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Integrated BMP Assessment for Improving Water Quality in a Rice/Soybean Dominated Watershed in the Arkansas Delta

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ABSTRACT: This study focused on evaluating performance of Best Management Practices (BMP) in controlling sediment and nutrient losses from an agricultural watershed to meet Total Maximum Daily Load (TMDL) requirements. The study was conducted in the L'Anguille River watershed, an intensively managed agricultural area consisting of more than 2,250 km^2, 80% of which are in row crop agriculture; predominantly soybeans, rice, and cotton. The drainage from these fields flows into the river carrying potentially large amounts of sediment, nutrients, and pesticide residues. The entire length of the L'Anguille River has been designated impaired due to high sediment concentrations assumed to be coming from intensive row crop agriculture. A total of 52 different BMP scenarios were analyzed and their impacts on water quality improvements were evaluated for three implementation schemes: optimization, targeting in high priority subbasins, and random placement. The results indicated that BMP optimization always resulted in the greatest reduction of sediment, total *P*, and total *N* losses from the watershed under a given cost-constraint compared to the targeting and random placement schemes. The results of this study indicated that under limited resources scenarios available for BMP implementation and maintenance, watershed management should focus on optimizing BMP placement so that maximum pollutant reduction from the watershed can be accomplished.

INTRODUCTION

Agricultural nonpoint source pollution has been recognized as the largest source of pollution to streams, rivers, and estuaries in the United States. Agricultural activities, such as, tillage practices and land application of fertilizer and animal manure are important factors contributing to NPS pollution, leading to excess runoff losses of sediment, nutrients and pesticides. A large percentage of water pollution is recognized to be originated from NPS pollution (Novotny, 1999) affecting more than 18% of the impaired river miles measured and 48% of assessed rivers and streams in U.S. (USEPA, 2001). Excess sediment loadings is the most important NPS pollutant of concern, as more than 50% of the sediment loadings in various waterbodies is contributed by the erosion of agricultural areas (Ritter and Shirmohammadi, 2001). The other important NPS pollutants of concern are Nitrogen (N) and Phosphorus (P) that, when present in increased concentrations, result in accelerated eutrophication of the waterbodies.

Typically, control of NPS pollutants to improve water quality in agricultural watersheds is achieved through implementation of Best Management Practices (BMPs) at farm or field level. BMP implementation within a watershed can be achieved using three approaches: (1) random placement; (2) targeting BMPs in critical source areas; and (3) optimizing BMP placement based on environmental and economic constraints. In the random placement approach, BMPs are implemented in fields that are randomly distributed across a watershed. This approach is common where a watershed management agency operates on a 'first come—first serve' basis to the farmers who are applying for financial assistance for BMP implementation. This type of approach can be expected to yield varying results and the associated water quality improvements are difficult to replicate in another watershed. In targeting approach, BMPs are placed in critical source areas of a watershed. Critical source areas are portions of a watershed that contribute disproportionately large amount of NPS pollutants and can be identified using a distributed parameter watershed model or detailed monitoring of water quality. In a large watershed with multiple farms and BMP options, there can be a large number of BMP targeting options that will result similar water quality improvement. Under such conditions, BMP optimization becomes effective in determining the optimum

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combination and placement of BMPs that will result in maximum reduction in NPS load with minimum BMP implementation and maintenance cost. However, BMP optimization requires searching through a large parameter and output domain and is computationally cumbersome. Development of such methods is still an active area of research. In addition, many watershed management agencies may not have needed technical skills to optimize BMPs in a given watershed.

The objective of this study was to develop a methodology to determine the most effective combination of BMPs to reduce the pollutant loads to improve water quality in agricultural watersheds. The relative effectiveness of three methods of BMP implementation schemes (i.e. optimization, targeting, and random placement) in improving water quality were compared. The methodology developed was evaluated in the L'Anguille River watershed, an agricultural watershed located in Arkansas, USA.

