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Optimizing Best Management Practice Selection to Increase Cost-effectiveness

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Abstract. With Best Management Practices (BMPs) being used increasingly to control losses of major agricultural pollutants to surface waters, establishing the effectiveness of these practices has become important. A methodology was developed for determining cost-effective watershed scenarios. This technique combines three existing tools: a genetic algorithm (GA), a watershed-level nonpoint source model (Soil and Water Assessment Tool, SWAT), and a BMP assessment tool. The GA combines initial pollutant loadings from SWAT with literature-based pollution reduction efficiencies provided by the assessment tool and BMP costs appropriate to the study area to determine cost-effective watershed scenarios. The methodology was successfully applied to a 300-ha farm within the Cannonsville Reservoir watershed in New York. The Cannonsville Reservoir is phosphorous (P) restricted, and planners are implementing BMPs to reduce P loading to the reservoir. The optimal scenario for the farm, under the presented methodology, achieved a cost-effectiveness of 0.6 kg dissolved P reduction per dollar spent. Additionally, the methodology determined alternative scenarios which met the pollution reduction criteria cost-effectively.

Keywords. genetic algorithm, BMP, SWAT, agricultural nonpoint source pollution

Introduction

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), exist that can be used to control pollutant losses. As reliance on BMPs for adequately controlling pollutant losses becomes more common, establishing their effectiveness in pollution reduction becomes more important (Dillaha, 1990).

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 cost considerations. Society, on the other hand, may be primarily interested in improved water quality and have little concern for costs unless pollution reduction costs are reflected in increased taxation or consumer-related costs.

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 environmental 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 BMP combinations, then, lies in optimizing selection and placement of the BMPs in order to determine the highest pollutant reduction at the least cost. Because there can be several workable and acceptable solutions to BMP placement for any 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). GAs search using the mechanics of natural selection and genetics. 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 objective of the presented study was to develop a methodology for determining optimal BMP selection and placement, with regard to the cost-effectiveness of nonpoint source pollution reduction and a focus on dissolved phosphorous (P). This objective was addressed by combining the Soil and Water Assessment Tool (SWAT; Arnold et al., 1998), a BMP assessment tool (Gitau et al., 2002), and an upgraded version of the GA presented in Veith et al. (2003). SWAT is a watershed-level, nonpoint source model that provides baseline pollutant loadings. The assessment tool includes literature-based P reduction efficiencies for both management and structural BMPs. The GA determines cost-effective farm or watershed scenarios by combining outputs from SWAT with reduction efficiencies from the assessment tool and BMP costs appropriate to the study area.

Previously, Chatterjee (1997), Srivastava et al. (2002), and Veith et al. (2003) used GAs in their optimization work with BMP selection and cost-effectiveness. As compared to previous GA work in which BMP effectiveness data was supplied through nonpoint source model runs, use of the assessment tool is more time efficient with regard to optimization runs. The tool also offers greater flexibility with regard to the types of BMPs that can be selected. In the absence of a fully monitored and sampled watershed, the technique uses an accepted watershed-level model for initial estimation of pollutant loadings under a baseline scenario.

Components

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 and is designed for use in ungaged 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 and sediment and nutrient losses throughout the watershed.

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. Entering known or measured values for these inputs improves accuracy of the watershed representation and thus, theoretically, overall model accuracy.

SWAT provides several levels of output: HRU, subbasin, reach, and watershed. The BMP placement methodology discussed in this paper used HRU-level output as input for the GA. SWAT also provides output on a variety of water quality parameters. Of interest to this study was dissolved P.

BMP effectiveness tool

The BMP assessment tool (Gitau et al., 2002), developed within Microsoft Access, was based upon effectiveness data obtained from published BMP monitoring studies. The underlying database contains data on particulate, dissolved, and total P reduction effectiveness, 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 paper). The database currently contains 32 BMPs grouped into three broad categories: erosion control, nutrient management, and barn yard management. At present, the database contains data analyzed for eight classes of BMPs: animal waste systems, barn yard runoff management, conservation tillage, contour strip cropping, crop rotations, field-level nutrient management plans, riparian forest buffers, and vegetated filter strips. 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 assessment tool was designed to allow site specific estimates of BMP effectiveness and to facilitate access to analyzed data and associated citations. The tool can be used either as a stand-alone application or in conjunction with a nonpoint source model.

