Environmental Management (2011) 48:448–461
DOI 10.1007/s00267-011-9696-2

Application of a Multi-Objective Optimization Method to Provide Least Cost Alternatives for NPS Pollution Control

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Received: 14 January 2010 / Accepted: 14 May 2011 / Published online: 12 June 2011

Abstract Nonpoint source (NPS) pollutants such as phosphorus, nitrogen, sediment, and pesticides are the foremost sources of water contamination in many of the water bodies in the Midwestern agricultural watersheds. This problem is expected to increase in the future with the increasing demand to provide corn as grain or stover for biofuel production. Best management practices (BMPs) have been proven to effectively reduce the NPS pollutant loads from agricultural areas. However, in a watershed with multiple farms and multiple BMPs feasible for implementation, it becomes a daunting task to choose a right combination of BMPs that provide maximum pollution reduction for least implementation costs. Multi-objective algorithms capable of searching from a large number of solutions are required to meet the given watershed management objectives. Genetic algorithms have been the most popular optimization algorithms for the BMP selection and placement. However, previous BMP optimization models did not study pesticide which is very commonly used in corn areas. Also, with corn stover being projected as a viable alternative for biofuel production there might be unintended consequences of the reduced residue in the corn fields on water quality. Therefore, there is a need to study the impact of different levels of residue management in combination with other BMPs at a watershed scale. In this research the following BMPs were selected for placement in the watershed: (a) residue management, (b) filter strips, (c) parallel terraces, (d) contour farming, and (e) tillage. We present a novel method of combing different NPS pollutants into a single objective function, which, along with the net costs, were used as the two objective functions during optimization. In this study we used BMP tool, a database that contains the pollution reduction and cost information of different BMPs under consideration which provides pollutant loads during optimization. The BMP optimization was performed using a NSGA-II based search method. The model was tested for the selection and placement of BMPs in Wildcat Creek Watershed, a corn dominated watershed located in north-central Indiana, to reduce nitrogen, phosphorus, sediment, and pesticide losses from the watershed. The Pareto optimal fronts (plotted as spider plots) generated between the optimized objective functions can be used to make management decisions to achieve desired water quality goals with minimum BMP implementation and maintenance cost for the watershed. Also these solutions were geographically mapped to show the locations where various BMPs should be implemented. The solutions with larger pollution reduction consisted of buffer filter strips that lead to larger pollution reduction with greater costs compared to other alternatives.

Keywords Multi-objective genetic algorithms · BMP tool · Nonpoint source pollution · Optimization · Atrazine · Biofuel

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Introduction

Nonpoint Source (NPS) pollutants such as phosphorus (P), nitrogen (N), sediment, and pesticides are major causes of water impairment in many water bodies globally (Carpenter and others 1998; Dowd and others 2008). Runoff and leaching losses of fertilizers and pesticides from agricultural lands are a major source of NPS pollution. P and N are the leading sources of eutrophication in the US (Alexander and others 2008). Similarly, excess sediment loading in the water bodies from upland agricultural areas due to soil erosion affects nearly 99% of the water bodies in the US (Ritter and Shirmohammadi 2001). The presence of excess sediments causes silting of stream beds which in turn reduces the carrying capacity of the water leading to increased flooding. Also, soil erosion is a major source for transportation of phosphorus, as phosphorus is attached to sediment (Carpenter and others 1998). Atrazine (6-chloro-N2-ethyl-N4-isopropyl-1,3,5-triazine-2,4-diamine) is one of the most extensively used pesticide in corn areas in the US. The pollution of surface and ground water bodies exposes humans to atrazine via drinking water. Research shows that atrazine in drinking water could possibly be a cause for small-for-gestational-age (SGA), defined as birth weight below the 10th percentile for a given sex and gestational week (Ochoa-Acuna and others 2009). In 2007, corn areas in the US received 6 million tons of N, 2 million tons of P, and 25,000 tons of atrazine (USDA 2007).

The problem of NPS pollutants can be expected to increase in the future with emphasis on increased corn production to meet bio-fuel (ethanol) demands. The United States Department of Agriculture (USDA) projects to produce 36 billion gallons of ethanol by 2022 with 20 billion gallons from corn based ethanol and 16 billion gallons from advanced biofuel crops such as swithgrass, woody biomass, and vegetable oils. An increase in corn acreage is expected to increment the NPS pollutant loadings to the Gulf of Mexico and the Atlantic coastal waters (Simpson and others 2008; Thomas and others 2009). Additionally an increase in the residue removal, to meet the cellulose based ethanol, can have an adverse impact by increasing the transport of NPS pollutants through accelerated surface runoff and erosion (Ullrich and Volk 2009).

Movement of NPS pollutants into receiving water bodies can be reduced significantly by properly implementing best management practices (BMPs) at the farm level (Fulton and others 1999; Ritter and Shirmohammadi 2001). Approximately $7.8 billion have been provided by the US Farm Bill in 2007 for conservation programs to reduce NPS pollution and improve water quality. For example, the National Resources Conservation Service (NRCS) in Indiana provides millions of dollars to farmers by providing annual rental payment and cost share for the establishment of BMPs on eligible acreages through the Continuous Conservation Reserve Program (CCRP), and Environmental Quality Incentive Program (EQIP). Effectiveness of such programs in reducing NPS pollution can be enhanced through development of watershed management tools that select farms for the placement of BMPs in a cost effective manner.

Selection and placement of BMPs are constrained by ecological, economical and crop management factors. Although BMPs are installed at the farm level, water quality standards are expected to be met at the watershed scale. Often monitoring resources available for BMP implementation and maintenance are limited and information about location of the most effective BMPs is lacking, resulting in non-attainment of water quality goals. Therefore, it is desirable to select a set of BMPs that would give the most reduction in pollutant loads for minimal implementation and maintenance costs in the watershed. For a given watershed with many farms and multiple BMP options in each farm, evaluating all possibilities becomes highly complex. For example, a small watershed consisting of 100 farms with four possible BMPs for every farm would require 4^{100} evaluations and simulating this using a watershed model is practically unfeasible. Obtaining solutions to this problem requires some kind of optimization technique that searches for the best solution among various different possibilities to achieve the multiple objectives of (a) maximum pollutant reduction and (b) minimum associated net cost.

Genetic Algorithms (GAs) have been previously applied to optimize BMP selection and placement in a watershed with an aim to optimize the two objective functions (Arabi and others 2006; Bekele and Nicklow 2005; Gitau and others 2004; Maringanti and others 2009; Srivastava and others 2002; Veith and others 2003a). Some of these optimization methods used a single objective function that combines the two objectives during optimization (Arabi and others 2006; Srivastava and others 2002) or sequential optimization of the two objective functions one after the other (Gitau and others 2004; Veith and others 2004). Recent advancements use multi-objective optimization algorithms that simultaneously optimize the two objective functions (Bekele and Nicklow 2005; Maringanti and others 2009; Rabotyagov and others 2010). One advantage with the multi-optimization techniques is that they aid in visualizing the tradeoff between the two objective functions during optimization. A large computation time needed for optimization was one of the main limitations of previous approaches because the watershed model was dynamically linked with the optimization model to estimate pollutant loads (Arabi and others 2006; Bekele and Nicklow 2005; Srivastava and others 2002). The large computation time is also directly linked to the watershed discretization (HRUs in the SWAT model) as large watersheds (>1000 km^2) usually lead to larger number of HRUs than a smaller watershed with the same land use/soil threshold used. Replacing the watershed model by a BMP tool has considerably reduced the time needed for BMP optimization (Gitau and others 2004; Maringanti and others 2009; Veith and others 2003b). Recent developments in BMP optimization strategies and management of large computational data have further improved the feasibility of implementing BMP optimization on large watersheds (Maringanti and others 2009; Rabotyagov and others 2010).

