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Multi-Criteria optimization of watershed management practices for sediment, nutrient, and pesticide control

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EXECUTIVE SUMMARY

Effective management of nonpoint source pollution from agricultural areas presents a challenge to watershed managers and planners around the world. The overarching goal of this study was to demonstrate a computational framework that enhances decision makers' capacity to design cost-effective watershed plans for sediment, nutrient, and pesticide control. To this end, the Soil and Water Assessment Tool (SWAT) and a cost evaluation model were reconciled with a genetic algorithm spatial search engine to explore the economic and environmental tradeoffs associated with implementation of conservation practices, also known as best management practices (BMPs). The utility of the optimization framework was demonstrated in an agricultural watershed in the Wildcat Creek Watershed (WCW), Indiana where elevated levels of atrazine –2-chloro-4-(ethylamino)-6-(isopropylamino)-s-triazine– is a drinking water quality concern.

While the water quality impacts of BMPs are derived from SWAT, the credibility of model simulations for the water quality constituents of interest, i.e. atrazine, was investigated. Challenges pertinent to modeling the fate and transport of pesticides in WCW were identified and addressed. First, three methods for the incorporation of pesticide management operations in SWAT were proposed and compared. Historical data on intra-seasonal planting dates were used to temporally assign the timing of tillage, nutrient application, and pesticide application to the cropland in the watershed. Detailed comparisons of observed and simulated pesticide load time series for each approach indicate that accurate representation of application dates over time and space is imperative. Second, the importance of accounting for impoundments such as reservoirs for modeling the fate and transport of atrazine was examined. Finally, this research revealed the spatial scale dependence of some of pesticide parameters of the SWAT model. In particular, it became evident that the optimal value of the pesticide percolation coefficient would increase when calibrating the model at stream outlets with larger drainage areas.

The enhanced modeling strategy provided a more credible basis for deriving effective abatement strategies for the mitigation of pesticide loads. Six targeting strategies were formulated to derive watershed plans most consistent with stakeholders' priorities. For example, a watershed plan was derived that would achieve the water quality targets at the lowest cost to stakeholders. Similarly, another plan was identified that would minimize pollutant loads at the watershed outlet subject to a predefined budget. The range of solutions that were developed allows a thorough evaluation of tradeoffs and targets for implementation of agricultural BMPs.

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PART I: Modeling the Fate and Transport of Pesticides in Agricultural Watersheds

While pesticides are intensively applied in agricultural areas to increase crop production, substantial ecologic and human health risks may be posed through the runoff and leaching of the pesticide into the environment. This tradeoff is particularly important in the Midwestern U.S. where nearly 80% of total corn and soybean crops in the U.S. are cultivated and produced (Kalkhoff et al., 2003). In order to maintain/ enhance crop productivity, more than 100,000 megagrams of pesticides are applied to cropland in the region annually (Battaglin and Goolsby, 1999). Atrazine (2-chloro-4-(ethylamino)-6-(isopropylamino)-s-triazine) is a common herbicide that is applied to control the growth of weeds in corn fields. Atrazine was the most used pesticide in Indiana in 1998, with an estimated 7.05 million pounds applied to 89% of the 5.8 million acres of corn crops (NASS, 1998). Accompanying this widespread use, many agricultural regions in the Midwest Corn Belt are reporting concentrations of atrazine in their stream networks that exceed the maximum contaminant level (MCL) for atrazine of 3 parts per billion (ppb) (USEPA, 2002). The physicochemical properties of atrazine contribute to its fate, transport, and degree of persistence in the aquatic environment (Kalkhoff et al., 2003). The persistence of atrazine in the environment not only creates problems for the health of natural aquatic habitats but also for the adequacy of water treatment plants and the safety of water for human contact in recreational areas due to its carcinogenic effects at higher levels (IDEM, 2004; USEPA, 2006).