The BMP tool requires selection of a hydrologic soil group, as defined by NRCS (1996), and a slope class for each HRU. Values for this study were obtained from soil maps in the National Soils Data Access Facility (http://soils.usda.gov/) soils database. The BMP tool "Estimates dialog" window is used to input soil and slope characteristics (Figure 1). Additionally, one must select the BMP category for which estimates are required: erosion control, nutrient management, or barn yard management. Once the three selections have been made, the tool is run. Tool output comprises various BMPs under the selected category and associated pollution reduction effects of each BMP.

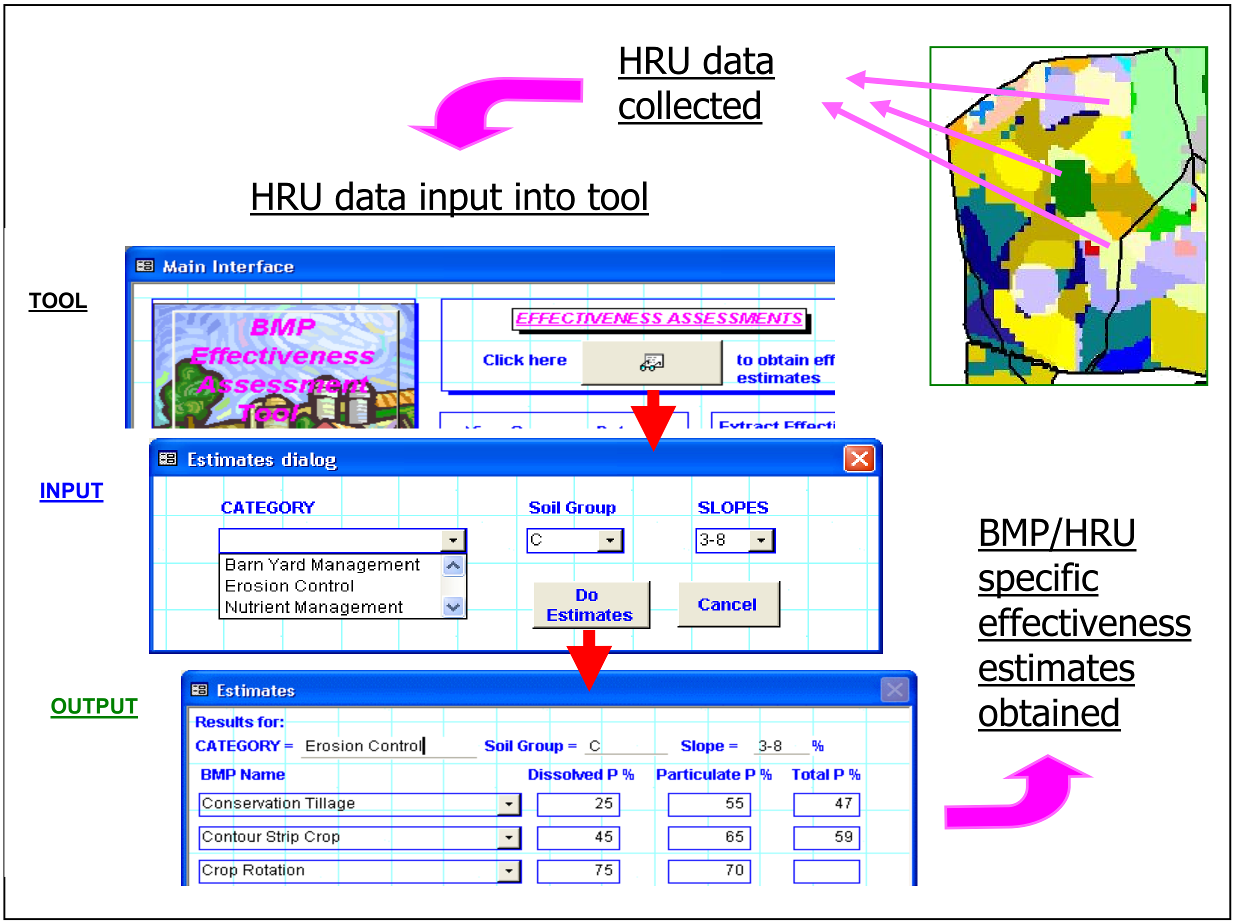

Figure 1. Applying the BMP tool to obtain HRU-specific effectiveness estimates.