Research to date indicates that GAs have been effective to search a global search space to obtain optimization solutions for selection and placement of BMPs for NPS pollution reduction. However, there are several questions that have not been addressed in previous research. For example, multi-objective optimization methods were used for P and nitrate-N reduction by Rabotyagov and others (2010), and sediment reduction by Bekele and Nicklow (2005). However, application of the multi-objective BMP optimization on multiple concurrent NPS pollutants of concern in corn areas such as P, N, sediment and pesticide has not been studied before. Atrazine, a very commonly used pesticide, has not been studied before during BMP optimization. Also, there are many combinations of BMPs that can be implemented at a farm level that produce different pollutant reductions for different costs of implementation. With recent advancement of obtaining cellulose based ethanol from corn stover, there is a need to examine how different levels of residue management impact the water quality and therefore the BMP optimization. There is a need to implement exhaustive BMP combination sets that have not been applied before in a single study, for NPS pollution control during BMP optimization.

The overall goal of this paper was to apply a GA based multi-objective optimization tool, utilizing the BMP tool, presented in Maringanti and others (2009) to efficiently optimize the selection and placement of BMPs in a predominantly agricultural watershed. The overall goal was achieved by the following tasks: (1) calibrate a watershed model (Soil and Water Assessment Tool or SWAT) to simulate streamflow, P, N, sediment, and atrazine; (2) develop pollutant reduction indices and their corresponding costs for different combination of BMPs planned for implementation; and (3) apply a multi-objective BMP optimization technique that optimally selects BMP combination sets to be placed at a field level in the watershed. The multi-objectives consisted of (a) minimization of net NPS pollutant loads combined into a single objective function and (b) minimization of net cost increase because of the placement of BMPs in the watershed. The multi-objective optimization tool provided a trade off (Pareto-optimal front), for the near optimal solution, between the two conflicting objective functions which aids decision makers to choose from a range of solutions. Also, a representation of all objective functions of optimization, using a spider plot, aids in visualizing a five-dimensional space.

Theoretical Background

Genetic Algorithms (GA)

Genetic algorithm (GA) optimization procedures belong to the family of heuristic evolutionary algorithms that mimic the natural evolutionary processes to search optimal solutions for diverse, complex, and globally distributed problems. Heuristic optimization methods provide near optimal solutions by searching a global variable space; however, they do not ensure global optimal solution. Nevertheless, the advantage of using heuristic algorithms is to search a discrete solution space globally which is not possible by gradient based search methods that require continuous solution space and have a possibility to get stuck in a local optimal solution. In brief, a GA consists of a population (represented as chromosome with genes as variables) of solutions that are initialized randomly and their fitness is estimated by evaluating the objective functions. In the selection process, the fittest individuals are duplicated and the weak ones are discarded. This process is repated to increase the fitness of the population (Fig. 1). Mutation and crossover are used to obtain a new set of individuals that are stronger than the parents. This process is continued for a given number of iterations known as generations. Usually an increase in population size and number of generations is used to enhance GA performance at the expense of computation time needed to reach an optimal solution.

In multi-objective problems, which can be solved by multi-objective genetic algorithms, the goal is to obtain

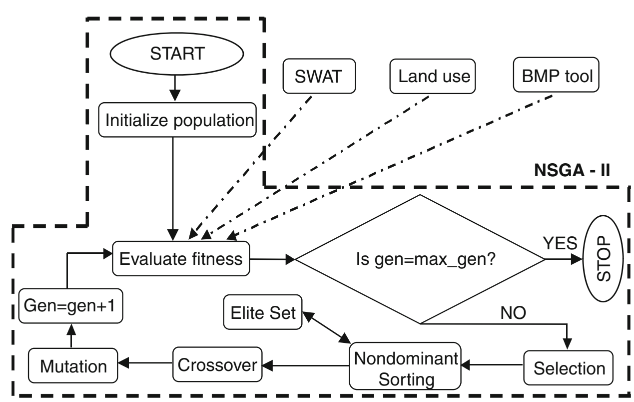


Fig. 1 Components and processes during the multi-objective optimization process for BMP selection and placement (adapted from Maringanti and others 2009)

interactions of conflicting objective functions to yield a range of non-dominated solutions known as Pareto-optimal solutions (Deb and others 2001). The non-dominated solutions can be plotted in a two or three dimensional plot to visualize the tradeoff between the different objective functions. Non-dominated Sorted Genetic Algorithm (NSGA-II) (Deb 1999; Deb and others 2002) is one of the widely used multi-objective genetic algorithm techniques for the selection and placement of BMPs. Non-dominated sorting and elitism are two important properties used by NSGA-II to ensure that the optimization solutions are diverse and have a good spread in all the objective functions (Zitzler and Thiele 1999). More details about NSGA-II can be obtained from Deb and others (2002). The NSGA-II algorithm was selected to perform multi-objective optimization in this study.

Description of the Watershed Model

Soil and Water Assessment Tool (SWAT) was used to simulate watershed response in this study. The model is developed to simulate long term effects of various watershed management decisions on hydrology and water quality response (Arnold and others 1998). It performs well for long-term continuous simulations at daily, monthly, and annual time scales (Borah and Bera 2004; Gassman and others 2007). Stream network and user defined outlets are used to divide the watershed into subwatersheds. Land use, soil, and slope properties are used by the model to further divide a subwatershed into hydrologic response units (HRUs); the smallest geographic area for which flow and transport of nutrients, sediment, and chemicals are performed by the model. The climatic input data required are precipitation, temperature, solar radiation, relative humidity, and wind speed on a daily or subdaily basis.

Surface runoff is computed using a modification of the SCS curve number technique or Green and Ampt infiltration method. Soil erosion is modeled at a field scale using the modified universal soil loss equation (MUSLE) (Williams 1975). Soil particle detachment, transport, and deposition by erosive forces such as surface flow of water are modeled. Surface cover, soil erodibility factor, management practice, topography, and the size of a soil particle are important in obtaining quantitative estimation of the amount of soil eroded from a particular field (Neitsch and others 2005).

Various components of the P and N cycles are represented in the SWAT model. SWAT distributes phosphorus into six different pools in the soil column (Neitsch and others 2005) with an equal number of inorganic and organic pools. Decomposition of P involves breakdown of fresh organic residue into simpler organic components. Mineralization is the conversion of organic P into plant available inorganic P. Surface runoff and soil erosion are major sources of P removal from a field. Also, P is allowed only to leach from the top 10 mm of soil into the first soil layer only due to its low mobility. Similarly, SWAT distributes N into five different pools in the soil column (two inorganic and three organic pools). Unlike P, N is highly mobile and is transported from a field mainly through denitrification, volatilization, and leaching (Neitsch and others 2005).

