-tillage).
Contour strip crop	Alternating strips of a row crop with a small grain or forage, planted on the contour (contour strip cropping) or across the slope (field strip cropping).
Crop rotation	A planned sequence of annual and/or perennial crops.
Vegetated filter strips	Strips of perennial grasses, planted across the slope, established adjacent to areas of high pollutant potential and managed for pollutant removal by overland flow.
Nutrient management plan	Managing the rate, timing, and placement of fertilizers, manures, and other nutrient sources to encourage maximum nutrient recycling and minimize nutrient runoff and leaching.
Riparian forest buffers	Areas of trees, shrubs, and grasses located adjacent to ponds, lakes, and streams to filter out pollutants from runoff and provide shade for fish and wildlife.

analyzed data and associated citations. Values from the tool represent the average effectiveness of each BMP over its expected lifetime. The tool can be used either as a stand-alone application or in conjunction with a nonpoint-source model.

In order to apply effectiveness information in the optimization, all effectiveness estimates were converted to BMP-specific reductions, computed as a fraction, based on effectiveness estimates:

$$reduction_{(BMP)} = 1 - \left(\frac{estimated\ effectiveness_{(BMP)}}{100} \right) \quad (1)$$

The reduction estimate refers to the fraction of the original pollution leaving the source after BMP implementation. For example, suppose 100 g of dissolved P leaves a field with 3% to 8% slope and hydrologic soil group C. Applying contour strip cropping, for which the BMP tool calculates an effectiveness of 45%, is estimated to result in 45 g of dissolved P remaining on the field and 55 g leaving the field.

BMP Costs

The BMP cost data are comprised of current implementation expenses and expected lifetimes of the BMPs. Because BMPs have varying lifetimes (for example, riparian buffers have a lifetime of 25 years, while nutrient management plans have a lifetime of one year), all costs were reduced to their annual values, using equation 2 (Degarmo et al., 1997, App. C). Annualizing BMP costs provides a means of comparing BMPs by cost and supplying cost values that can be utilized in conjunction with time-averaged pollutant load and BMP effects.

$$A_{BMP} = \frac{Z\left(\frac{r}{100}\right)}{1 - \left(1 + \frac{r}{100}\right)^{-n}} \quad (2)$$

where

A_{BMP} = annualized cost for a BMP ($)
Z = capital cost of the BMP ($)
r = time value for money (%)
n = lifetime of the BMP (years).

Problem Representation

To solve a problem with the GA heuristic, the problem must be clearly represented in terms of the GA framework. In this study, the farm is represented as a chromosome and is divided into SWAT HRUs with each HRU represented as a gene. Each HRU is assigned an allele set comprised of the management practices and combinations of practices feasible for that HRU. Any HRU not in production is assigned a single allele, representing the baseline value, and maintains a fixed set of management practices. A farm scenario is formed by assigning, for all HRUs in the farm, one feasible management practice or a combination of practices to each HRU. Each scenario becomes a potential solution to the BMP placement problem.

Scenario Fitness

Within a GA, fitness functions establish the degree to which a scenario meets the objective criteria as compared to the other scenarios. The GA for this study uses a two-part fitness equation: optimizing first for pollution control and next for cost reduction. For each scenario, farm-level pollutant loss is determined by calculating pollutant loss from each HRU, after any BMPs have been applied, and then routing these losses through the stream network. Pollution reduction for the working scenario is stated as a function of the baseline scenario pollutant level and the target pollutant reduction level:

$$P = \begin{cases} 1 & \text{for} \quad p_w \le p_t \\ \dfrac{p_b - p_w}{p_b - p_t} & \text{for} \quad p_t < p_w < p_b \\ 0 & \text{for} \quad p_b \le p_w \end{cases} \quad (3)$$

where

P = pollutant score (dimensionless)
p_b = pollutant loading from baseline scenario (units of mass)
p_t = target pollutant loading (units of mass)
p_w = pollutant loading from working scenario (units of mass).

Due to the goals of the optimization procedure, scenarios giving pollutant loadings less than the user-specified target load are preferred. For a pollutant load between the target and baseline loads, the score increases linearly as pollutant load decreases (fig. 2). Fitness scores of scenarios with pollutant loading larger than the baseline are set to zero, removing these scenarios from the optimization process. The baseline loading was chosen as an upper limit in order to prevent negative fitness scores but retain flexibility in the use of the optimization procedure over a range of applications.