Genetic Algorithm

A genetic algorithm (GA) is used to optimize BMP placement with respect to cost and pollution reduction. Basic GAs model individuals of a population as chromosomes, with genes on the chromosome defining relevant traits of the individual. Highly fit chromosomes are most likely to survive into the next generation, and all chromosomes, regardless of fitness, are subjected to random mutations. As a random search algorithm, GA does not require continuity in the input variables. At each generation the GA evaluates multiple solutions, often from different areas of the search space. This parallelism decreases susceptibility to becoming fixed at local minima (Buckles and Petry, 1992).

The GA for this research uses a steady state, tournament selection replacement scheme, in which a given percentage or a set number of the population is replaced each generation. 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.

Problem representation

The optimization problem lends itself to a straightforward representation within a GA. Each watershed scenario can be thought of as an array of numbers or a chromosome. Thus, a possible solution to the problem is represented as a chromosome, and each HRU as a gene on that chromosome. In nature the value of each gene along the chromosome is chosen from a set of possible values, or alleles, for that gene. In the watershed scenario representation, each member of the array acts as a placeholder for the member's respective field or HRU; the value in that position represents the specific management practice on that field.

The baseline scenario is the scenario to which each new scenario is compared. This is not required to be the scenario used for initializing the GA. However, meeting this requirement does simplify the process because the allele set for each gene is defined independently based on the value of that gene in the initializing genome. Using the baseline scenario to define the array of allele sets allows the GA to be initialized with a random population where each individual is subject to the constraints of the allele array. Thus, any land use area not in production is assigned a single allele, representing the baseline value, and maintains a fixed set of management practices. Land use areas in production are assigned a set of alleles, corresponding to the set of acceptable BMPs.

Fitness

The GA uses a two-part fitness equation, optimizing first for pollution control and next for cost reduction. Pollutant loads for each scenario are determined at the watershed outlet by calculating the pollutant loss from each HRU, after any BMPs have been applied, and then routing the 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 (Equation 1).

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

where

P = pollutant score [dimensionless]
p_b = pollutant loading from baseline scenario [units of mass],
p_t = target pollutant loading [units of mass], and
p_w = pollutant loading from working scenario [units of mass].

Based on 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 (Figure 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.

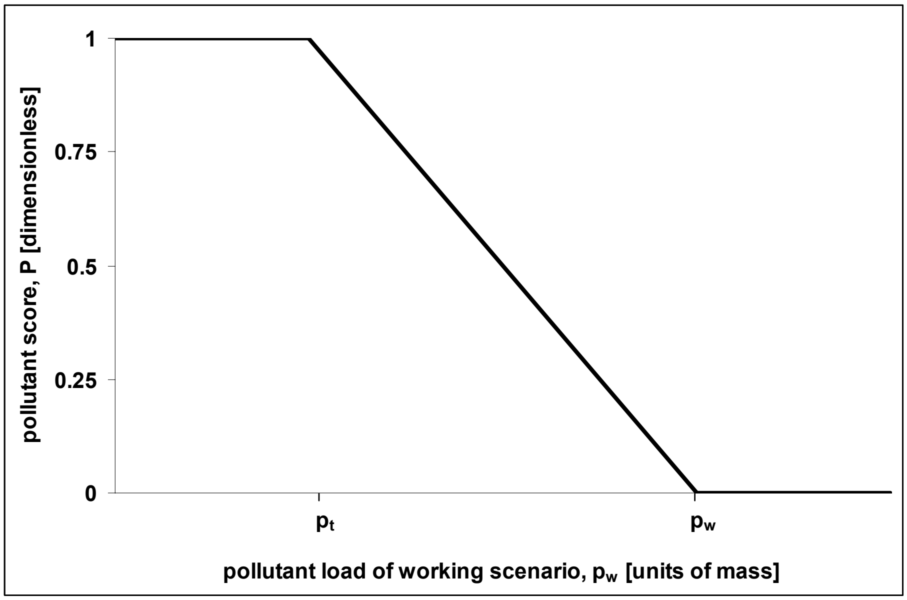

Figure 2. Pollutant score function

Scenario cost increase is the direct sum, across all HRUs in the watershed, of implementing the BMPs. The cost fitness function (Equation 2) 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.