SWAT algorithms for the processes that govern the fate and transport of pesticides such as wash-off, degradation, and leaching were adapted from GLEAMS (Leonard and others 1995). Most of the pesticides, including atrazine, are organic carbon containing compounds which are degraded by microorganisms. The degradation typically follows first order kinetics for pesticide present in both soil and plant foliages. Pesticide transport through surface runoff occurs in solution or adsorbed forms. The SWAT model considers one pesticide at a time to incorporate routing and in-stream pesticide transformations (Neitsch and others 2005) based on the equations proposed by Chapra (1997).

The SWAT model interface enables representation of various BMPs by changing appropriate parameter values in the model input files. In this study we have used the BMP tool developed by Maringanti and others (2009) to estimate the effectiveness of BMPs for a particular pollutant reduction.

Methodology

A flow chart for the processes that follow during the multi-objective optimization are shown in Fig. 1. Each variable that was optimized constitutes a BMP or a set of BMPs that needs to be placed in an HRU in the watershed. Therefore, the total number of variables equal the total number of HRUs in the watershed that need to be optimally placed with BMPs for the reduction of various NPS pollutants. The chromosome string for each population consists of variables and each variable used binary coding of the genes. The variables were initiated randomly for a given population size. The HRU level pollutant loading simulated by the SWAT model under baseline conditions (assuming no BMPs placed in the watershed), an allele set representing land use constraints for BMP placement, and a BMP tool representing pollution reduction efficiency and corresponding BMP costs were required by the optimization algorithm to evaluate the objective functions (one for the pollutant load, and a second for the cost) for the initialized population and each subsequent generation. Mutation and crossover were used to create a new population for the next generation. The model terminated when the maximum generation was reached, which was the stopping condition to provide a range of optimized solutions for the two objective functions.

Study Watershed

Wildcat Creek (WCC) Watershed (Fig. 2) (8 digit USGS HUC 05120107) located in northcentral Indiana, with a drainage area of 1,956 km^2, was used for testing the optimal BMP selection and placement. The watershed is predominately agricultural with 74% row crops (36% soybean, 38% corn), 21% pasture, and 3% urban area, and has a mean annual precipitation of 1,054 mm. The watershed has a flat terrain with an average slope of 1.5%. The high pesticide (atrazine) loading from the agricultural areas has degraded the water quality in most of the watersheds in Indiana (Homes and others 2001). Phosphorus concentrations in the watershed streams are considered to be elevated. Similarly, many of the streams in the watershed violate ammonia standards (Tetra Tech 2008). A total of 117 water bodies in the watershed are listed in the 303(d) list of impaired water bodies. Various NPS pollution reduction projects are being undertaken in the watershed. However, success for these projects can be increased by evaluating the efficiency of various BMP selection decisions and implementing those with the greatest economical and ecological benefits.

Calibration of the SWAT Model to Simulate Flow and Water Quality

The SWAT model was calibrated for daily streamflow at the USGS gauging station (03333700) located near Kokomo (Fig. 2) using the coefficient of determination (R^2) (Eq. 1) and the Nash-Sutcliffe efficiency coefficient (R^2_{NS}) (Eq. 2) where O and P stand for observed and predicted outputs respectively.

$$R^2 = \left[\frac{\sum_{i=1}^{n} (O_i - \overline{O})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n} (O_i - \overline{O})^2 \sum_{i=1}^{n} (P_i - \overline{P})^2}} \right]^2 \quad (1)$$

$$R^2_{NS} = 1 - \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (O_i - \overline{O})^2} \quad (2)$$

Calibration for the water quality was performed for a Indiana Department of Environmental Management (IDEM) water quality fixed station that coincided with the USGS gauge location. Measured water quality data included total phosphorus (P) in kg, total nitrogen (N) in kg, sediment load (SLD) in tons as well as atrazine in part per billion (ppb) which were available for only a few days during each year. Therefore, a LOADEST model (Runkel and others 2004) was used to estimate the daily loads for P, N, and sediment based on the measured pollutant concentrations and daily streamflow. LOADEST model has been used previously as a regression tool to develop rating curves that are used to estimate water quality loads from sparsely available grab sample data to calibrate the SWAT model (Jha and others 2007, 2010; Mukundan and others 2010). The SWAT model was calibrated for water quality on a monthly scale using the LOADEST estimated loads as the observed values. However, we did not use the LOADEST model to estimate pesticide concentrations and instead minimized the absolute difference between the measured and simulated total annual average pesticide loads. This method was used as most of the pesticide output was observed for only a few months each year following the application and the exact application timing of pesticide in different fields in the study watershed was not available. As we could not match up the exact daily

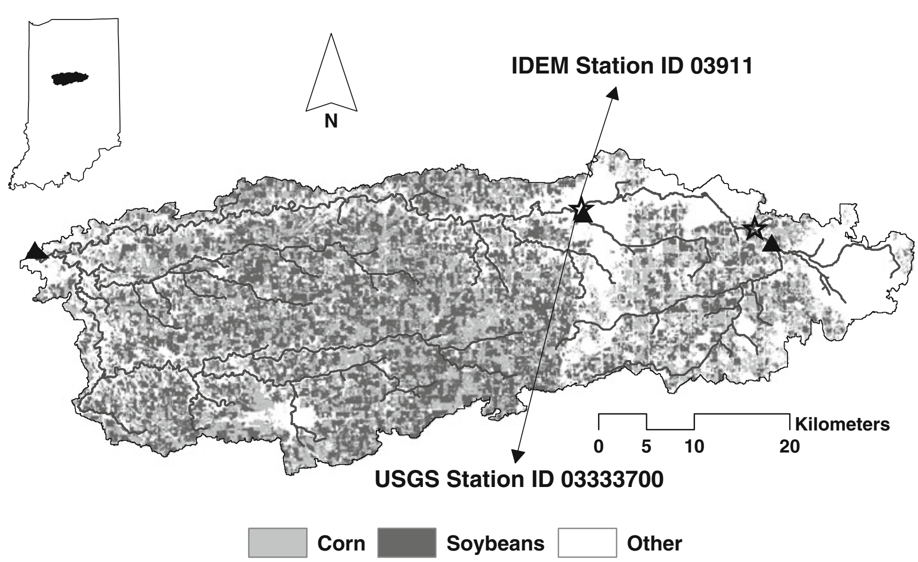


Fig. 2 Location of Wildcat Creek Watershed in Indiana and the observed gauge locations

streamflow time period contributing the observed pesticide loads in the watershed we chose to estimate the total simulated loads at an annual scale which were then compared against the observed annual loads.