DESCRIPTION OF THE STUDY WATERSHED

Effectiveness of BMP implementation schemes in improving water quality were evaluated using data from the L'Anguille River Watershed (LRW), located in Eastern Arkansas, USA (Figure 1). The LRW is primarily an agricultural watershed with an area of 2,250 km^2. The principal land use in the watershed is agricultural row crop production. According to the 2004 land use, the basin consisted of 40% soybeans, 25% rice, and 17% forest, with only 2% urban areas. The soils in the basin consist of poor draining hydrologic soil group C soils on the eastern part of the watershed and group D soils to the west consisting of Henry and Calloway soils.

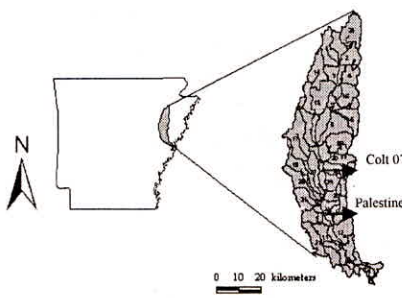

Fig. 1: Location of L'Anguille River Watershed in Arkansas, location of USGS stream gauging stations in the watershed, and subwatershed delineation used in SWAT modeling

The LRW is listed in the EPA 303d list due to excessive turbidity caused by suspended sediment (ADEQ, 2005). The impaired designation culminated over 150 years of direct human interaction with the L'Anguille River. Since the early 19th century, the hardwood bottoms and swampy lowlands of the area have been subjected to timber harvesting, draining, and agricultural production practices. By 1945, the upper reaches in Poinsett and Craighead Counties, had been straightened and channelized to provide improved drainage for agricultural production. The remainder of the channel remains in its meandering form, with various lengths of levees and other structures. The sediment that results from erosion of farmland is transported by the upper, straightened portion of the river, and is deposited along the slower moving meanders of the natural length resulting in channel aggradations and flooding. In the Cross County area the extended inundation of the hardwood forest has resulted in large areas of dead standing timber. The flooding has also negatively impacted agricultural production in the affected areas. A Total Daily Maximum Load (TMDL) has been developed for the watershed requiring a reduction of 48% in spring, and 46% in summer, respectively, in sediment loading from agricultural production areas in the basin (ADEQ, 2002). This reduction in sediment loading is expected to meet the in-stream turbidity standard of 45 NTU or a sediment concentration goal of 35 mg/L.

The USGS monitors stream flow in the watershed at two locations: Colt (USGS Gauge no. 07047942) and Palestine (USGS Gauge no. 07047950). Daily stream flow data for Colt gauging station was available since 1992 and for Palestine gauging station since 1997. In addition, 14 months of sediment and nutrient load and concentration data were available at Palestine gauging station. These data were used in model development and BMP analyses.

DESCRIPTION OF THE WATERSHED MODEL

The Soil and Water Assessment Tool (SWAT) model was used in this study to quantify BMP effectiveness in reducing pollutant loads in the watershed. The SWAT model is a physically-based, quasi-distributed, deterministic, continuous, daily time step model (Arnold *et al.*, 1998). The SWAT model has been used extensively to determine the effects of management practice implementation of hydrologic and water quality response at various spatial and temporal scales (Behera *et al.*, 2005; Bracmort *et al.*, 2006; Gassman *et al.*, 2007; Gitau *et al.*, 2004; White and Chaubey, 2005). The ability to define the management scenarios in detail, including fertilization levels, irrigation methods, and cultivation techniques, makes the SWAT model a powerful tool to evaluate watershed response to management changes. It has also been used to identify Critical sub-basins within watersheds (Tripathi *et al*., 2003) where management practices may have the greatest impact. A detailed model description can be obtained from (Neitsch *et al*., 2002) or the model web-site located at http://www.brc.tamus.edu/swat.