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

where

C = cost score [dimensionless]
c_m = maximum allowable cost increase from baseline scenario [$],
c_t = target cost increase from baseline scenario [$], and
c_w = cost increase of working scenario from baseline scenario[$].

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

The GA evaluates each scenario by combining the pollutant and cost fitness scores into a single objective function (Equation 3).

$$F = \begin{cases} P & \text{for} \quad P < 1 \\ C & \text{for} \quad P = 1 \end{cases} \tag{3}$$

where

F = total fitness score [dimensionless],
P = pollutant score [dimensionless]
C = cost score [dimensionless].

Each scenario is first examined to see if its pollutant load meets the pollutant-targeting criteria. Fitness scores are continuous and range from zero to two. All scenarios that meet the pollutant-targeting criteria (i.e., having a pollutant score of one) are ranked based on their economic scores. Thus, their fitness scores equal their economic scores (ranging from one to two). All scenarios not meeting the pollutant-targeting criteria are ranked by their pollutant scores so that their fitness scores equal their pollutant scores (ranging from zero to one). Hence, for each population and for the GA as a whole the scenario that meets the pollutant-targeting criteria for the least cost has the highest fitness score.

Recent Upgrades

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, MA. http://lancet.mit.edu/ga/. Accessed 12 July 2001). The version discussed in this paper incorporates four major upgrades made to the basic component described by Veith et al. (2003).

- 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 respective average loss percentages 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.
- Construction of allele sets, which create groupings of BMPs or BMP combinations acceptable to a particular HRU, was modified to improve customization of the watershed representation. The user now specifies the allele sets desired, drawing from all possible BMP combinations. The user then assigns an allele set to each HRU. Through these upgrades 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 adjust the contributing area of an HRU by the percentage that specifically contributes to load reduction as a result of applying facility BMPs, such as animal waste systems, barn yard runoff management, or vegetated filter strips.

Case Study

Site description

An optimization study was carried out for a single farm within Town Brook watershed (TBW), Delaware County, New York. TBW is part of the Cannonsville Reservoir watershed (Figure 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, barn yard runoff, and soil loss (WAC, 1997) with P being the main pollutant of concern.