Allele Set Preparation

The BMPs selection depends on land use/cover, i.e. every land use has specific BMPs, represented as an allele set, that are feasible to be implemented in the particular region. Furthermore a BMP set that consists of a combination of BMPs (based on the allele set) was created. The allele set was input to the optimization model and narrowed the search space for a given land use to a definite combination of BMPs that could be selected. Table 1 shows the allele set of BMPs in the Wildcat Creek Watershed. Since corn and soybean are the dominant agricultural areas in the watershed, BMPs were considered for selection in these areas only. All other farms were given a value of 'Null', indicating that the search process did not change the management in these farms from the baseline scenario, thus narrowing the search for finding the optimal solution only to the fields where BMPs could be applied.

BMP Tool

The BMP tool consisted of pollution reduction effectiveness values, determined from the SWAT model, and the cost for each candidate BMP. To develop the BMP tool, all the HRUs in the watershed that had a common land use were selected. A BMP scenario consisted of implementing one BMP set, corresponding to the chosen land use, using SWAT model in the entire watershed. Outputs from a particular BMP scenario were average annual watershed loads of total phosphorus (TP), total nitrogen (TN), sediment, and atrazine. The cost information estimated the total costs for the placement of the BMP sets considering both implementation and maintenance (Table 2). The BMP pollution reduction along with the corresponding cost of each BMP set was stored in a database. Use of the BMP tool eliminated the need for dynamically linking the SWAT model with the optimization model. More details about the BMP tool and its applicability can be obtained from Maringanti and others (2009). One limitation with the BMP tool method of estimating pollutant loads in the watershed is that the loads approximated might be different from the loads estimated using a watershed model for each BMP implementation scenario during optimization. However, it was observed by Maringanti and others (2009) that the solutions obtained during the optimization and simulated using the SWAT model lead to similar responses (but of different magnitudes) as the ones obtained by the BMP tool (Fig. 3).

Table 1 Allele set of BMPs in Wildcat Creek Watershed

BMP	Allele set
Filter strips	0, 5, 10, 20, and 30 m
Contour farming	'Not Present' and 'Present'
Residue management	1000, 3000, 5000, and 7000 kg/ha
Parallel terrace	'Not Present' and 'Present'
Tillage	Conservational and No-till

Table 2 Cost information and type of best management practices used in the BMP tool

BMP	BMP Type (#)[a]	Cost	Unit
Filter strips	0, 5, 10, 20, 30 m (0–4)	12.2	\$/ha/m[b]
Contour farming	NP, P[c] (0–1)	16.8	\$/ha
Residue management	1000, 3000, 5000, 7000 kg/ha (1–4)	0	\$/ha
Parallel terrace	NP, P[c] (0–1)	74.9	\$/ha
Tillage	Conservational, No-till (1–2)	53.1	\$/ha

[a] BMP Type corresponds to the number used to plot Fig. 3

[b] Cost of filter strips per unit width

[c] NP and P stand for Not Present and Present for the respective BMP

The BMP costs consisted of annual net costs per unit area (\$/ha) and included both implementation and maintenance costs. The costs for the tillage management practice in corn were obtained from the University of Illinois Extension Service publication (FEFO 2006). The other cost information for the various BMPs for year 2007, as shown in Table 2, were obtained from Indiana Environmental Quality Incentives Program (EQIP). For each of the BMPs, the total cost (c_{td}) for the design life was estimated by incorporating maintenance, interest rate, and design life (td) information evaluated by the following equation (Arabi and others 2006):

$$c_{td}(\$/\mathrm{ha/yr}) = c_0\left((1+s)^{td} + \mathrm{rm}\left[\sum_{\tau=1}^{td}(1+s)^{\tau-1}\right]\right)/\mathrm{td}$$

$$\Rightarrow c_{td}(\$/\mathrm{ha/yr}) = c_0\left((1+s)^{td} + \mathrm{rm}\left(\frac{(1+s)^{td}-1}{s}\right)\right)/\mathrm{td} \tag{3}$$

where c_0 represents the current BMP implementation costs (\$/ha), rm is the ratio of maintenance to implementation cost (1% for filter strips), and s is the fixed interest rate (6%). A design life (td) of 10 years was considered for filter strips, and parallel terrace; a td of 1 year was considered for residue management, contour farming, and tillage BMPs. These numbers for rm, s and td were used from Arabi and others (2006). The change in yields

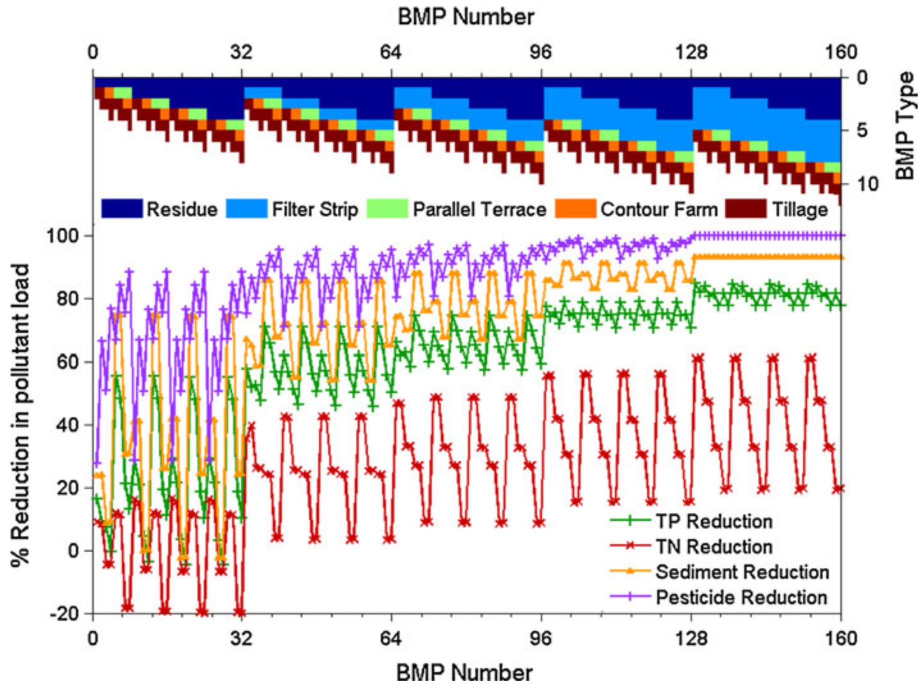


Fig. 3 Pollution reduction efficiency for the various combinations of BMPs that can be implemented in the watershed (BMP Type information provided in Table 2)

possible due to the implementation of BMPs was not considered while estimating the costs.