MODEL DEVELOPMENT, CALIBRATION AND VALIDATION

The SWAT model input data consist of three main categories; GIS data, weather data, and point source discharge information. The GIS data required include a Digital Elevation Map (DEM), soil data in the digitized Soil Survey Geographic (SSURGO) format, 2004 summer land use data, and weather station location information. The DEM used was from the National Elevation Dataset (NED) developed by the USGS in 2002 in a 1 arc second (approximately 30 m) resolution. These data were available in a seamless, 8 digit Hydrologic Unit Code (HUC) layer from http://seamless.usgs.gov/. The SSURGO soil data were available from USDA soil data mart by county at http://soildatamart.nrcs.usda.gov/. It was the highest resolution digitized soil information available during the study period. All other GIS information including 2004 land-use information and weather station location information was obtained from the Center for the Advanced Technologies (CAST), the University of Arkansas. The weather data were obtained from National Oceanic and Atmospheric Administration (NOAA). The point source discharge information was provided by the ADEQ in the form of Discharge Management Reports (DMRs) for permitted discharges for the study period.

The model was set up and the watershed was delineated using the automatic delineation tool in AVSWAT 2005. The watershed was divided into 30 sub-basins. One additional sub-basin was added to ensure output information at an existing USGS gauging station to enable the model calibration. Each sub-basin was divided into multiple Hydrologic Response Units (HRU) with the land-use and soil type thresholds set at 5% each. This resulted in 506 HRUs in the watershed.

The majority of the managed land use in the watershed is in row crop agriculture, primarily irrigated soybeans and rice. The typical crop rotation is a combination of these two with an additional winter wheat crop when profitable on suitable soils. The management scenarios used for modeling these crops were determined using the published verification information from the watershed area, the individual crop handbooks published by the University of Arkansas Cooperative Extension Service (UACES), and information obtained directly from the farmers in the watershed. Fertilization application rates of 24 kg/ha phosphorous and 80 kg/ha nitrogen in rice, and 22 kg/ha phosphorous in soybeans were used in the model. All other crops were set to auto-fertilize nitrogen by the model based on crop nutrient stress.

The auto-calibration feature available in SWAT 2005 was utilized for sensitivity analysis and model calibration (van Griensven and Bauwens, 2003). The most sensitive parameter for flow and sediment was the Curve Number (CN2), and the most sensitive parameters for the nutrient outputs were the SOL_ORGN and SOL_ORGP for Nitrogen (N) and phosphorous (P) respectively. The output for flow was used for auto-calibration at the Colt gage, and the outputs for flow, sediment, total N, and total P were used for auto-calibration at the Palestine gage. The objective functions used for model calibration were maximization of the coefficient of determination (R^2) and Nash-Sutcliffe Coefficient of Model efficiency (E_{NS}^2) calculated as,

$$R^2 = \left[\frac{\sum_{i=1}^{n} (O_i - O_{avg})(P_i - P_{avg})}{\left[\sum_{i=1}^{n} (O_i - O_{avg})^2 \sum_{i=1}^{n} (P_i - P_{avg})^2 \right]^{0.5}} \right]^2 \quad \text{... (1)}$$

$$E_{NS}^2 = 1 - \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (O_i - O_{avg})^2} \quad \text{... (2)}$$

where O is measured values, P is predicted outputs and i = number of values (Nash and Sutcliffe, 1970).

BMP Optimization Plan Development

The BMP optimization was accomplished using an optimization algorithm (NSGA-II) (Deb *et al*., 2002) and the SWAT model. The NSGA-II is a genetic algorithm based optimization technique and is reported to give a good spread of solutions through faster convergence rate for BMP solutions (Deb *et al*., 2002). Sets of BMPs, called allele sets, applicable to various land use and land cover were prepared and used in the optimization model (Table 1). During the optimization process, the algorithm searches for a particular management practice from the given allele set for a particular land use, and subsequently estimates the pollution loading and the cost estimates for the placement of this particular BMP in the selected farm. The pollutant loading and the costs are summed up for all the farms to get an estimate at the watershed level. The allele set forms the variable space for the BMP selection and the watershed level estimates form the objective functions for the optimization model.

