Optimization Tool for Allocation of Watershed Management Practices for Sediment and Nutrient Control

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Abstract
Implementation of conservation programs are perceived as being crucial for restoring and protecting waters and watersheds from nonpoint source pollution. Success of these programs depends to a great extent on planning tools that can assist the watershed management process. Herein, a novel optimization methodology is presented for deriving watershed-scale sediment and nutrient control plans that incorporate multiple, and often conflicting, objectives. The method combines the use of a watershed model (SWAT), representation of best management practices, an economic component, and a genetic algorithm-based spatial search procedure. For a small watershed in Indiana located in the Midwestern portion of the United States, selection and placement of best management practices by optimization was found to be nearly three times more cost-effective than targeting strategies for the same level of protection specified in terms of maximum monthly sediment, phosphorus, and nitrogen loads. Conversely, for the same cost, the optimization plan reduced the maximum monthly loads by a factor of two when compared to the targeting plan. The optimization methodology developed in this paper can facilitate attaining water quality goals at significantly lower costs than commonly used cost-share and targeting strategies.

Keywords
Optimization; nonpoint source pollution; best management practices; modeling, SWAT

INTRODUCTION

Best management practices (BMPs) are widely accepted as effective control measures for agricultural nonpoint sources of sediments and nutrients. The 2002 Farm Bill provided up to $13 billion for conservation programs aimed at protecting water quality from agricultural nonpoint source (NPS) pollution (USDA, 2003). In addition, under the Clean Water Act Section 319 Nonpoint Source National Monitoring Program and wetland protection programs, the EPA supports programs to reduce the negative impacts of runoff from agricultural, urban, and industrialized areas. Similarly, the Natural Resources Conservation Service (NRCS) provides hundreds of millions of dollars in federal funds to support agricultural best management practices (BMPs) in an effort to reduce the movement of pollutants into our waterways. Success of such programs, however, is contingent upon availability of efficient watershed-scale planning tools.

Implementation of BMPs is challenged by complexities in incorporation of conflicting environmental, economic, and institutional criteria. Environmental assessments in watersheds hinge on resolving social benefits such as achieving the goal of swimable and fishable water bodies under the EPA's Total Maximum Daily Load (TMDL) agenda. While BMPs facilitate achievement of such targets, their establishment bears additional cost for watershed management and/or agricultural producers. Since management practices are usually implemented under a limited budget, costs associated with unnecessary/redundant management actions may jeopardize attainability of designated water quality goals. Identifying optimal combinations of watershed management practices requires systematic approaches that allow decision makers to quickly assess trade-offs among environmental and economic criteria.

Research to date indicates the promise of heuristic optimization for cost-effective allocation of watershed management practices (Srivastava et al., 2002; Veith et al., 2004; Muleta and Nicklow, 2005). Unlike gradient-based approaches, heuristic techniques do not require linearity, continuity, or differentiability either for objective/constraint functions or for input parameters. Thus, they are well-suited for cost-effective allocation of watershed management plans. However, several questions still defy answers. A decision making tool that can clearly accommodate economic, environmental and institutional criteria is still lacking. The means for imposing target values for pollutant loads, and total watershed cost of implementation of management plans needs to be explored.

The main goal of this study is to develop an optimization framework that enhances decision makers' capacity to evaluate a range of agricultural and environmental management alternatives. The tool will be designed to identify near optimal watershed plans that reduce pollutant loads at a watershed outlet to below regulatory or target values with minimum cost. We hypothesize that reductions of pollutants at watershed outlets can be attained at significantly lower cost by optimized implementation of conservation practices than by current cost-share and targeting approaches. This overall goal is achieved by the following specific steps:

i. Development of a novel genetic algorithm-based spatial search model. This step will focus on formulating versatile objective and constraint functions for the optimization model that can handle multi-criteria and landscape characteristics.
ii. Integration of an NPS model (SWAT; Soil and Water Assessment Tool), a new BMP representation method, and a cost-benefit economic relationship with the GA-based spatial optimization model to identify optimal spatial allocation of best management practices.
iii. Demonstrate the application of the optimization tool through a case study.