Multi-Objective Genetic Algorithm Model Development

The HRUs, delineated by SWAT, also correspond to the variables for which the BMPs were searched to meet the two objective functions of (a) minimization of NPS pollutant loads and (b) minimization of the net cost increase at the watershed due to BMP placement. The chromosome string corresponding to the optimization problem consists of genes equal to the number of HRUs in the watershed (Fig. 4). The two objective functions are mathematically expressed as:

$$\min[(f_{1-4}(\mathbf{X})) \wedge (g(\mathbf{X}))] \tag{4}$$

where $f_{1-4}(\mathbf{X})$ is the Normalized Aggregate Pollutant Value (NAPV) calculated as the product of reduction in

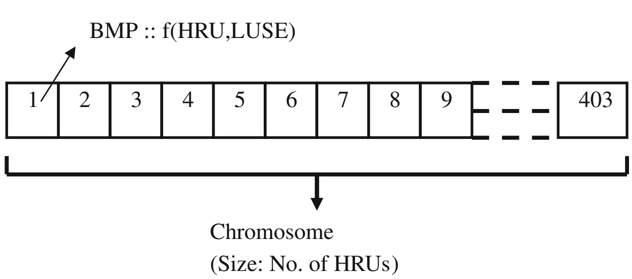


Fig. 4 Gene string for BMP representation in a watershed (adopted from Maringanti and others 2009)

the nitrogen, phosphorus, sediment, and pesticide loads. This is expressed as a single objective that designates total pollutant loss reduction for various HRUs in the watershed (Eq. 5). $g(\mathbf{X})$ represents the net cost incurred due to the placement of the BMPs in the watershed (Eq. 6).

$$f_{1-4}(\mathbf{X}) = \prod_{i=1}^{4} \left(\frac{\sum_{x\in\mathbf{X}} (\mathbf{P}_i(x) \times \mathbf{A}(x))(1-\mathbf{R}_i(x))}{\overline{\mathbf{P}}_i \times \sum_{x\in\mathbf{X}} \mathbf{A}(x)} \right) \tag{5}$$

$$g(\mathbf{X}) = \frac{\sum_{x\in\mathbf{X}} \mathbf{C}_i(x)\mathbf{A}(x)}{\sum_{x\in\mathbf{X}} \mathbf{A}(x)} \tag{6}$$

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

The SWAT model simulated HRU level NPS pollution loads along with an allele set and the BMP tool are used to estimate the two objective functions during optimization. During the optimization process, the algorithm searches first for the BMP set to be implemented in each HRU. The BMP tool provided pollution loading and associated BMP cost. For example, an HRU #122 which has corn as the land use (allele value = 1) and is to receive a BMP set consisting of conservation tillage, 10 m buffer, contour farming; the corresponding values for pollutant reduction and net costs for implementation are obtained from the BMP tool. HRU weighted averages of NAPV and net costs, the two objective functions that were minimized during the optimization (Eq. 4), were calculated using Eqs. 5 and 6.

Sensitivity Analysis and Estimation of GA Parameters

Influence of GA parameters on the Pareto-optimal fronts was quantified using a sensitivity analysis. The Pareto front presents the tradeoff between the two objective functions with the *x*-axis representing the pollutant load and *y*-axis representing the net costs. Each solution on this tradeoff curve represents a set of BMPs that need to be implemented in each HRU in the watershed. Each GA parameter, i.e., population size, number of generations, mutation, and crossover probability, was changed, one at a time, in the sensitivity analysis. Crossover and mutation probability range from 0 to 1 and were varied to cover the entire range of parameter values. Results were plotted to quantify improvement or degradation in the Pareto-optimal fronts. The sensitivity analysis was performed for pesticide and similar behavior in the GA operational parameters was assumed for other NPS pollutants.

Estimating the goodness of the solutions in the Pareto-optimal front is subjective. As the front moves towards the origin, it is ensured that the magnitude of the objective functions for the solutions get reduced in both the directions. Therefore, the Pareto-optimal front as close to the origin as possible is desired. The parameter value resulting in the least sum of distances to each solution on the Pareto-front from the origin in sensitivity analysis was selected as the final parameter values for the optimization process.

Results and Discussion

SWAT Model Calibration

The watershed consisted of 52 subbasins and 403 hydrological response units (HRUs). For the analysis each HRU was approximated to be a farm, and the BMPs were selected for placement at each of the HRUs. The SWAT model was calibrated for stream flow (USGS # 03333700) for 3 years (2001–2003) and the daily calibration statistics had an R^2 and R^2_{NS} equal to 0.68 and 0.60 respectively (Fig. 5). The model validation was performed for the years 2004–2005 and the corresponding R^2 and R^2_{NS} was 0.56 and 0.51 respectively. Monthly phosphorus loads estimated by the LOADEST model were used to calibrate the monthly loads simulated by the SWAT model with model performance measures for R^2 and R^2_{NS} equal to 0.84 and 0.54 respectively (Fig. 6a). Similarly nitrogen and sediment loads simulated by the SWAT model were calibrated against the LOADEST estimated loads with R^2 equal to 0.84 and 0.88, and R^2_{NS} equal to 0.64 and 0.62 respectively (Fig. 6b, c). Overall, it was observed that the performance measures for the streamflow, P, N, and sediment at their

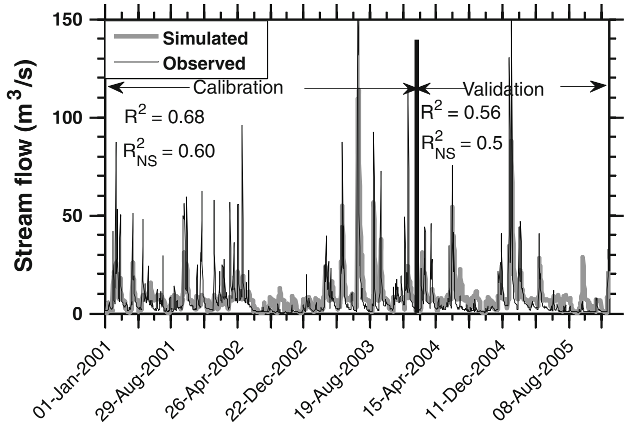


Fig. 5 Daily stream flow calibration at the USGS gauge station ID 03333700

respective time scales were in the good-very good range published in literature (Moriasi and others 2007; Santhi and others 2001). Figure 7 presents the observed versus the simulated pesticide concentrations during the calibration period. Due to the small quantity of available data, R^2 and R^2_{NS} could not be calculated. The parameters that were modified during the calibration process are provided in Table 3.

BMP Tool

For each HRU with corn and soybean as land use, 160 different BMP sets (5 filter strips × 2 contour farming × 4 residue management × 2 parallel terrace × 2 tillage) were possible for placement, including the possibility of multiple BMP sets in a single HRU. The different BMPs considered for placement are described in Table 2. For example, the BMP scenario number 1 consisted of a residue management of 1000 kg/ha (Type #1 for residue management) and conservation till (Type #1 for tillage) and scenario number 33 consisted of a 10 m filter strip (Type #2 for filter strips) in addition. Based on the type of BMP set being implemented, the corresponding input files in the SWAT model were modified to incorporate all management practices present in the BMP set according to the method suggested by Arabi and others (2008). The baseline model was considered to have no best management practice placed in the watershed. The percentage reduction from the baseline due to BMP placement represented the BMP effectiveness for all the NPS pollutant loads. Figure 3 presents the pollution reduction efficiencies of various combinations of BMPs when implemented in the watershed for NPS pollution control. Contour farming had negative impact on the total nitrogen and total phosphorus by increasing the pollutant load in the watershed when no filter strip was present. Filter