Several streams and water bodies in Indiana are afflicted with atrazine pollution. Elevated levels of atrazine loads are of particular concern in watersheds that are source of drinking water for urban areas. The Wildcat Creek watershed (WCW) is the source of drinking water for city of Kokomo, Indiana, and was selected for the present study. According to a database created by the Indiana Department of Environmental Management (IDEM, 2004), 126 instantaneous samples of atrazine taken over the period from 1997-2004 in the Wildcat Creek Watershed included 26 incidences of exceeding the 3 ppb MCL for atrazine. A study by Pappas (2008) suggests that measurement campaigns for herbicides like atrazine should be optimally carried out on a daily basis with a more intensive sample collection during storm events. Since a sampling plan of this caliber is uncommon and is not available for these watersheds, the information that is available must be used to its fullest potential. High production of corn and the common use of atrazine in these watersheds necessitate a thorough understanding of the fate and transport of atrazine in order to create an effective pesticide management plan.

In many cases a comprehensive environmental monitoring campaign that covers all processes that govern the transport of pesticides over time and space are fiscally unfeasible. Alternatively, a simulation model that can incorporate the spatially and temporally distributed characteristics of a watershed including soil, land use, topography, temperature, precipitation, and hydraulic features would create a framework from which these physical processes can be described. The use of computer models facilitates the representation of the complex hydrologic and chemical processes that occur in a watershed and allows for the understanding of the inherent physical workings of the hydrologic system (Yu et al., 2004).

The Soil and Water Assessment Tool (SWAT) is a river basin scale, continuous time model with the capability to integrate these characteristics (Arnold et al., 1998). SWAT can also simulate and estimate pollution generation at the source and its movement from the source to the receiving water body while providing flow and concentration levels at various points in the watershed. Although the capability to model pesticides in SWAT is available, accurate representation is often difficult due to the challenges that accompany pesticide modeling. While SWAT has been used broadly for the evaluation and simulation of streamflow, sediment, and nutrients, few studies have evaluated pesticide modeling using SWAT.

Some past studies present pesticide modeling techniques (Kannan et al., 2006; Vazquez-Amabile et al., 2006; Larose et al., 2007; Parker et al., 2007; Gevaert et al., 2008; Holvoet et al., 2008; Luo et al., 2008; Quansah et al., 2008), but they did not assess different methods in representing the application of pesticides in the watershed nor evaluate the potential impacts of storage structures in the watershed that may significantly alter the pathways and routing of pesticides. Both Vazquez-Amabile et al. (2006) and Quansah et al. (2008) modeled atrazine application as a function of the percentage of crops planted with data from crop progress reports and applied a multiple application ratio to all fields in the watershed. Quansah et al. (2008) expanded on Vazquez-Amabile's work by incorporating tillage timing and evaluating its effects on atrazine pollution. The techniques applied in both studies have not been tested in different watersheds and have not considered various characteristics of the watershed including reservoirs and land use changes. Bosch (2008) highlights the fact that reservoirs may have a significant effect on the transport of water quality constituents in a watershed. They showed that the modeled nutrient loads downstream of a reservoir doubled when the reservoir was removed from the simulation. By resolving the shortfalls of previous research, this study puts forth a more realistic methodology for modeling pesticides at the watershed scale.

The goal of this study is to develop a framework for exploring and resolving challenges associated with modeling the fate and transport of pesticides, particularly atrazine, and other water pollutants. The methods and conclusions of the study will be corroborated in WCW to show consistency in solutions to these challenges. In order to accomplish this goal, several objectives will be addressed. First, the WCW will be analyzed and parameterized for streamflow and atrazine on varying temporal scales (i.e., daily and monthly time steps) in order to effectively assimilate the sparse measured data. Second, the dependency of pesticide transport on application dates and application rates both spatially and temporally will be examined. Next, a variety of challenges unique to each watershed, particularly the influence of impoundments, will be presented. Lastly, the scale dependence of pesticide related parameters will be evaluated at various outlets with differing contributing areas.

PART II: Techniques for Optimizing Tradeoffs between Pollution Reduction and Economic Cost in Midwest Watersheds

Confirming research has been conducted that shows optimization-based approaches are likely to facilitate development of watershed management plans that achieve water quality goals (TMDLs) at significantly lower costs (Arabi et al., 2006).