METHODS

The optimization model developed in this study is comprised of the SWAT model for simulating pollutant loads, a BMP representation tool, an economic component, and a GA-based spatial optimization technique. A MATLAB computer program (The Mathworks, Natick, MA) was developed to provide the linkage among various components of the model as shown in Figure 1. The model was tested for optimization of the location of field borders, parallel terraces, grassed waterways, and grade stabilization structures in the Dreisbach watershed. SWAT simulations were performed for a 10-year period from January 1st, 2000 through December 31st, 2009. In the analysis, 1991-2000 precipitation data, 2000 USDA-National Agriculture Statistics Service (NASS) land use and 2002 Soil Survey Geographical Database (SSURGO) were utilized to establish a base-case SWAT run. Parameter values in the base-case run were selected from a

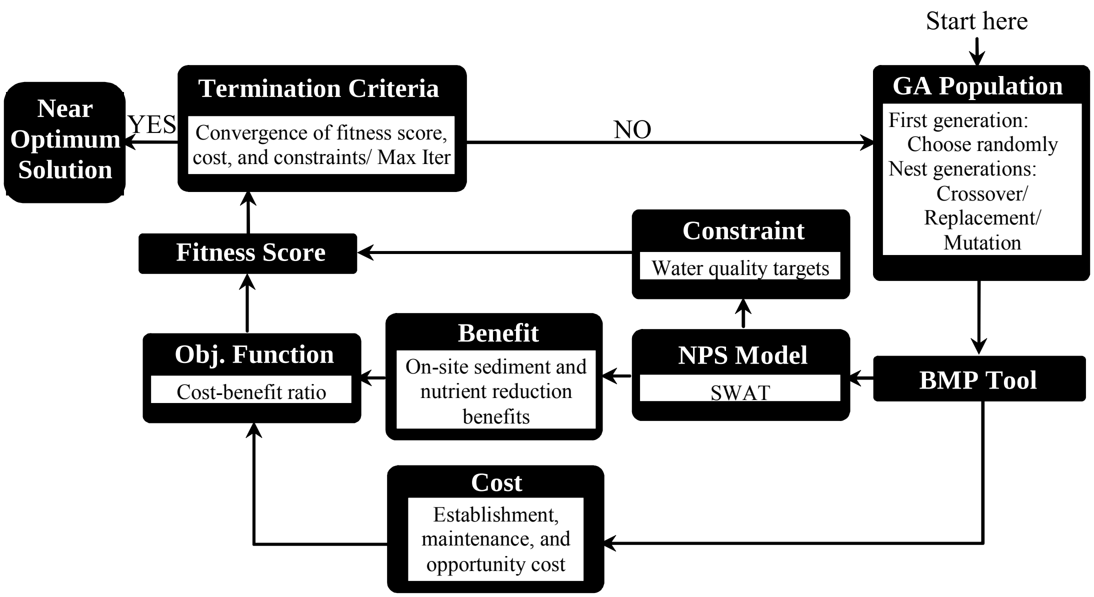


Figure 1. Schematic of the proposed optimization procedure (Arabi et al., 2006).

manual calibration (Arabi et al., 2004). Portions of the watershed classified as urban and forested areas were not considered for implementation of BMPs.

Case Study Watershed

The utility of the optimization framework was examined for a subwatershed in the Black Creek basin. The Black Creek watershed located in northeast Indiana is a typical watershed in the upper Maumee River basin in the Midwestern portion of the United States. In mid 1970's and early 1980's, several BMPs were implemented in the watershed and detailed water quality monitoring was carried out at various locations within the watershed to examine short-term water quality impacts of soil and water conservation techniques. Data collected from automated samplers at the outlet of the Dreisbach watershed (6.23 km^2) within the Black Creek basin were the most complete and were used in this study. Figure 2 depicts the location of the Dreisbach watershed. The dominant hydrological soil group in the study watershed is type C. Available data, land use distribution, and other information for the watersheds can be obtained from Arabi et al. (2004).