Table 1: Allele set of BMPs in L'Anguille River Watershed

Crop	*Allele Set*
Rice	Type 1. NMP 1, NMP2, NMP 3[a]
Soybean	Type 1. NMP 1, NMP 2, NMP 3 Type 2. Buffer 0 m, 5 m, 10 m Type 3. Conservative till, no till

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

A BMP Tool that provided the BMP cost estimate and the HRU level pollutant reduction was developed and used with the optimization tool. The use of BMP tool eliminated the need for the dynamic SWAT model runs required to search the optimal BMP combinations. However, a limitation with the BMP tool is that the effectiveness for only one pollutant can be performed at a time. Another limitation is that the BMP tool gives pollutant reduction at the HRU level and does not perform any routing to determine the transport of the pollutant as it moves through various stream segments. The BMP effectiveness for sediment was computed by calculating the percentage reduction due to the placement of the BMP. The objective functions used in BMP optimization were: (1) minimization of pollutant loading; and (2) minimization of the net cost increase at the watershed scale due to placement and maintenance of the BMPs. The two objective functions that need to be optimized are mathematically expressed as,

$$\min\left[\left(f_i(X)\right)\wedge\left(g_i(X)\right)\right]\forall i\in\left[P,N,Sed\right] \quad \dots (3)$$

Total reduction in the pollution load is expressed as weighted average of the HRUs in the watershed $f(x)$,

$$f_i(X)=\frac{\sum_{x\in X}\left(P_i(x)\times A(x)\right)\left(1-R_i(x)\right)}{\sum_{x\in X}A(x)} \quad \dots (4)$$

The net cost of the placement of BMPs in the watershed is estimated as $g(x)$,

$$g_i(X)=\frac{\sum_{x\in X}C_i(x)A(x)}{\sum_{x\in X}A(x)} \quad \dots (5)$$

Where X represents the HRUs in the watershed, P_i is the unit pollutant load i from a HRU, R_i is the Pollutant reduction efficiency of BMP, A is the Area of HRU; and C_i is the unit cost of the BMP. BMP costs used in the model were annual net cost per unit area of the watershed, including establishment, maintenance, and opportunity costs. The cost informations for the various BMPs for year 2007 were obtained from University of Arkansas Cooperative Extension Service (USACES, 2007) rice and soybean production budgets. The cost information included the costs of production (fertilizers, fungicides, herbicides, irrigation, labor, fuel, seed, etc.) for different tillage systems (Rodriguez *et al.*, 2007). Some of the BMPs considered resulted in increased crop yields, which was also added into the cost component. All the cost estimates were made per unit area ($/ha). During the optimization process, the algorithm searches first for a particular management practice from the given allele set for a particular land use. The subsequent estimation of the pollution loading and cost estimates for the placement of this particular BMP in the selected HRU was obtained from the BMP tool. A weighted average of the pollutant loading and the net costs at HRU level was calculated to get an estimate at the watershed level.

BMP Targeting Plan Development

The calibrated and validated SWAT model was used to predict sediment loads from each of the 31 sub-basins in the watershed. Best management practices are land use specific. Targeting of BMPs for effective sediment control requires identification of areas and watershed characteristics that contribute significantly to the sediment load. The following steps describe the methodology used for selecting BMPs using targeting approach:

1. Subbasins were ranked based on the total average pollution loading for sediment, phosphorus and nitrogen estimated by the SWAT model (Figure 2).
2. In order to compare the effectiveness of BMPs under optimization and targeting schemes, one optimal solution (population), at a time, was selected from the optimized set described above and the total area receiving BMPs through this solution was computed.
3. A number of subbasins were selected that equaled at least to the total BMP area obtained through optimization solution in step 2).