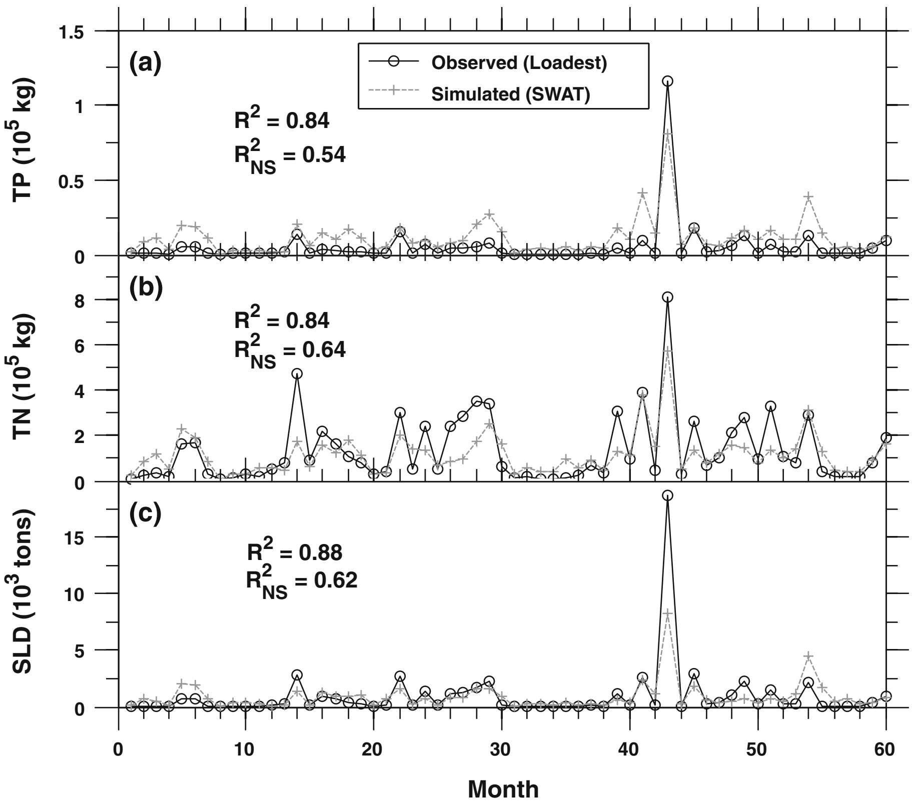


Fig. 6 Monthly calibration (2001–2005) of the SWAT model for total phosphorus (**a**), total nitrogen (**b**) and sediment (**c**) loads at IDEM station ID 03911

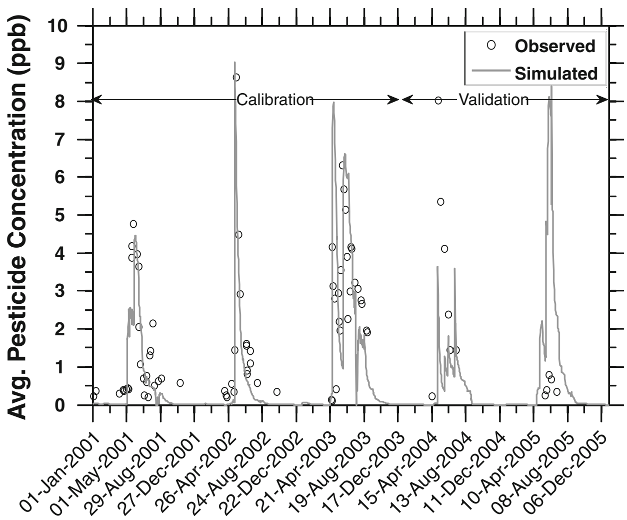


Fig. 7 Observed and simulated average (area weighted) pesticide concentration at IDEM station ID 03911

strips as well as presence of parallel terrace were observed to produce higher percentage of pollution reduction, while residue management did not impact the pollutant reduction considerably. Contour farming only improved the percentage reduction of pesticide. No-till had a positive impact on the percentage reduction of pesticide load, and a slight negative impact on total phosphorus reduction. Tillage practices had no effect on percentage reduction in sediment and total nitrogen load. It was also observed that the SWAT model algorithms overestimated the sediment and pesticide load reductions as compared to LOADEST when the filter strip width reached 30 m.

Sensitivity and Estimation of GA Operational Parameters

The results obtained from the optimization indicate that increasing the population size from 10 to 100 considerably improved the performance of the model (Pareto-optimal front). A further increase in population size resulted in no appreciable improvement in the Pareto-optimal front. A population size of 800 gave a better spread when compared to the other population sizes considered (Fig. 8a).

The Pareto-optimal front improved as the number of generations was increased from 100 to 5,000 (starting with 100, 1000 and then incrementing by 1000 generations during each successive simulation). Further increase in the number of generations to 10,000 did not display any improvement in the results compared to the results obtained at 5,000 generations (Fig. 8b).

The uniform crossover operation was not as sensitive in perturbing the objective space when compared to other GA parameters. As the crossover increased from 0.1 to 0.5, the

Table 3 Parameters modified during the calibration process

Parameter	Description	Component	Calibrated value
SURLAG	Surface runoff lag coefficient	Flow	0.50
ALPHA_BF	Base flow recession parameter	Flow	0.30
GWQWMN	Threshold depth of water in the shallow aquifer for return flow to occur	Flow	200
ESCO	Soil evaporation compensation factor	Flow	0.55
OV_N	Manning's "n" for overland flow	Flow	0.20
CN_F	Curve number	Flow	+0.13%
PERCOP	Pesticide percolation coefficient	Pesticide	0.20
NPERCO	Nitrogen percolation coefficient	Nitrogen	0.20
USLE_P	USLE practice factor	Phosphorus	0.70

Curve number is changed as a percentage from the original value

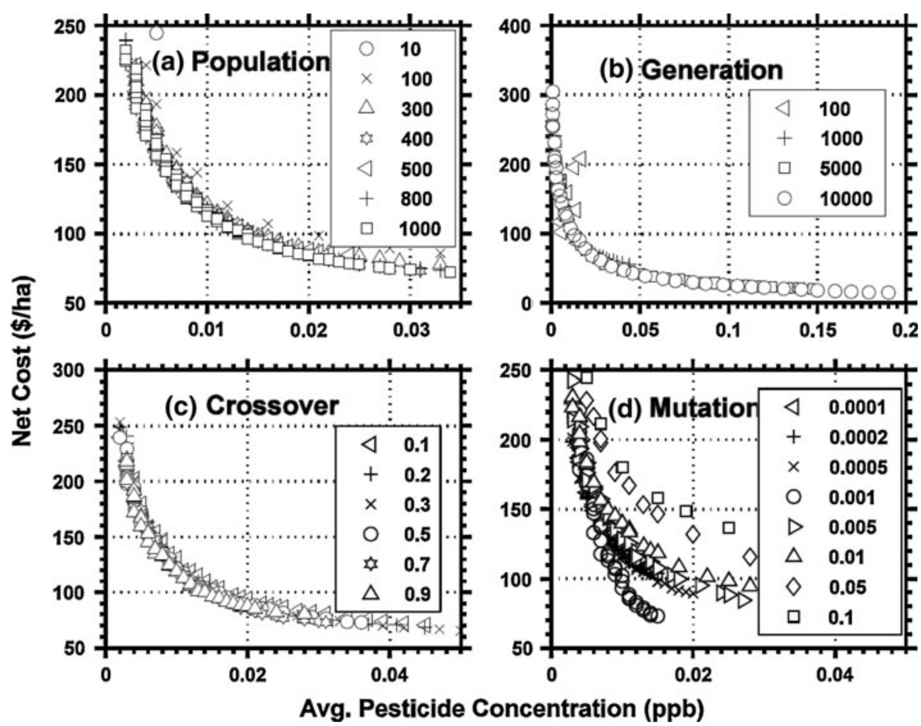


Fig. 8 Pareto-optimal front for the sensitivity analysis of GA parameters (in order to visualize better, solutions at an interval of ten populations are shown in the figure)

Pareto-front approached the origin. However, when the crossover rate was further increased to 0.9, the Pareto-front moved away from the origin. Overall the change in the Pareto-optimal front was very small for different crossover fractions (Fig. 8c). Therefore, the closest front, corresponding to a crossover value of 0.5, was chosen for the optimization process.