Watershed Model

The Soil and Water Assessment Tool, or SWAT (Arnold et al., 1998), is a process-based watershed model that simulates flow, sediment, erosion, nutrients, pesticides, and bacteria. The current version, SWAT 2005, is based on a foundation of 30 years of hydrologic/water quality modeling research and development by the USDA, other federal and state agencies, and universities. SWAT has also been adopted as part of the US EPA Better Assessment Science Integrating Point & Nonpoint Sources (BASINS) software package. The model has been validated under a wide variety of conditions and in watersheds ranging from small to large (reviewed by Arnold and Fohrer, 2005), and a significant base of researchers continues to expand the science and functions within SWAT. The widespread use of SWAT within the U.S. and internationally will facilitate replication and expansion of the methods we develop and use in this project for other watersheds. Although as a watershed-scale model, SWAT generalizes watershed

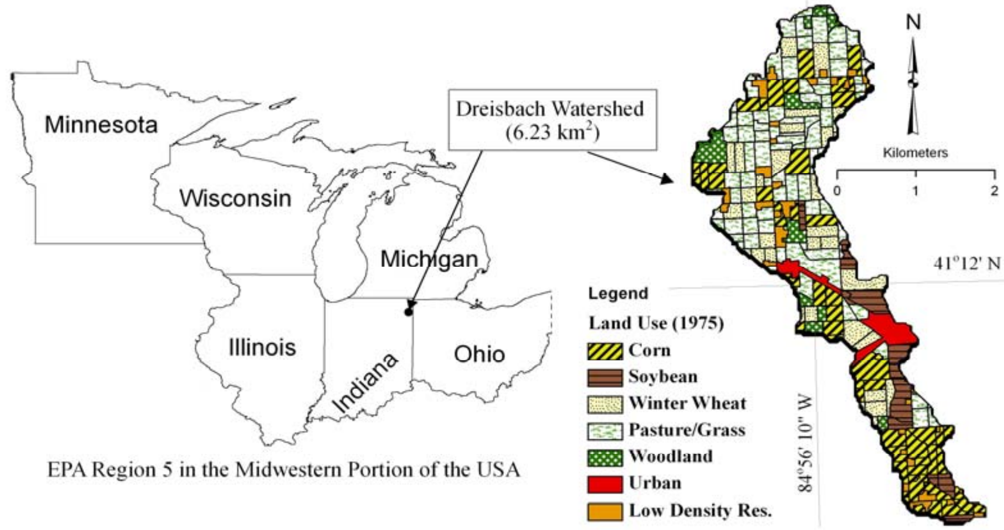


Figure 2. Study watershed.

processes in hydrologic response units (HRUs), it has nevertheless been shown to effectively represent many BMPs. Kalin and Hantush (2003) reviewed key features and capabilities of widely-cited watershed-scale hydrologic and water quality models, with emphasis on their ability to represent watershed management practices for TMDL development, and found that SWAT offers the most management alternatives for modeling in agricultural watersheds.

Genetic Algorithm (GA)

A genetic algorithm (GA) was employed to optimize spatial allocation of BMPs. In this GA component, each optimization string corresponds to a specific watershed management plan. The length of each string (*m*) corresponds to the total number of genes, i.e., individual management actions that are considered in optimization. For example, in a watershed with 50 fields considered for implementation of field borders and/or parallel terraces, and 20 reach segments considered for implementation of grassed waterways and/or grade stabilization structures, the total number of genes on each management string is equal to m= [$2\times50+2\times20$=] 140. The alleles are binary values, with “1” or “zero” indicating that the corresponding BMP “be” or “not be” implemented.