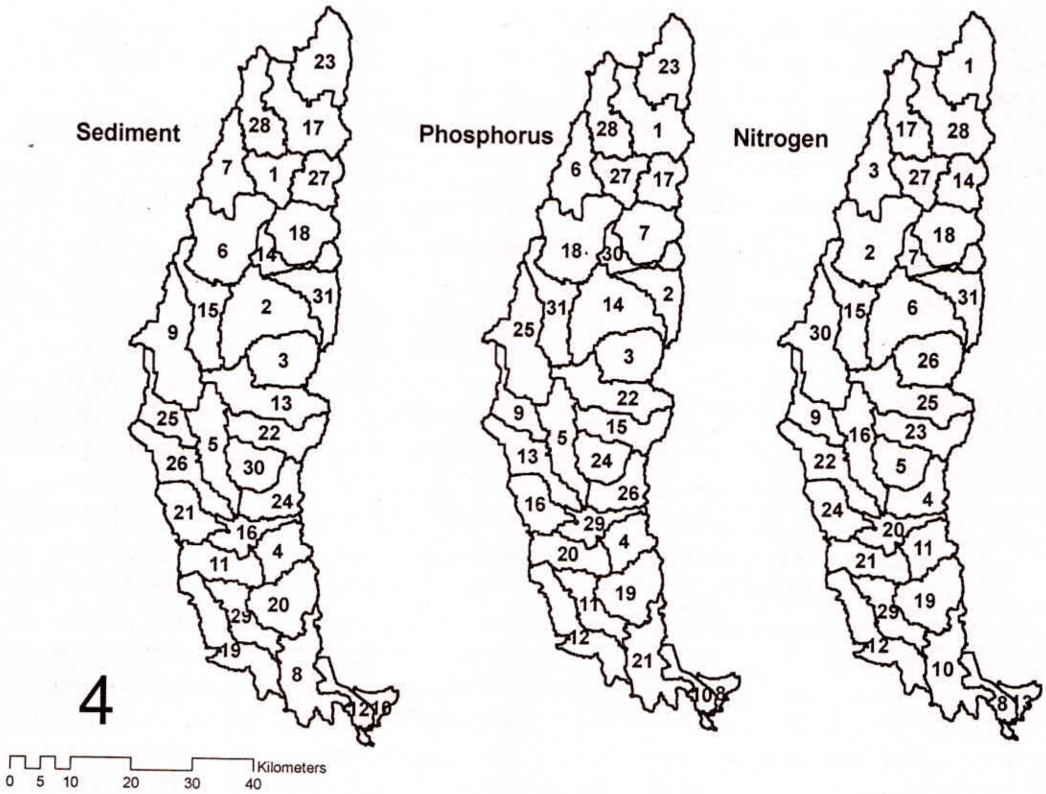

Fig. 2: Subbasin ranking from SWAT model for sediment, total *P*, and total *N* loadings

4. All the HRUs in the selected subbasins were placed with a particular BMP from the different BMPs possible that met the land use constraints.
5. Total pollutant load and net cost increase for each of the BMP placements were computed.
6. Steps (2) through (5) were repeated with the next optimal solution (population) until the last optimal solution was reached.

The BMPs included in this study were no till and conservation tillage in soybean fields, conservation tillage in rice fields, and 0 and 10 m grass filter strips installed at downslope ends of soybean fields, and various fertilizer application rates (Table 1). These BMPs were selected based on discussions with county extension personnel and farmers and their potential to be used in the watershed for NPS pollution control.

RESULTS AND DISCUSSION

SWAT Model Performance

The SWAT model was calibrated from 1992 to 1999 and validated using measured flow data from 2000 to 2001 at Colt gauging station. Similarly, model was calibrated from 1998 to 2004 using measured flow data at Palestine gauging station. The model performance in simulating flow at these two stations is shown in Figure 3. The R^2 ranged from 0.43 to 0.70 and E_{NS}^2 ranged from 0.41 to 0.68, respectively.

A sensitivity analysis was performed on GA parameters to determine the influence of these parameters on the pareto-optimal front. The various GA parameters (population size, generations, mutation, and crossover probability) were changed, one at a time, to evaluate the effects of each parameter on the Pareto-front. The parameter value for which the pareto-front was closest to the origin in sensitivity analysis was taken as the parameter estimate for the optimization process. Figure 4 shows the sensitivity of GA parameters, viz, population size, number of generations, crossover probability, and mutation probability. The various parameters that were used for the development of the model are shown in Table 2.