The cost of implementing management practices are frequently covered with a cost-share system between landowners promoted by government agencies such as the United States Department of Agriculture's National Resources Conservation Service (USDA-NRCS). Although these field-scale plans may result in the improvement of water quality in the immediate region of the involved fields, the impact these small-scale solutions have on the overall watershed is unknown. A variety of individual plans may replicate or overlap each other thus reducing their synergistic potential to benefit the entire watershed. Also, the water quality impacts of the practices are specific to each site since the solutions are based on landform characteristics, and therefore, may not have the same effectiveness at a different location in the watershed. Thus, a more holistic approach on a watershed scale would be more suitable than a source-by-source, pollutant-by-pollutant approach. EPA's Clean Water Act supports the need for watershed scale approaches (EPA, 2003).

One type of watershed scale approach is a targeting strategy in which pollution control measures are allocated to critical source areas, or portions of the watershed that intensively contribute to nonpoint source pollution. This targeting approach has become unattainable in many large complex watersheds due to the exponential number of scenarios associated with the number of fields in the watershed. To make this process more feasible, a tool has been developed that can search for an optimal scenario effectively.

With the accessibility of powerful computers for application of mathematical program heuristics used to solve complex and computational cumbersome problems, there is an opportunity to evaluate scenarios with multiple objectives to converge to a solution or a number of possible solutions. Watershed management is a multi-objective task that is challenged by the complexities associated with economic, environmental, and institutional criteria. Considering the interaction of these multiple factors and seeking a near optimal plan based on landscape characteristics within the context of a computer program can greatly contribute to the effectiveness of watershed management. Also, with the creation of a range of optimal solutions, flexibility is provided both for the decision makers and the landowners actually implementing the solutions. Arabi et al. (2006) have already provided an example of such efforts where a genetic algorithm-based spatial search model was developed for cost-effective implementation of agricultural best management practices (BMPs). Their research clearly illustrates that the optimized plan would cost nearly one third the price of a targeting strategy that provides the same level of sediment and nutrient pollutant load reductions.

The primary goal of this research is to evaluate the application of an optimization-based watershed management tool that can assist in optimal watershed plans that are cost-effective. A versatile optimization formulation is needed to maximize pollution reduction and minimize cost of management practice implementation at the same time. Using a genetic algorithm approach, the optimization model was tested for proof of convergence and for demonstration of effectively evolving toward the global optimum that identifies the best set of BMPs and their spatial placement within a watershed. In order to fully assess and build upon the use of a genetic algorithm for BMP optimization, several objectives must first be completed. Initially, the watershed must be well parameterized with an applicable model such as the Soil and Water Assessment Tool for stream flow and water quality constituents. Next, an approach for economic evaluation needs to be developed by creating benefit and cost equations as well as researching the costs of each BMP, target budgets from watershed management plans, and constraining TMDLs for pollution loads. Once these tasks have been completed, six different objective functions can be evaluated for performance of convergence and optimization with the genetic algorithm. The combinations to be evaluated include:

1. Maximizing benefit
2. Minimizing cost
3. Minimizing cost minus benefit
4. Minimizing normalized pollutant load
5. Maximizing aggregated normalized pollutant load reductions
6. Maximizing the benefit to cost ratio

By applying the optimization tool using multiple objective functions to a watershed impacted with pesticides or other pollutants, a variety of optimal management plans will be identified based on these criteria which can be evaluated by the decision maker.

SECTION 2. CASE STUDY WATERSHED AND THE WATERSHED MODEL

2.1. CASE STUDY WATERSHED

The Wildcat Creek Watershed (WCW), located in Northcentral Indiana, is an 8-digit Hydrologic Unit Code (HUC 0512017) watershed that covers an area of about 201,000 hectares, originated in central Indiana and drains towards the west. The major land use distributions are 4.8% urban, 5.6 % forest, 20% pasture, 34% soybean, and 32 % corn crops (USDA-NASS, 2003). The main soil groups in the area are mostly composed of hydrologic soil groups B and C with moderately high and moderately low drainage capacities, respectively. The historical average annual precipitation was about 1000 mm. The average high temperature is about 16 degrees Celsius while the average low is about 6 degrees Celsius (NOAA-NCDC, 2004). The area is relatively flat, since it has less than a 200 meter difference between the highest and lowest point in the watershed. For this research, the eastern portion of the WCW was analyzed since this region has the most ample supply of historical data. This area is of the source of drinking water for the city of Kokomo, Indiana, and will be referred to as the WCW henceforth. Figure 1 indicates the location of WCW in the Great Lakes Region of the United States.