The mathematical representation of the objective function used in this paper was:

$$\text{Maximize}\, z = \frac{bt}{\max(ct,1)} = \frac{\sum_{\tau=1}^{td}\sum_{i}\left[\left(\Delta y_{i,\tau} bm_i\right)(1+s)^{(\tau-1)}\right]}{\max\left(c_0(1+s)^{td} + c_0\cdot rm[\sum_{\tau=1}^{td}(1+s)^{(\tau-1)}],1\right)} \quad 1$$

subject to water quality constraints:

$$\Gamma_1(x,t,td,\alpha) = ymax_i(x,t,td,y,\alpha) - yt_i \le 0 \quad 2$$

and budget constraints:

$$\Gamma_2(x,t,td,\alpha) = ct(x,t,td,\alpha) - w\cos t \le 0 \quad 3$$

where $ymax_i$ is maximum delivery of pollutant constituent i after implementation of BMP combination (α) estimated with SWAT simulations over period *td*; and yt_i is the allowable load of constituent i. Variable *ct* is the total cost of implementation of α, and *wcost* is the total available budget for implementation of management plans. The denominator in 1 was designed such that it will never be zero.

The optimization constraints in 2 and 3 are typically defined by regulatory and implementation agencies. For example, allowable sediment and nutrient loads (yt_i) may be obtained from a Total Maximum Daily Load (TMDL) for a given watershed. While yt_i and $ymax_i$ can be expressed on a daily, monthly, or annual basis, as loads or concentrations, their units should be consistent. The cost constraint represents available budget for implementation of watershed management scenarios and may be specified by implementation agencies.

The fitness score (*fs*) for each string was evaluated by the objective function (*z*) associated with the string from Eq 1. Infeasible solutions, i.e., solutions that do not satisfy the constraint functions Γ_1 and Γ_2 in 2 and 3, were penalized by applying a penalizing factor *k* as:

$$fs = k \times z;$$
$$k = \begin{cases} 10^{-5} & ;\Gamma_1 \vee \Gamma_2 > 0 \\ 1 & ;\Gamma_1 \wedge \Gamma_2 \leq 0 \end{cases} \qquad 4$$

A more detailed description of the optimization procedure can be obtained from Arabi et al. (2006).

BMP Representation

For this study, a method presented by Arabi et al. (2004) was utilized to evaluate the water quality impacts of grassed waterways, grade stabilization structures, field borders and parallel terraces. The method was developed based on published literature pertaining to BMP simulation in hydrological models and considering the hydrologic and water quality processes simulated in SWAT. Based on the function of the BMPs and hydrologic and water quality processes that are modified by their implementation, corresponding SWAT parameters were selected and altered. Arabi et al. (2004) provides a detailed description of the method used for representation of field borders, parallel teraces, grassed waterways, and grade stabilization structures.

Economic Component

An economic component was developed for the optimization model that is comprised of a cost function in addition to an economic return (benefit) function. Both cost and benefit are a function of watershed characteristics and time. The total cost of implementation of BMPs was evaluated by establishment, maintenance, and opportunity costs. Establishment costs included the cost of BMP installation, and technical and field assistance. Maintenance cost is usually evaluated as a percentage of establishment cost. The opportunity cost is a dollar value that would be produced over the BMP design life as a result of investing the establishment and maintenance costs by purchasing saving bonds. The benefit function reflects the impact of BMPs on sediment and nutrient reductions. The economic return of implementation of BMPs was determined by assigning monetary values to onsite and offsite benefits of sediment and nutrient reductions. A detailed description of the economic component of the optimization framework in Figure 1 is available in Arabi et al. (2006).

RESULTS

The optimization procedure shown in Figure 1 was used to allocate four types of structural BMPs in the Dreisbach watershed. These BMPs included parallel terraces, field borders, grassed waterways, and grade stabilization structures. The analysis aimed at allocating BMPs such that maximum sediment, phosphorus, and nitrogen loads over the simulation period (2000-2009) ($ymax_i$ in Eq 2) did not exceed the ones corresponding to a targeting plan. The purpose of comparing targeting and optimization results was to compare the total watershed cost (c_t in Eq 3) of the two cases while providing the same level of water quality protection.

In the optimization case, constraints of the GA included only water quality constraints that were set equal to maximum monthly sediment and nutrient loads from the targeting strategy. The GA terminated once one of the pollutant constituents reached its maximum allowable value. A total number of 150 optimization generations, each with a population of 20 strings, were computed. Prior to optimization evaluations, allowable sediment and nutrient loads, *yt* in 2, were set equal to values from the targeting case to be able to compare the total watershed cost of the optimization plan with the targeting plan for the same level of reduction of sediments and nutrients.