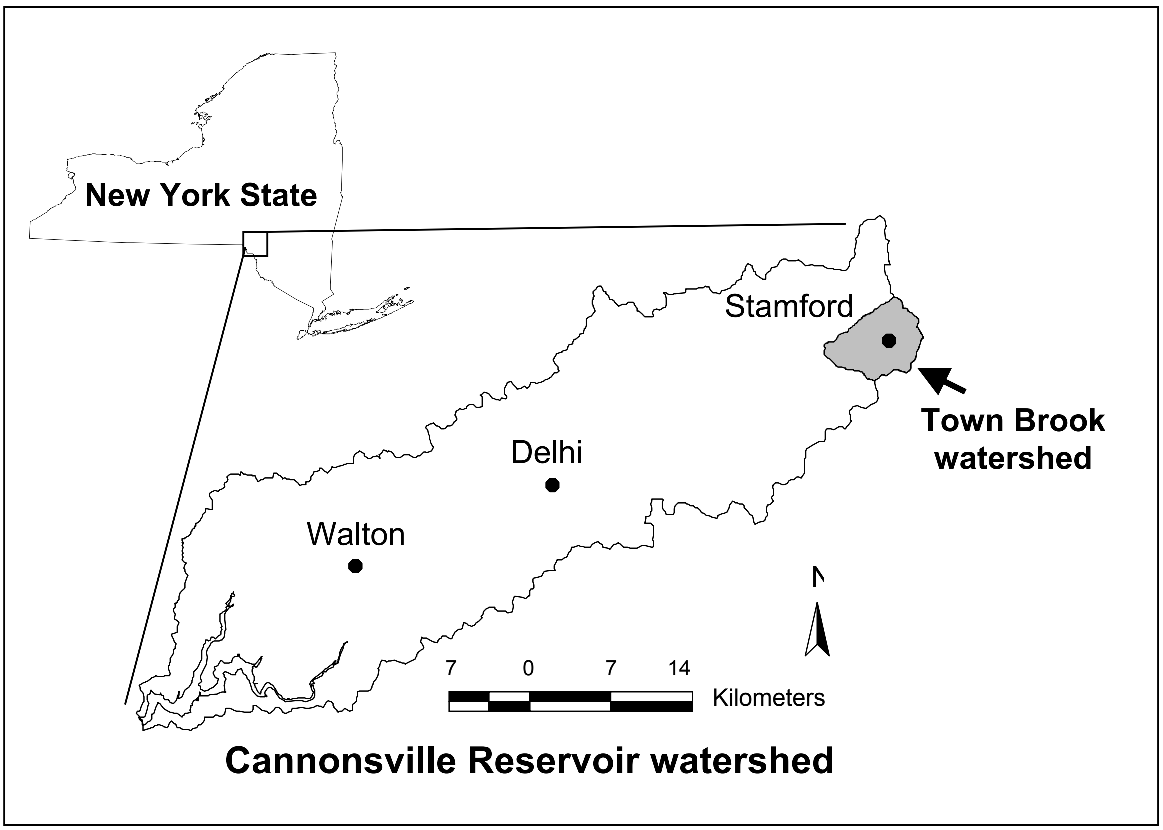

Figure 3: Location of the Town Brook and Cannonsville Reservoir watersheds within New York.

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 Watershed Agricultural Council, a body that oversees BMP implementation in the New York City watersheds. There has also been a continuing effort towards monitoring stream flow 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 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.

Initial pollutant loadings

The SWAT model was applied to TBW to obtain pollutant loadings associated with each HRU. 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 (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. A total of 186 HRUs were identified as falling 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, while temperature data were taken from the next nearest station, Delhi, as Stamford did not have sufficient temperature data for making the necessary SWAT runs. The Penman method was used in the computation of ET, 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 obtained from the SWAT weather database.

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 positioning in 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.

For purposes of comparison with the optimization results, a baseline scenario of the farm was modeled in SWAT. This scenario used conventional management practices that were representative of TBW before intervention by the New York City Watershed Agricultural Council (CCE, 1987; Gary Lamont, NRCS Walton, NY, 2002. Pers. Comm.). After running SWAT on TBW, pollutant loadings for HRUs within the study farm were extracted for further analyses.

Determination of BMP effectiveness

Starting with the baseline scenario from SWAT, 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. 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.

The BMP assessment tool was used to derive effectiveness estimates of dissolved P for the ranges of slope and soil conditions existing on the farm. Effectiveness is a measure of the ability of the BMP to retain the pollutant at the source. For each soil-slope combination a BMP-specific reduction was computed as a fraction, based on effectiveness estimates (Equation 4).

$$reduction_{(BMP)} = 1 - \left(estimated\ effectiveness_{(BMP)} \big/ 100 \right) \qquad (4)$$

The reduction estimate refers to the fraction of the original pollution leaving the source after BMP implementation. For example, suppose 100 kg of dissolved P is leaving a field with 3-8%

slope and hydrologic soil group C. Applying contour strip cropping, which has an effectiveness estimate of 45% (Figure 1), is estimated to result in 45 kg of dissolved P remaining on the field and 55 kg leaving the field.

Reduction estimates obtained for predominant slope and soil conditions in the farm are shown in Table 1. In cases where there was not sufficient data to allow estimates to be made based on both slopes and soils, effectiveness was estimated based on data analyzed separately by slope and by soil, or based on an overall average for the BMP, regardless of soils and slopes.

Table 1. Reduction estimates for dissolved phosphorous on predominant slopes (3-8%, 8-15%) and hydrologic soil groups (B, C) of the farm.

Best Management Practice (BMP)	**3-8% Slope**		**8-15% Slope**	
	B	**C**	**B**	**C**
Contour Strip Cropping	0.75	0.55	0.65*	0.68**
Nutrient Management Plan	0.75	0.36	0.50	0.43*
Riparian Forest Buffers	0.38	0.38*	0.38**	0.38**

*Estimated based on effectiveness data grouped separately by soils and by slopes.
**Estimated based on overall average.