Mutation probability operator was observed to be a moderately sensitive parameter (Fig. 8d). There was no particular pattern observed when the mutation operator was increased from 0.001 to 0.05. However, a value of 0.005 provided the best solution (with Pareto front closest to the origin) as compared to the others.

Multi-Objective Optimization Model

Table 4 summarizes the default and optimal values for the GA parameters that were used for optimization. The optimization model run with a population of 800 and 5,000 generations took 2 h to complete on a Centrino-Duo@2.16 GHz computer. During the first generation of the GA, the variables of the population were initiated randomly. However, for the further generations the variables were modified using the genetic operators of crossover and mutation. Figure 9 shows the progress of the Pareto-optimal front during the optimization of the two objective functions, NAPV and net cost. Solutions during

Table 4 Default and optimal parameters chosen for GA from sensitivity analysis

Parameter	Default	Optimal
Population	400	800
No. of generations	500	5000
Crossover probability	0.7	0.5
Mutation probability	0.001	0.005

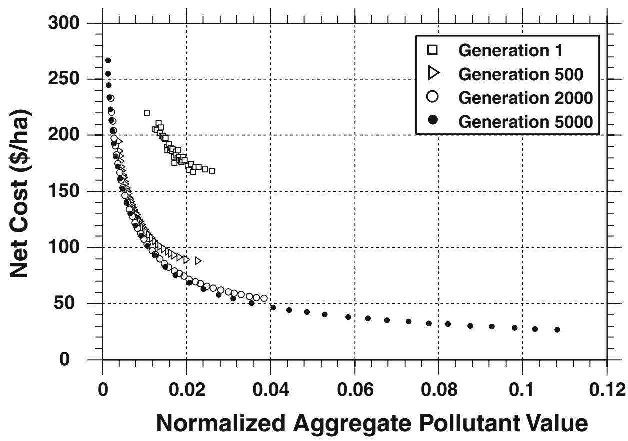
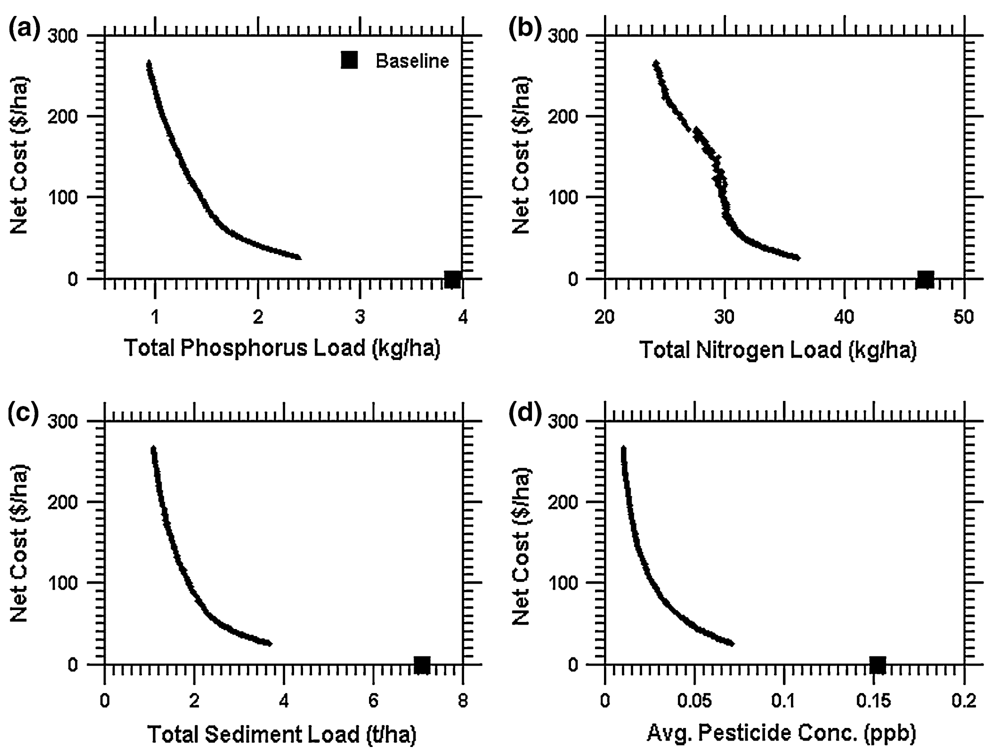


Fig. 9 Progress of the Pareto-optimal front during optimization of the model (in order to visualize better, solutions at an interval of 20 populations are shown in the figure)

the first few generations are highly scattered and non-dominance is not exhibited by the solutions. However, as the optimization progresses the scattering of solutions is minimized, i.e., solutions are non-dominated and the Pareto-front moves towards the origin; the spread of the solution is improved, thus providing a wider choice for the selection of optimized set of BMPs to be placed in the watershed.

Figure 10 shows the various pollutant loads obtained by implementing solutions from the final generation of optimization. A range of solutions that cost \$25–\$275/ha provide a reduction of 37–76, 23–49, 45–83, and 53–93% respectively for P, N, sediment loads and atrazine concentration. Figure 11 represents the pollutant loads along with the costs for implementation of BMPs for each output of interest as a spider plot. This plot can be used to estimate the different variables corresponding to a particular variable of concern (a pollutant or cost). The solutions from the multi-objective optimization model, unlike the single solution obtained from single objective optimization models, provide the decision maker choices to optimize the funds available. In other cases where the goal is to obtain a solution to meet the specified water quality improvement goals in a watershed, the solutions should at least produce the specified reduction; therefore the optimized solution that costs the least for achieving the particular water quality goals is selected. However, if equal weight is to be given to the two objectives of pollution reduction and net cost

Fig. 10 Pareto-optimal front after the final generation (5000) of the multi-objective optimization