Table 2: Default and Optimal Parameters Chosen for GA from Sensitivity Analysis

Parameter	*Default*	*Final*
Population	100	200
No. of generations	1000	40000
Crossover probability	0.9	0.9
Mutation probability	0.0001	0.001

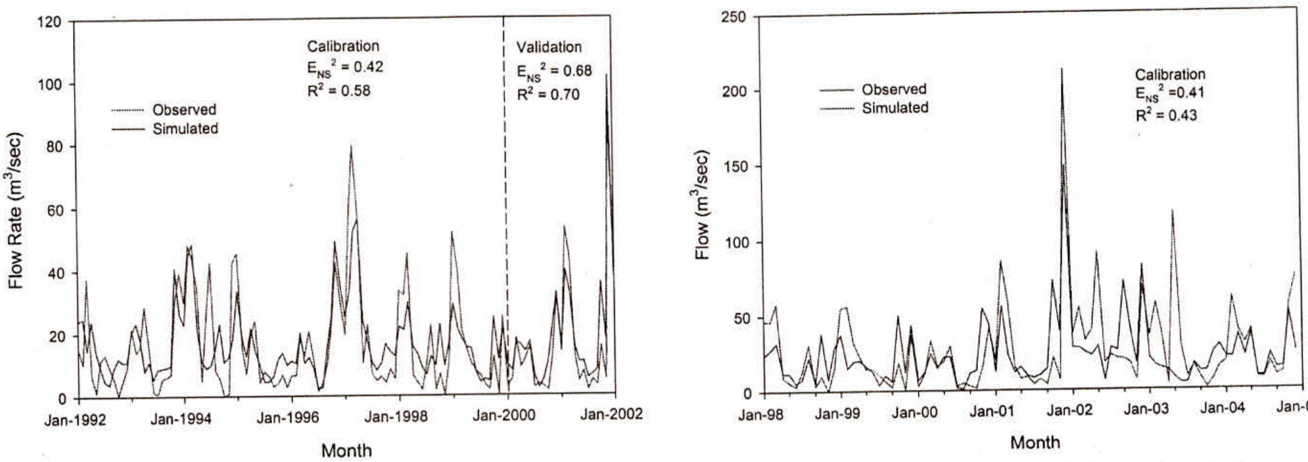

Fig. 3: The SWAT calibration and validation results for flow for Colt (left) and Palestine (right) gauging stations

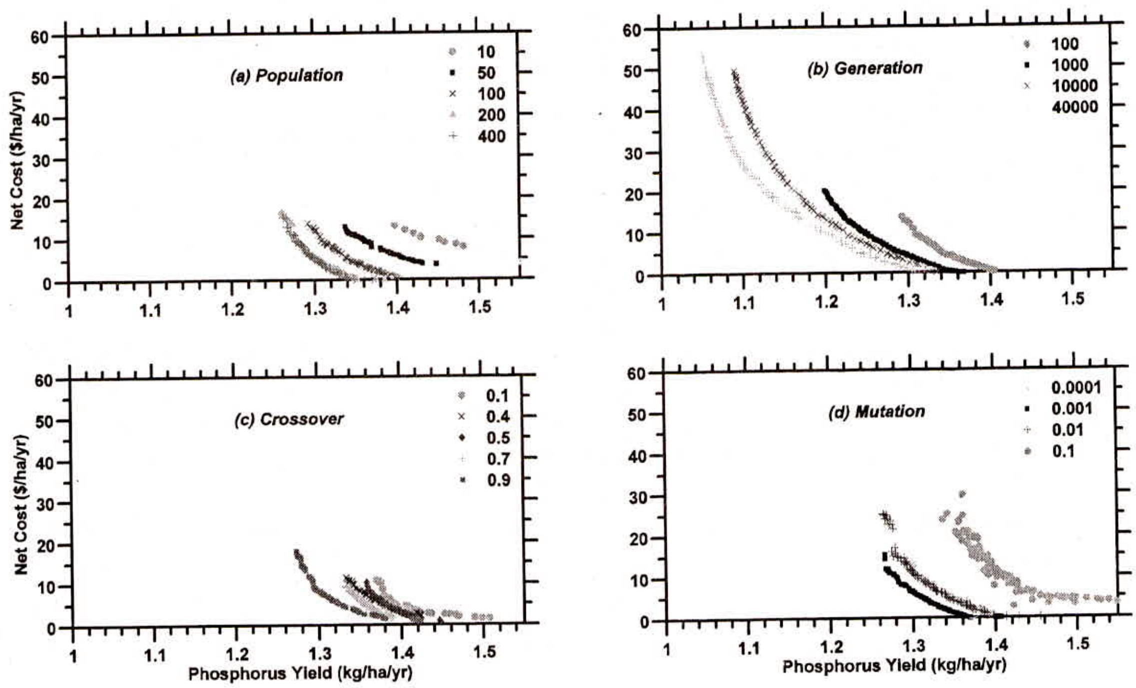

Fig. 4: Sensitivity analyses results for various GA parameters used for BMP optimization