Determination of BMP cost

BMP cost data were mainly obtained from the Delaware County BMP cost records (Ed Blouin, NYC-DEP Kingston, NY, 2002 and Gary Lamont, NRCS Walton, NY, 2002. Pers. Comm.). The data include capital costs, representing current implementation expenses, and expected lifetimes of the BMPs. All costs were reduced to their annual values, using Equation (5) (Degarmo et al., 1997; App. C), and are shown in Table 2.

$$A_{BMP} = \frac{\mathrm{Pr}}{1-(1+r)^{-n}} \tag{5}$$

where

- A_{BMP} = annualized cost for a BMP [$],
- P = capital cost of the BMP [$],
- r = time value for money [dimensionless], and
- n = lifetime of the BMP [years].

Table 2. Annualized costs of enhancements considered for the farm.

Best Management Practice	**Annual Cost ($/ha)**
Contour Strip Cropping	11.39
Nutrient Management Plan	27.17
Riparian Forest Buffers (establishment and land rental)	1,941.54

Determination of fitness

For this case study, 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). A pollution reduction target of 60% of the baseline was established in order to demonstrate the methodology.

Starting with the baseline scenario in which no BMPs were implemented, the GA created a random population of 15 feasible scenarios for the farm. For each HRU on which the GA placed a BMP, computed reductions from the BMP tool were applied to the baseline pollutant loading obtained from SWAT. On any HRU for which a BMP was not selected, baseline management practices were maintained and the baseline pollutant loading was used. The fitness of each scenario was then determined in terms of pollution reduction (Equation 1), cost increase (Equation 2), and overall fitness (Equation 3). As the GA progressed, the more fit scenarios had a higher probability of being replicated and combined to form new scenarios. At each step the most fit scenarios were carried over to the next generation, driving the GA toward optimality.

By definition, optimal scenarios meet user-specified pollution reduction criteria. 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 criteria can be used to ensure that potable water is supplied to New York City. Additionally, the limits placed on cost increase drive the GA to find a scenario costing, as nearly as possible, the amount approved by the Watershed Agricultural Council.

Case study results and discussion

As expected during the progression of the GA run, fitness scores rose while scenarios met the pollution reduction and cost increase criteria to an increasing extent (Figure 4). The 60% pollution reduction target, shown in Figure 4 by the vertical dashed line, was met by generation 55, as indicated by a fitness score of one. At this point in the GA run, the focus of optimization switched from pollution reduction to cost minimization.

A total fitness of 1.95 out of 2 was achieved within 300 generations (Figure 4, top graph). For the parameters set in this case study, a scenario meeting the pollutant-target criteria and having the same cost as the baseline scenario would have a total fitness score of 2. Thus, a fitness score of 1.95 indicates the cost of the final scenario was 5% greater than the baseline scenario, as compared to the maximum allowable cost.

The optimal scenario achieved a dissolved P loading of 587 kg (Figure 4, middle graph). This is a 60% decrease from the baseline loading, which was 1471 kg. Implementation of BMPs within the optimal scenario were estimated to have an annual cost of $1,430 (Figure 4, bottom graph). Thus, application of the presented methodology on the farm resulted in a solution scenario cost-effectiveness of 0.6 kg reduction per dollar spent or $1.62 per kg reduction.

The selection and placement of BMPs within the optimal scenario is shown in Figure 5. For this case study, the GA assigned BMPs only to the cropland. None of the HRUs in pasture, with generally lower erosion rates than cropland, were selected for BMP placement. One cropped field, bordering the stream, was assigned buffer. As indicated from Figure 5, 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.

Figure 4 shows data for only the most fit scenario at each generation and Figure 5 shows the optimal solution at the end of the GA run. However, as an optimal scenario is identified, the GA also identifies scenarios that are equal, or nearly equal in fitness from among the range of feasible solutions. Thus, watershed planners receive an indication of the sensitivity of the watershed response to specific BMP placements. This information can be useful in incorporating qualitative criteria and farmer-specific concerns into the process of determining the most widely-acceptable final solution.