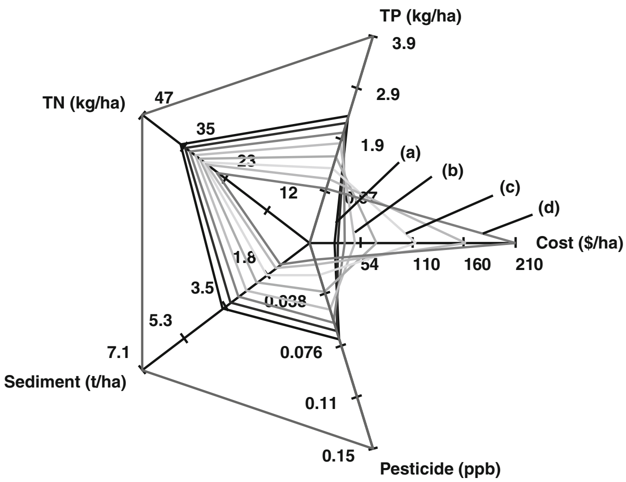


Fig. 11 Spider plot showing the different NPS pollutant loads after the final generation. Detailed spatial representation of the four solutions (a, b, c, d) are provided in Fig. 12. Line with cost 0 $/ha designates the baseline with no BMPs placed

increase, the solution that is closest to the origin is selected, i.e. a solution for which Eq. 7 is the least.

$$\sqrt{(f(\mathbf{X}))^2+(g(\mathbf{X}))^2} \tag{7}$$

Figure 12 demonstrates the spatial placement of BMPs in the watershed, at the HRU level. Four different scenarios indicated in Fig. 11 were represented spatially for different costs for placement of BMPs in the watershed. It can be noticed that the solutions that cost the most contain the BMP combinations with filter strips of 30 m (the red color emphasis that BMP 128 to 160 are preferred). On the other had low cost solutions did not include filter strips as one of the BMP options.

Summary and Conclusions

Watershed management to minimize pollutant loads and associated BMP costs requires finding an optimal solution from a very large number of feasible alternatives. In this research we have applied an optimization methodology that uses a BMP tool embedded in genetic algorithms (GAs) developed in our previous research (Maringanti and others 2009) in a watershed that has corn as the dominant land use and is susceptible to unintended consequences due to the increase in biofuel demand (Melillo and others 2009). It was observed that the BMP tool based optimization takes less computation time when compared to the time taken by models that use dynamic linkage to estimate the pollutant loads. The BMP tool required running the SWAT model for all 160 combinations of feasible BMPs that were specific to the study watershed. BMP pollution efficiency was computed for each combination of BMPs by comparing the

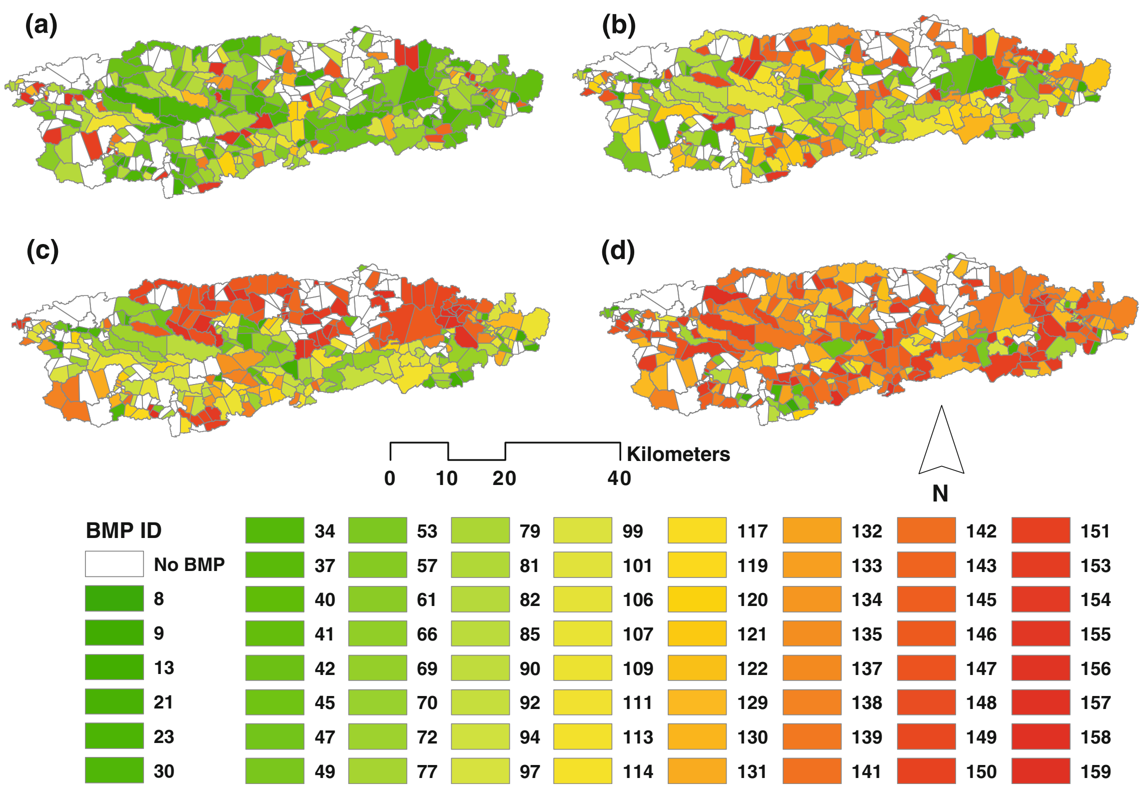


Fig. 12 Type and location of optimal BMPs selected in Wildcat Creek Watershed for different costs as provided in Fig. 11

pollutant load with the baseline, where no BMPs were implemented. A novel contribution of this research was the combination of structural and non-structural BMPs optimized to reduce four different NPS pollutants in a watershed. In this study we developed optimal solutions that would reduce all the pollutant loads in the watershed simultaneously using a novel concept of normalized aggregate pollutant value (NAPV) that combines all the NPS pollutant loads into a single value. The multi-objective optimization of the two objective functions (NPS reduction and cost) was performed using the genetic algorithm NSGA-II. Inputs for the optimization model included the SWAT output (baseline scenario) for the pollutant loading at the HRU level, a BMP tool providing the BMP effectiveness estimated from SWAT runs and the corresponding cost, and allele sets for each different land use. NSGA-II parameters were estimated using a sensitivity analysis for pesticide (atrazine). The final optimized result gave a trade-off between the two objective functions of NAPV and net cost. Overall, the optimization model performed well in reducing the pollutant load from the watershed.

The optimization model developed in this study can be easily extended to any other watershed model to develop the Pareto-optimal fronts, provided the watershed model is calibrated (if required) and a suitable set of BMPs needed for pollutant reduction is available. The optimized results provide a range of watershed management options for pollution reduction and corresponding costs for the BMP implementation. This trade off can aid watershed managers in TMDL development and estimate the corresponding cost for the placement of BMPs to achieve watershed management goals.

Acknowlegments The authors would like to thank USDA-NIFA (07-51130-03876) and DOE (Award No. DE-EE0004396) for providing funds for this study. This research was also supported in part by the National Science Foundation through TeraGrid resources provided by Purdue University and the Computing Research Institute. We sincerely thank Dr. Rao S. Govindaraju for providing useful inputs during the progress of the research. Comments provided by the Associate Editor, two anonymous reviewers Claire Simond improved an earlier version of this manuscript.

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