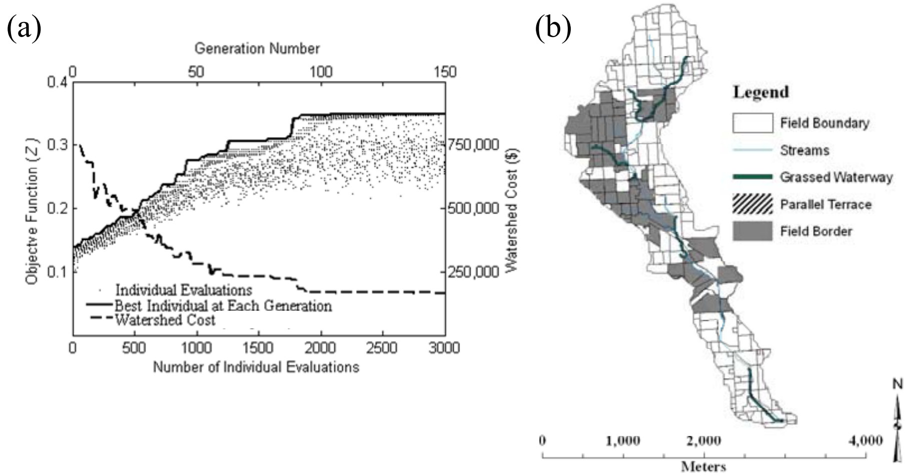
A summary of results for targeting and optimization cases in the study watersheds is provided in Table 1. It was estimated that the targeting plan would cost \$414,690. The cost of the near optimal plan that attained the same water quality benefits was estimated to be \$165,370, nearly 2.5 times less than the cost of the targeting plan. Comparison of the results reveals that in the Dreisbach watershed, BMPs selected and placed by optimization would also yield nearly three times better benefit-cost ratio, while providing the same level of protection against phosphorus and providing even higher protection against sediment and nitrogen pollution.

Table 1. Results for targeting and optimization cases

Variable	Symbol	Units	*Targeting*	*Optimization*
Maximum monthly sediment yield	$ymax_s$	t/ha/m	0.17	**0.06**
Maximum monthly phosphorus yield	$ymax_p$	kg/ha/m	0.15	0.15
Maximum monthly nitrogen yield	$ymax_n$	kg/ha/m	2.1	1.55
Objective function	z	\$/\$	0.12	0.35
Watershed cost	ct	\$	414,690	165,370

Figure 3a shows a sample of the results, with the left y-axis reflecting the objective function for all model evaluations (dots), and the right y-axis is total cost of implementation of the best solution in each optimization generation (dashed line). The first generation represents a random combination of BMPs, while the last generation shows the near optimum solution. It is evident that maximum and median fitness of generations improved as optimization progressed to next generations. This pointed to the efficiency of the developed algorithm. Conversely, the total watershed cost associated with the best solutions of GA generations generally reduced in successive generations.

Figure 3.
(a) Optimization outputs for the Dreisbach watershed;
(b) Spatial allocation of BMPs from optimization procedure.



CONCLUSIONS

A GA-based optimization procedure was developed for selection and placement of BMPs. The sensitivity of the model to different combinations of GA operating parameters, including population size and replacement rate, was tested in order to identify the most efficient combination that converges rapidly for a given runtime. For two small watersheds in Indiana, a setup with a higher number of generations and lower population size was more efficient. However, these results may be site-specific and vary for watersheds with different spatial scale and characteristics.

The cost effectiveness of the optimized BMPs was compared to that of BMPs prescribed through targeting strategies in the study watersheds. It was demonstrated that the BMPs from optimization would achieve the same level of sediment and nutrient reductions with nearly one third of the cost required for implementation of the targeting scenario. Conversely, it was shown that an optimized management scheme would likely provide nearly twice higher level of protection against sediment and nutrient loads for the same amount of money that would be spent for implementation of the targeting plans in these watersheds.

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