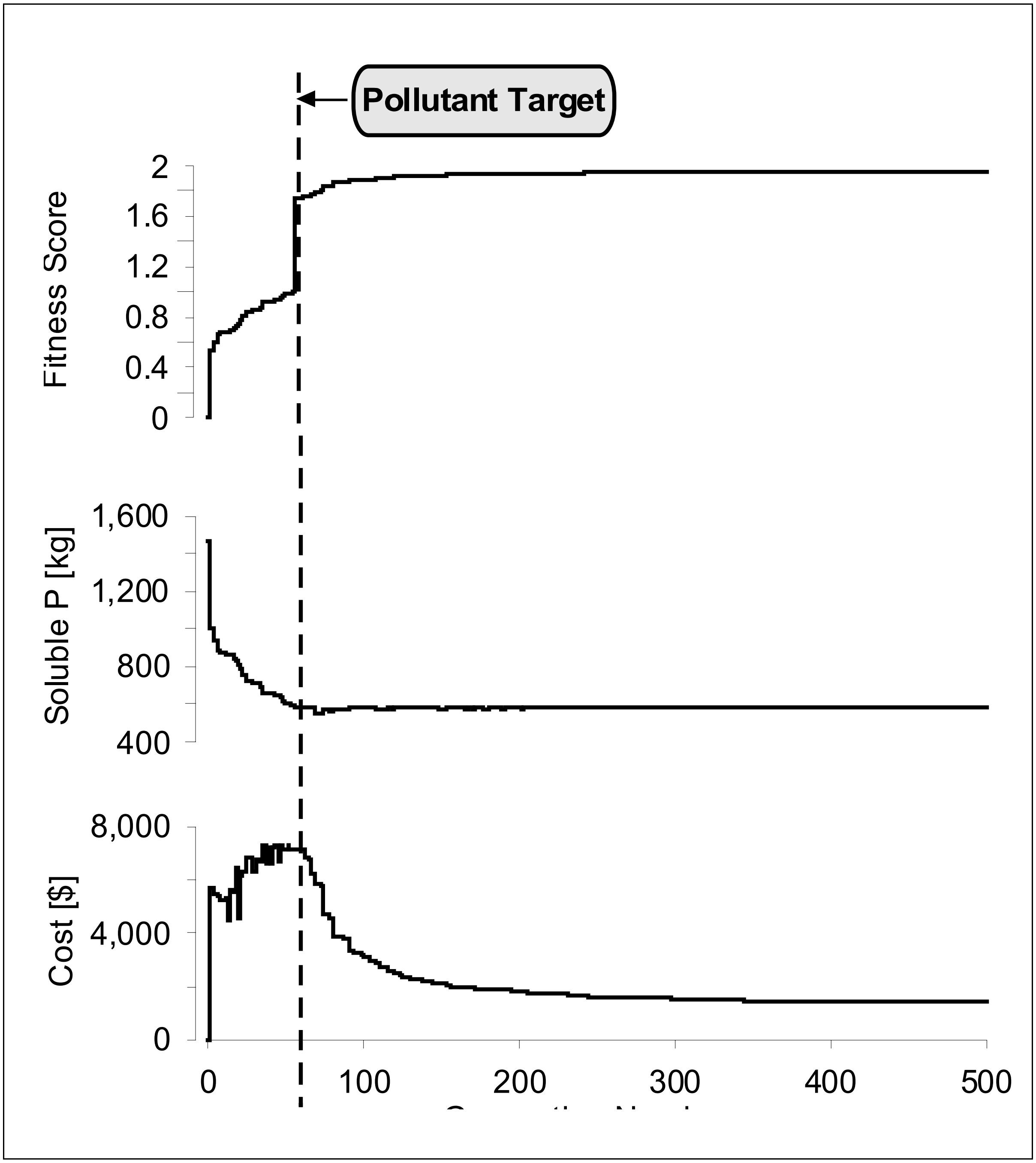

Figure 4: Progression of best-of-generation scenario values throughout optimization run.