Scenario cost increase from the baseline is the direct sum, across all HRUs on the farm, of implementing the BMPs in that scenario. The cost fitness function scales the total cost increase of the working scenario in relation to the maximum and minimum desired cost increases by mimicking the pollutant fitness function:

$$C = \begin{cases} 2 & \text{for} \quad c_w \le c_t \\ 1 + \dfrac{c_m - c_w}{c_m - c_t} & \text{for} \quad c_t < c_w < c_m \\ 1 & \text{for} \quad c_m \le c_w \end{cases} \quad (4)$$

where

C = cost score (dimensionless)
c_m = maximum allowable cost increase from baseline scenario ($)
c_t = target cost increase from baseline scenario ($)
c_w = cost increase of working scenario from baseline scenario ($).

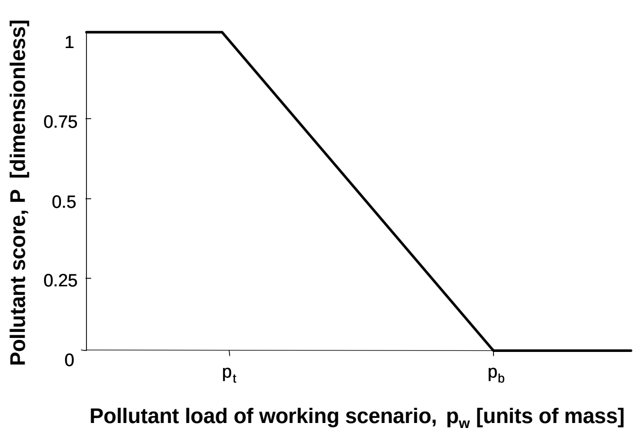

Figure 2. Pollutant score fitness function.

A lower bound of one instead of zero is used for the cost fitness function to simplify connection with the pollutant fitness function. For this study, the target cost increase from the baseline scenario was set at zero. However, in situations where a fixed amount of money is provided for water quality, the target cost may be used as a threshold at which all less expensive scenarios meeting the pollutant-target criterion are considered equally fit. In such cases qualitative measures, such as farmer acceptance, may be used to choose among cost-effective scenarios.

The GA evaluates each scenario by combining the pollutant and cost fitness scores into a single objective function:

$$F = \begin{cases} P & \text{for} \quad P < 1 \\ C & \text{for} \quad P = 1 \end{cases} \qquad (5)$$

where

F = total fitness score (dimensionless)

P = pollutant fitness score (dimensionless)

C = cost fitness score (dimensionless).

The overall fitness (eq. 5) of each scenario is then determined based on pollution reduction (eq. 3) and cost increase (eq. 4). Each scenario is first examined to see if its pollutant load meets the pollutant-targeting criterion. All scenarios that meet the pollutant-targeting criterion (i.e., have a pollutant fitness score of one) are then ranked based on their economic fitness scores. Hence, for each population and for the GA as a whole, the scenario that meets the pollutant-targeting criterion for the least cost has the highest total fitness score.

As the GA progresses, scenarios that meet the pollution reduction criterion but cost less than previous scenarios have a high probability of being replicated and combined to form new scenarios. In contrast, scenarios that meet the pollution reduction criterion but cost more than some or all previous scenarios have a low probability of being carried through in the optimization. By continually promoting the low-cost, pollution-reducing scenarios, future scenarios will contain BMP placement and selection combinations from the promoted scenarios and will themselves become even lower cost (i.e., more optimal).

Modifications to Initial Optimization Component

The GA used in this study builds on one developed by Veith (2002) and described by Veith et al. (2003). The optimization component was written as a console executable program in C++ using the GALib GA package (ver. 2.4.4. Matthew Wall, Massachusetts Institute of Technology, Cambridge, Mass. Available at: http://lancet.mit.edu/ga/. Accessed 12 July 2001). Four major modifications to the optimization component were made to improve flexibility in creating allele sets and to accommodate SWAT and the BMP tool in place of the previous nonpoint-source module:

- Routing of each subbasin follows the structure used by the SWAT watershed configuration file (Neitsch et al., 2002). The percentage of transport loss for each subbasin is an input based, for example, on the subbasin's average transport loss reported by SWAT for the baseline run.
- The amount of each land management area, or HRU, within a user-specified buffer zone can be input. Additionally, each BMP is classified as applicable to buffers, non-buffered land, or both. Thus, the pollution reduction and cost impacts of each BMP on each HRU are a function of the type of BMP and the amount of the HRU that is within the buffer zone.
- In the previous version, two functional allele sets, one for cropland and one for grassland, were available. In the modified version, allele sets for each HRU are completely user-specified, increasing the ability to uniquely define each HRU and to improve customization of the watershed representation. Through these modifications, an HRU may remain permanently unchanged from the baseline, groups of HRUs may have the same allele set, or every HRU may have a unique allele set.
- A variable was added to reduce the contributing area of an HRU to the percentage specifically contributing to load reduction as a result of applying facility BMPs, such as animal waste systems, barnyard runoff management, or vegetated filter strips.