BMP PERFORMANCE UNDER OPTIMIZATION, TARGETING AND RANDOM PLACEMENT SCHEMES

The baseline watershed response consisted of conservative tillage for both rice and soybean with no buffer strips and Nutrient Management Plans (NMP) implemented. The annual average HRU area weighted baseline loadings from the watershed for sediment, total *P*, and total *N* yield were 1.8 t/ha/yr, 1.5 kg/ha/yr, and 17.4 kg/ha/yr, respectively.

Figure 5 shows the sediment loading under various BMP placement schemes. Similarly load reductions and associated costs for total *P* and total *N* are shown in Figures 6 and 7, respectively. These figures show the final optimization solutions that were obtained. The optimization model run using number of generations as 20,000 and a population of 100 took 45 minutes on a CentrinoDuo@2.16GHz computer. It can be noticed that the optimal solutions had a very good spread range which showed that there was a good nondominance sorting for the different optimal solutions reached by the individuals in the population. For optimization, the sediment loadings from the watershed could be reduced in the range of 30–33% with associated BMP implementation cost of 0–$50/ha in the watershed (Figure 5). Similarly, a net reductions in total *P* loads ranged from 16 to 31% under optimization for a net cost of 0–$59/ha (Figure 6). For total *N*, a net reduction up to 13% could be obtained with BMP optimization with associated BMP cost of \$50/ha (Figure 7). All BMP optimizations resulted in significant load reduction for sediment, total *P*, and total *N* compared to the baseline loads of the same pollutants. An interesting observation made was that for some of the BMP scenarios the pollutant reduction was noticed without an increase in the total net cost (Figure 5). This can be explained as the increase in the crop yield because of the placement of a certain BMP nullifies the increase in cost because of implementation and maintenance of the BMPs at a watershed scale. Such a reduction can be termed as 'zero net cost BMP scenario'.

The ranking of subbasins for BMP targeting was different for different pollutants of concern (Figure 2) showing that a pollutant specific subbasin ranking should be prepared for BMP targeting. A subbasin ranking for one pollutant of concern may not be valid when a different pollutant is considered. When areas under BMP implementation were same for optimization and targeting, a significantly smaller pollutant reduction was obtained for sediment (Figure 5), total *P* (Figure 6) and total *N* (Figure 7) under the targeting scheme compared to the optimization scheme. The load reductions ranged from 0–1% for sediment, 0–3% for total *P*, and 0–1% for total *N*, respectively. It should be noted that some of the BMP scenarios resulted in net increase of total *P* and total *N* from the watershed compared to the baseline loads, possibly due to increased fertilizer applications. Comparison of BMP costs under two schemes indicated that for the same net cost of BMP implementation, optimization always resulted in greater reduction in pollutant loads from the watershed.

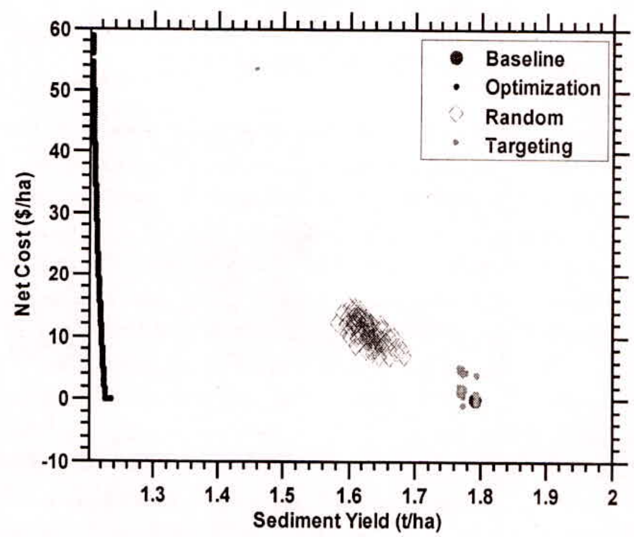

Fig. 5: Reduction in the sediment yield and associated cost for various BMP schemes in the L'Aguille River watershed