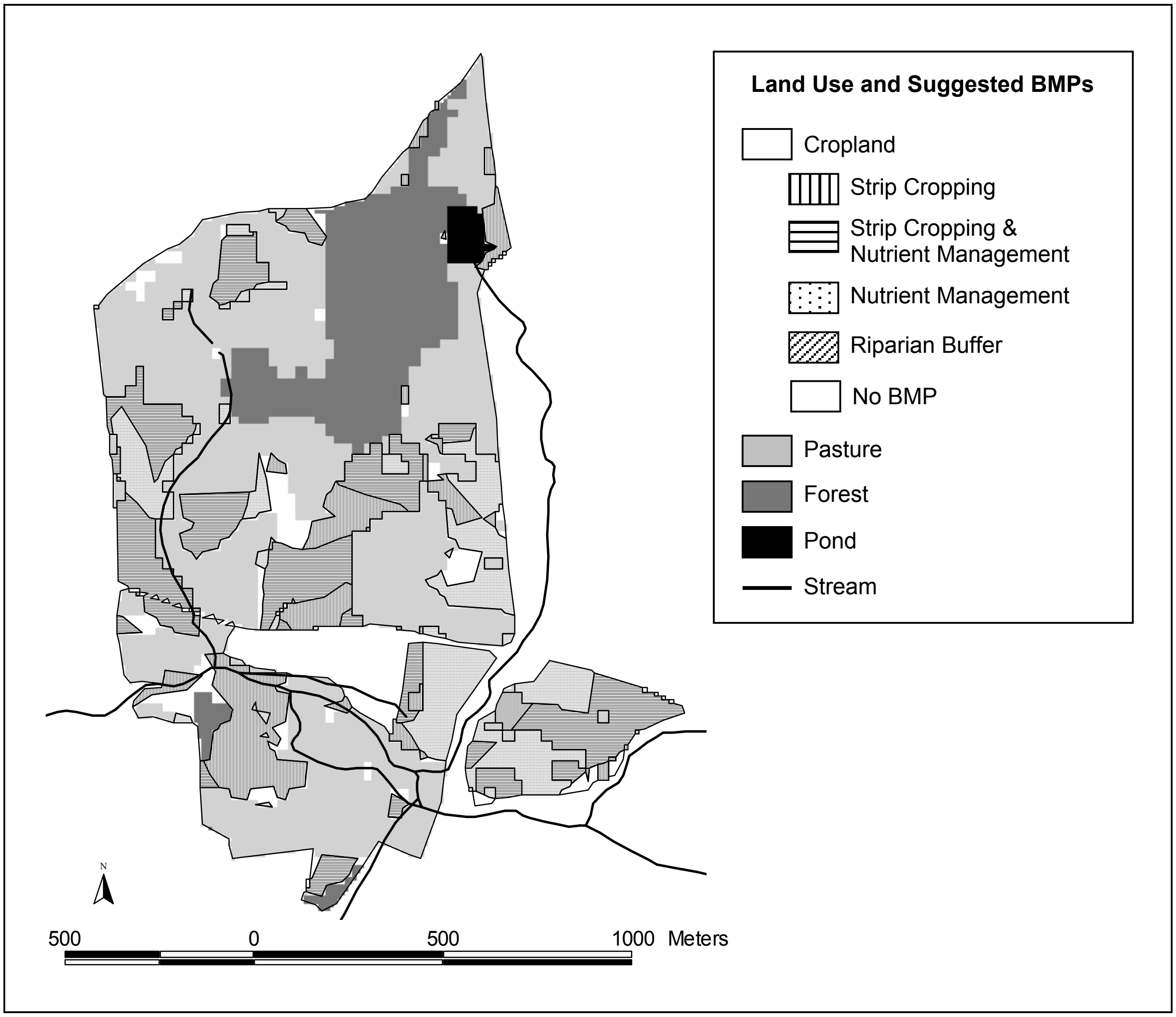

Figure 5: Optimal scenario for the farm, indicating suggested BMP selection and placement.

Conclusion

Methodology was developed to determine the specific combination of BMPs, from a list of feasible BMPs for each HRU, which optimized cost-effectiveness for a given farm or watershed. This methodology combines a nonpoint source model for estimating watershed-specific pollutant loadings, a BMP assessment tool which incorporates field studies from the literature, and a GA for determining the most cost-effective scenario among all the feasible alternatives.

The methodology was demonstrated for a 300-ha farm in New York state. A solution scenario which met the specified pollution reduction criteria at the preferred cost-level was readily identified by the GA.

This methodology is applicable to any area for which baseline pollutant loadings can be estimated and for which field study data or effectiveness estimates for the BMPs under consideration are available. Use of this method can aid watershed planners in determining cost-effective solutions to watershed-level agricultural nonpoint source pollution concerns.

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