Case Study

This study used the described methodology to optimize BMP selection and placement for a farm located within the New York City water supply watersheds. The study combined baseline P loadings from the farm as simulated by the SWAT model, site-specific BMP effectiveness estimates from a BMP tool, and annualized BMP costs as determined from Delaware County, New York, data to provide input data for running the GA. The GA used this information to optimize BMP placement on the farm with regard to cost-effective control of farm-level P losses.

Site Description

For demonstration of the methodology, a single farm within Town Brook watershed (TBW), Delaware County, New York, was selected. TBW is part of the Cannonsville Reservoir watershed (fig. 3), which in turn is part of the Catskill/Delaware system, a watershed system that supplies the majority of New York City's potable water. Agriculture in the Catskill/Delaware region is focused on dairy production and supporting cropland practices. As a result, water quality is at risk from excess manure and fertilizer application, barnyard runoff, and soil loss, with P being the main pollutant of concern (Watershed Agricultural Council, 1997).

Ongoing work to control P loss in the TBW has involved systematic implementation of BMPs across several pilot farms within the watershed. This effort has been guided by the New York City Watershed Agricultural Council, a body that oversees BMP implementation in the New York City watersheds. There has also been a continuing effort towards monitoring streamflow and nutrients at the watershed outlet as well as data collection on climatic parameters and management operations.

The 300 ha farm used in this optimization study is one of the pilot farms and was selected because its digitized field boundaries and detailed management data were readily available. Land use on the farm is comprised of 44% cropland, in a rotation of corn silage and hay, and of 19% pasture. The remainder of the land is either forested or inactive. For this case study, dissolved P was considered the target pollutant to be controlled. Dissolved P is readily available for algal uptake (Sharpley and Beegle, 2001) and is thus the most critical form of P.

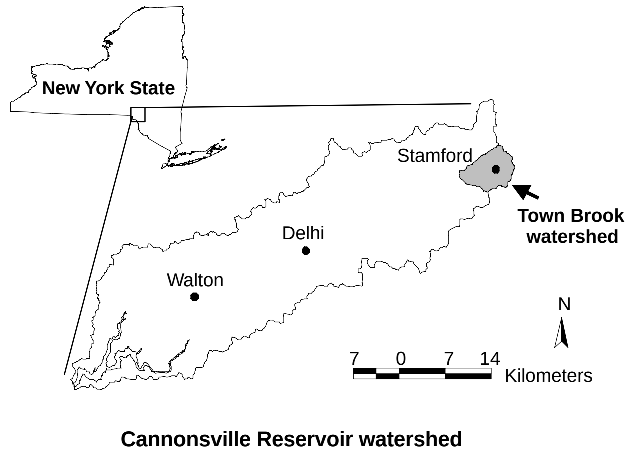

Figure 3. Location of the Town Brook and Cannonsville Reservoir watersheds within New York.

Baseline P Loadings

The SWAT model was applied to TBW to obtain baseline phosphorus loss values for the watershed. For the baseline scenario, management practices of conventional tillage and daily manure spreading, representative of TBW before intervention by the New York City Watershed Agricultural Council (CCE, 1987; Gary Lamont, NRCS, Walton, N.Y., personal communication, 2002), were applied.

Base topography, land use, and soils data were obtained from the New York City Department of Environmental Protection. A 10 m DEM provided base elevation data for watershed and subwatershed definition. Base land use data was obtained from a 10 m land use classification grid derived from 1992 LandSat Thematic Mapper imagery. Detailed soil information was obtained from the SSURGO soils database (NRCS, 1996; http://soils.usda.gov/). Both land use and soil distribution thresholds for defining SWAT HRUs were set at 0% to avoid lumping of land uses and soils. The resulting HRU map was overlaid with the farm boundary to identify the HRUs, a total of 186, within the farm.