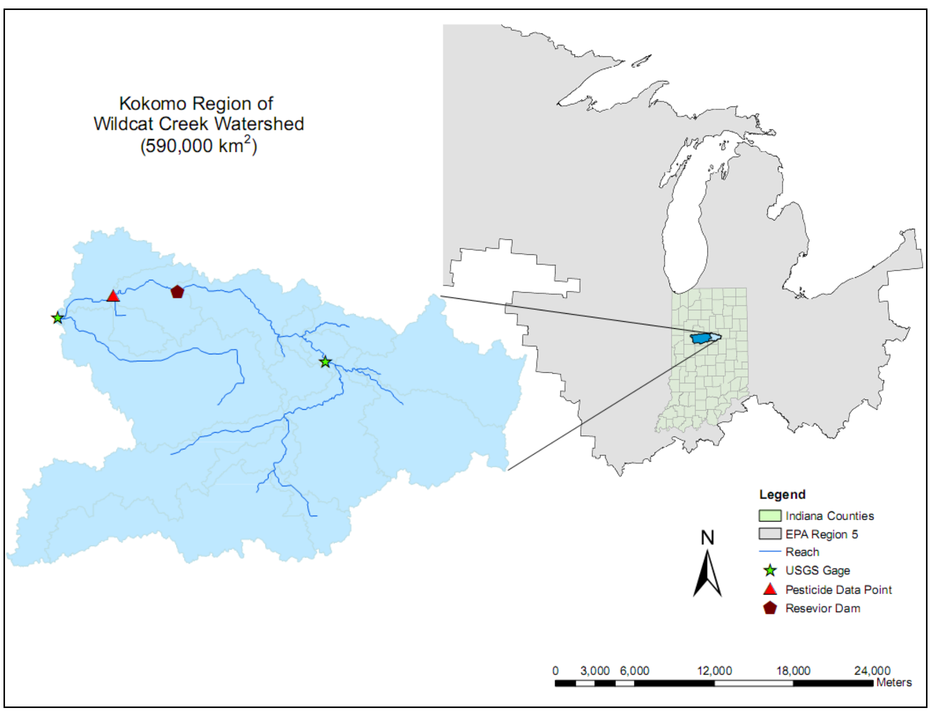

Figure 1. Location of Wildcat Creek Watershed

Figure 2 depicts the gage locations, landuse, soils, and elevation of the region. As indicated in the maps, two USGS gages were used for streamflow calbiration and two weather stations were available in the area for anaylsis. One prominent station had available water quality data with a reservoir located just upstream of this station.

2.2. WATERSHED MODEL DESCRIPTION

The Soil and Water Assessment Tool (SWAT) was selected to represent hydrologic and water quality processes in the study watersheds. SWAT operates on a daily time step and was originally developed to predict the impact of management actions on water, sediment, and agricultural chemical yields in ungauged basins (Arnold, et al. 1998). The spatially distributed model is process based, computationally efficient, and capable of continuous simulation over long time periods. Major model components include weather, hydrology, soil temperature and soil properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management.

Hydrologic processes simulated by SWAT include evapotranspiration (ET), infiltration, percolation losses, surface runoff, and lateral shallow aquifer and deep aquifer flow. The SWAT model incorporates shallow groundwater flow, reach routing transmission losses, sediment transport, chemical transport, and transformations through streams, ponds, and reservoirs. SWAT is able to route in-stream pesticide transformation and reservoir transformation into the model as well (Parker et al., 2007). Algorithms from GLEAMS (Ground Water Loading Effects on Agricultural Management Systems) (Leonard et al., 1987) are used to model pesticide movement and fate. This process is divided into three components: (i) pesticide processes in land areas, (ii) transport of pesticide from land areas to the stream network, and (iii) in-stream pesticide processes. Algorithms from EPIC (Erosion- Productivity Impact Calculator) (Williams et al., 1985) are used in SWAT to model the governing movement of soluble and sorbed forms of pesticide from land areas to the stream network. The SWAT model incorporates a simple mass-balance method developed by Chapra (Chapra, 1997) to model the transformation and transport of pesticides in streams. Only one pesticide can be routed through the stream network in a given simulation (Neitsch et al., 2001). In SWAT, a watershed is divided into multiple sub-watersheds, which are then further subdivided into hydrologic response units (HRUs) that consist of homogeneous land use, management, and soil characteristics. The HRUs represent percentages of the sub-watershed area and are used for hydrologic analysis.