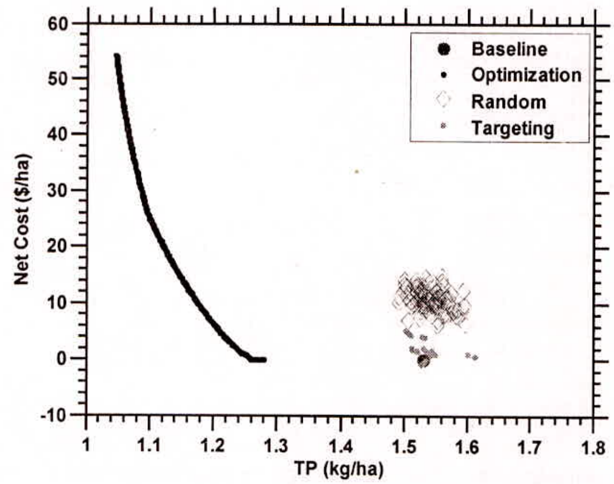

Fig. 6: Reduction in the total *P* yield and associated cost for various BMP schemes in the L'Aguille River watershed

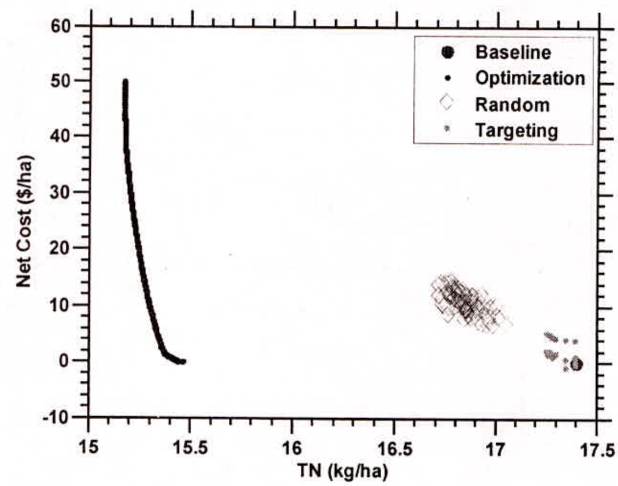

Fig. 7: Reduction in the total *N* yield and associated cost for various BMP schemes in the L'Aguille River watershed

When BMPs were randomly placed, the net reduction in pollutant loadings were intermediate compared to targeting and optimization, i.e. they were less than BMP optimization and greater than BMP targeting. A greater pollutant load reduction compared to the targeting could be due to larger areas under random BMP placement (20% of the watershed). However, none of the random placement scenarios resulted in pollutant load reduction similar to optimization scheme. In addition, the main limitation of the random BMP placement is that the results are not reproducible in other watersheds.

SUMMARY AND CONCLUSIONS

Reducing pollutant loads from agricultural watersheds require placement of BMPs at strategic locations that can maximize loads reduction with minimum associated cost. This study evaluated effectiveness of three BMP implementation schemes in reducing sediment, total N, and total P losses from an agricultural watershed: optimization, targeting in high priority sub-basins and random placement to minimize net-cost increase and pollutant losses. BMP optimization results gave a range of solutions with corresponding net cost increase due to BMP implementation. The maximum reduction under the optimization objective functions was 33% at a net cost of $55/ha for sediment. Similarly, maximum reduction in total P and total N were 31% and 13%, respectively, with associated costs of $59/ha and $50/ha. Both targeting and random placement resulted in significantly smaller pollutant reduction compared to BMP optimization. The results of this study indicated that under limited resources available for BMP implementation and maintenance, watershed management should focus on optimizing BMP placement so that maximum pollutant reduction from the watershed can be accomplished.

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