Base climate data was obtained from the National Climate Data Centre (NCDC) database (http://lwf.ncdc.noaa.gov/oa/climate/climatedata.html) for a ten-year period (1992-2002). Precipitation data were obtained from the Stamford climate station located within the watershed (fig. 3); temperature data were taken from the next nearest station, Delhi, as Stamford did not have sufficient temperature data for the necessary SWAT runs. The Penman-Monteith method (Singh, 1988) was used in the computation of evapotranspiration, requiring additional data for solar radiation, wind speed, and relative humidity. As neither Stamford nor Delhi had these data, values were generated using Cooperstown, New York, data supplied by a weather database provided with SWAT. SWAT was calibrated for monthly and annual streamflow at the TBW outlet. Calibrated streamflow rates corresponded to observed data for both annual (R^2 = 0.9998; Nash-Sutcliffe = 0.84) and monthly (R^2 = 0.7642; Nash-Sutcliffe = 0.44) values. Visual comparison of daily hydrographs showed that the model tended to underpredict streamflow in the winter months and overpredict in the summer months.

After running SWAT on TBW, the ten-year average annual dissolved P loading for each HRU within the study farm was extracted. These loadings were then used as initial pollutant loading inputs for the GA.

BMP Effectiveness and Cost

All cropland and pasture HRUs (149 of the 186 HRUs) on the farm were considered for BMP implementation. Three BMPs were considered, both individually and in appropriate combinations. For the purpose of this study, these were defined as described in table 1. Specifically, nutrient management plans were considered for both cropland and pasture. Riparian forest buffers were considered on all agricultural land bordering a stream. Contour strip cropping was considered for all cropland. Due to the cool climate in the study region, conservation tillage was not considered a feasible BMP. The area of the farm considered for the case study did not incorporate farmstead land, including feeding, processing, and storage facilities. Thus, animal waste, barnyard management, and vegetated filter strip BMPs were not considered. Phosphorus reduction estimates (computed using eq. 1) were obtained for predominant slope and soil conditions on the farm (table 2). BMP cost data were obtained from the Delaware County BMP cost records (Ed Blouin, NYC-DEP, Kingston, N.Y., and Gary Lamont, NRCS, Walton, N.Y., personal communication, 2002) and are also shown in table 2.

Optimization Settings

A pollution reduction target of 60% of the baseline dissolved P average annual loading from the farm was established in order to demonstrate the methodology. By definition of the fitness function (eq. 3), optimal scenarios will meet the user-specified pollution reduction criterion. This is crucial for ensuring that water of acceptable quality is provided to the end user. For example, in the case study, the pollution reduction criterion can be used to ensure that potable water is supplied to New York City.

Table 2. Reduction estimates for dissolved phosphorus on predominant slopes (3% to 8% and 8% to 15%) and hydrologic soil groups (B and C) of the farm and annualized costs of BMPs considered for the farm.

	3% to 8% Slope		8% to 15% Slope		Annual Cost
Best Management Practice	Group B	Group C	Group B	Group C	($/ha)
Contour strip cropping	0.75	0.55	0.65[a]	0.68[b]	11
Nutrient management plan	0.75	0.36	0.50	0.43[a]	27
Riparian forest buffers	0.38	0.38[a]	0.38[b]	0.38[b]	1,942[c]

[a] Estimated based on effectiveness data grouped separately by soils and by slopes.
[b] Estimated based on overall average, independent of soil and slope.
[c] Includes establishment, incentive, and land rental.

Table 3. Cost-effectiveness of the baseline and two near-optimal scenarios.

	Baseline	Near-Optimal Scenario 1	Near-Optimal Scenario 2
Optimization fitness score		1.95	1.94
Phosphorus (P) loss (kg)	1471	587	588
Reduction of P loading from baseline (kg)	−−	884	883
Cost increase from baseline ($/year)	−−	1,430	1,683
Cost-effectiveness ($/year/kg)	−−	1.62	1.91
BMPs implemented as % of cropland			
Contour strip cropping	−−	8.0	9.0
Nutrient management plan	−−	11	14
Riparian forest buffers	−−	0.4	0.1
Contour strip cropping/nutrient management plan combination	−−	16	18

GA crossover and mutation rates of 0.9 and 0.01, respectively, were used with an initial population of 15 under 70% replacement. These values were chosen based on the parameter analysis of Veith (2002). The maximum allowable cost increase was set at $28,551 per year, which reflects the annual cost of applying all possible BMPs to the farm. As BMP life expectancies vary, it was assumed that all BMPs remain in place throughout the evaluation period (ten years) and that BMPs with lifetimes shorter than ten years are re-implemented as necessary. On any HRU for which the GA does not select a BMP, baseline management practices are maintained and the baseline pollutant loading is used.