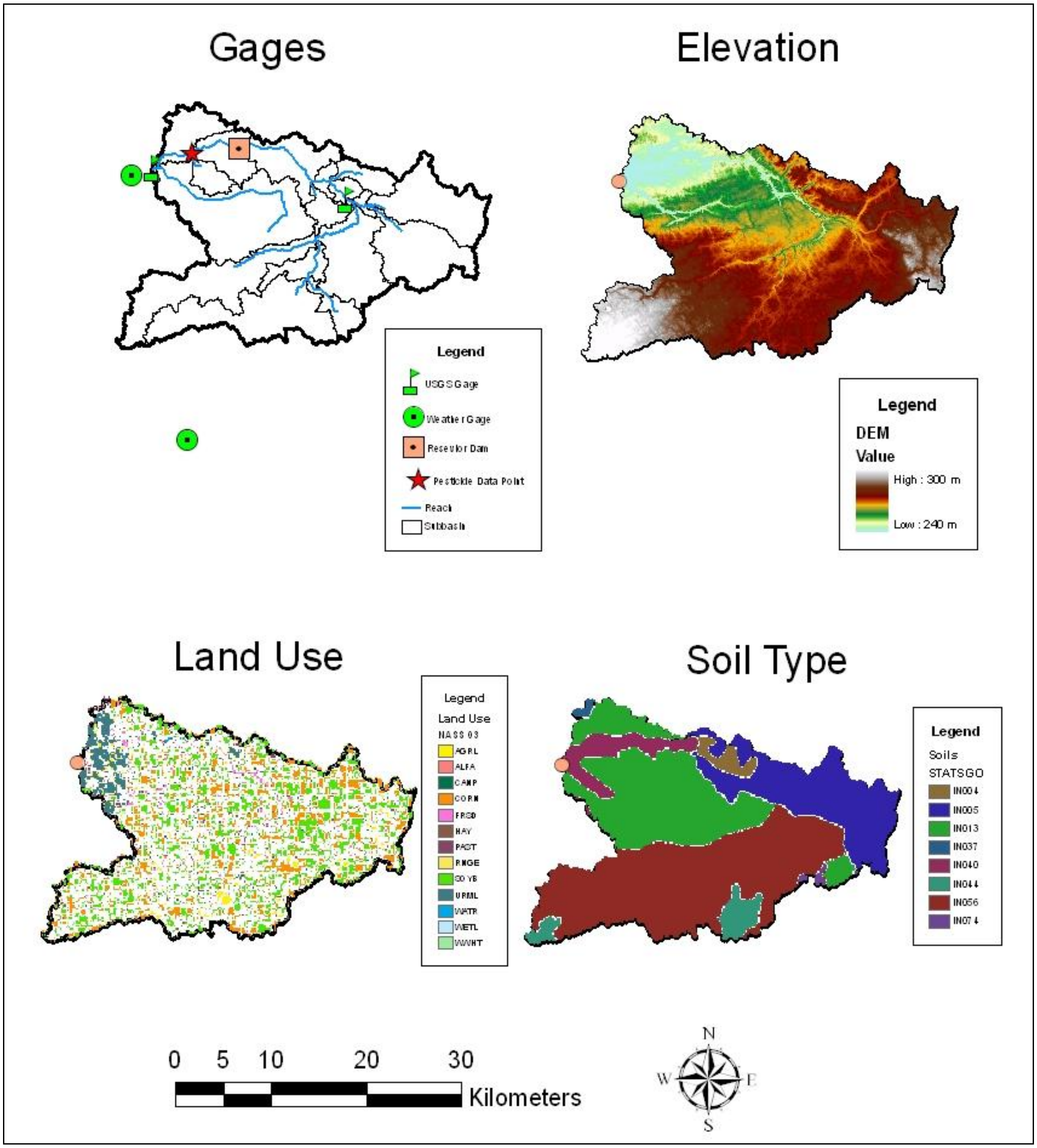

Figure 2. Wildcat Creek Watershed characteristics

Several sources of information were used to fulfill the required inputs for SWAT. Table 1 lists the origins of the data used for each of the watersheds. The WCW was subdivided into 45 subwatersheds and a total of 426 hydrologic HRUs. For this project in particular, the outlets were defined in a way to best correspond to the 12 digit HUC for consistency across the project and for more precise analysis.