Results and Discussion

The GA generated a number of near-optimal scenarios for the farm by selecting and placing BMPs as was best suited (fit) to maximizing P loss reduction and minimizing costs. Two highly fit scenarios from the optimization run were analyzed for cost-effectiveness and for BMP selection and placement (table 3, fig. 4). The first (scenario 1) achieved a fitness score of 1.95 out of a possible score of 2, while the second (scenario 2) achieved a fitness score of 1.94. Both scenarios met the established 60% dissolved P pollution reduction target with cost increases from the baseline of $1,430 and $1,683 per year, respectively (table 3). Scenario 1 was found to be slightly more cost-effective, saving about $0.30 per year per kg reduction of dissolved P loading from the watershed.

The selection and placement of BMPs within the scenarios is shown in figure 4. For this case study, the GA assigned BMPs mainly to cropland. Based on the GA allocations, scenario 1 applied BMPs to less acreage of the farm than did scenario 2. Additionally, the areas in specific BMPs and BMP combinations, other than buffers, were smaller in scenario 1 than in scenario 2, thus the slightly higher costs associated with scenario 2. As indicated in figure 4, placement of the selected BMPs varied between the scenarios, with some HRUs that had previously not been allocated a BMP being allocated one BMP or a combination in the second scenario. In both scenarios, the pollutant target was met, implying that both scenarios suitably reduced P. Routing structures used in this methodology are not detailed enough to reflect variable source area hydrology. In particular, near-stream areas are not necessarily more preferred for BMPs than areas farther from the streams.

As the GA was set to first find scenarios that met the pollutant reduction criterion, a variety of scenarios offering similar levels of pollutant reduction can be obtained. Costs and cost-effectiveness of these scenarios will likely vary. However, the presence of alternatives allows a farmer to choose among the scenarios that are most personally suitable, weighing tradeoffs between convenience and costs. For example, a farmer might view buffer areas as loss of productive land and opt for a scenario with less area in buffers, such as scenario 2. A different farmer might, say for management reasons, find it convenient to implement a solution that has less in-field BMPs and more area in buffers, such as scenario 1. For this farm, the difference in areas in buffers was not large. However, for solutions with large areas in buffers, opting for more area in buffers, as opposed to in-field BMPs, might lead to less cost-effective scenarios.

Summary and Conclusion

An optimization methodology was developed to determine the specific combination of BMPs, from a list of feasible BMPs for each HRU, that optimized cost-effectiveness for a given farm or watershed. This methodology combines the SWAT nonpoint-source model for estimating watershed-specific pollutant loadings, a BMP tool that estimates effectiveness from field studies reported in the literature, and BMP costs with the GA optimization heuristic in order to determine the most cost-effective scenario among all the feasible alternatives.

The methodology was demonstrated for a 300 ha farm in New York State. Two solution scenarios for the case study farm, which met the specified pollution reduction criterion at the preferred cost-level, were readily identified by the GA. These scenarios were analyzed for impact of BMP selection and placement on cost-effectiveness.

Because the GA identifies scenarios that are equal, or nearly equal, in fitness from among the range of feasible solutions, watershed planners receive an indication of the sensitivity of the watershed response to specific BMP placements as demonstrated by the comparison between scenarios 1 and 2. This information can be useful in incorporating qualitative criteria and farmer-specific concerns into the process of determining the most widely acceptable final solution.

This methodology is applicable to any area for which average annual baseline pollutant loadings can be estimated and for which field study data or effectiveness estimates for the BMPs under consideration are available. Because the methodology is designed to work on an average annual basis, baseline pollutant loading, field study data, and effectiveness

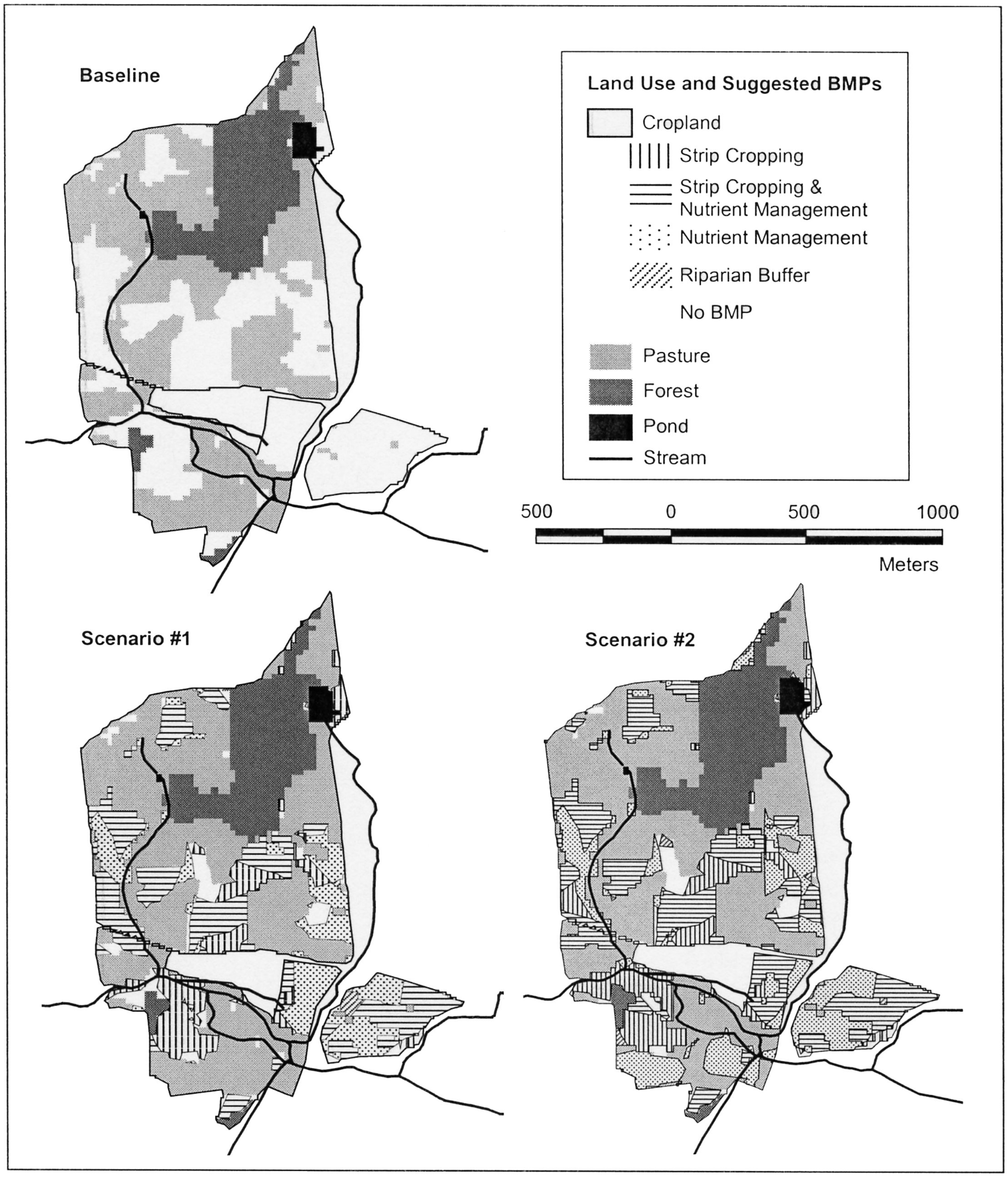

Figure 4. BMP placement for baseline and two near-optimal scenarios for the farm.

estimates should be representative of average expectations over time. Thus, base data spanning at least 5 to 10 years would be most appropriate. Use of this method can aid watershed planners in determining cost-effective solutions to watershed-level agricultural nonpoint-source pollution concerns.

As noted earlier, the results are site-specific, and BMP selection and placement for one farm or watershed can only be extended directly to another when the latter has similar land uses and site characteristics. In particular, while the methodology itself is readily applicable to watershed-wide BMP evaluations, the results obtained from the presented case study cannot be directly scaled up and used to make decisions at a watershed level. A watershed is likely to have more varied land uses as compared to those associated with the case-study farm. Consequently, the number and variety of BMPs implemented on the watershed would be larger, including BMPs that are more expensive, such as barnyard runoff management. Thus, confirmations and additions to the input data sets should be made to appropriately represent the area being modeled.

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