Table 1. Model inputs for SWAT used for each watershed

	Data Type	Source
Elevation	30-m DEM	USDA/NRCS - National Cartography & Geospatial Center
Land use	NASS, 2003	USDA's National Agricultural Statistics Service
Soil types	STATSGO	USDA/NRCS State Soil Geographic Database
Climatic data	NOAA	NOAA National Climate Data Center
Agricultural data	NASS	Indiana Agricultural Statistics Reports
Stream flow data	USGS	USGS, Nation Water Information System
Water quality data	IDEM	Indiana Department of Environmental Management
Dams	NDI	National Dam Inventory from the Army Corps of Engineers

2.3. MODEL CALIBRATION

To calibrate the SWAT models, the suggested protocol for hydrologic and water quality modeling according to Engel et al. (2007) was followed as closely as possible (Engel et al., 2007). After clearly defining the goals of the project and discerning the applicability of SWAT, the most sensitive SWAT parameters are found with a sensitivity analysis. Autocalibration method is then used to optimize the best statistical relationship between the observed and simulated data using the selected parameters. These statistical values include the relative error (RE), the percent bias (BIAS), the sum squared error (SSE), the relative means square error (RMSE), the coefficient of determination (R^2), and the Nash Sutcliffe Efficiency coefficient (NSE) (Nash and Sutcliffe, 1970). While RMSE is widely used in the calibration process, NS indicates how well the plot of observed versus simulated values fits the 1:1 line. It can range from -∞ to a perfect match of +1. The equations for RMSE and NS are described by:

$$RMSE = \sqrt{\frac{\sum \left(X_{i,s} - X_{i,o}\right)^2}{n}} \tag{1}$$

$$NS = \frac{\sum_{i=1}^{n} \left(X_{i,o} - X_{i,s}\right)^2}{\sum_{i=1}^{n} \left(X_{i,o} - \overline{X}_{i,o}\right)^2} \tag{2}$$

where $X_{i,s}$ is the simulated output for day i, $X_{i,o}$ is the observed output for day i. $\overline{X}_{i,o}$ is the average observed value measured during the simulation period. The parameter n denotes the number of time steps included in the calibration process. Results from these statistical parameters were considered good if the

NS≥ 0.75 and satisfactory if 0.36≤NS≤0.75 (Van Liew and Garbrecht, 2003). Goal relative error values should be less 15 and goal values of NS should be greater than 0.7. R^2 values should be greater than 0.5. Auto-calibration was also used to select the optimal magnitudes of the selected parameters based on the evaluation of the statistical values mentioned above.

2.3.1. Sensitivity Analysis

An initial set of streamflow parameters was obtained from a screening sensitivity analysis called Morris's One-at-A-Time method (Morris, 1991). This method looks at the interactions between parameters and assesses the sensitivity of each parameter relative to each other. Thus, the interactive parameters that have higher rankings are more sensitive than ones with lower rankings. This analysis identified the importance of the parameter compared to the other parameters not the magnitude of their sensitivity.

2.4. Calibration and Validation

Calibration and corroboration were preformed for both hydrologic and water quality components in WCW. A daily and monthly assessment was taken for all of the available water quality data provide for by the USGS and the IDEM. The monthly data was developed by using a mean-flow concentration averarging method.

Streamflow Calibration

Morris reported that for streamflow, fourteen parameters were found to be sensitive. These results are shown in Table 2. Of these fourteen parameters, five streamflow parameters were used in the calibration. The other parameters were not considered since they did not have a significant effect on the simulated streamflow when observing local sensitivity and in order to simplify potential variables for future calibration of pesticides and nutrients.

The five stream flow parameters used in the calibration included SURLAG, ALPHA_BF, CN_F, CH_KII, and SOL_AWC. SURLAG is the surface runoff lag coefficient that controls the amount of total water available to enter a reach on any one day. As SURLAG goes down, more water is held in storage. For the calibration of the Kokomo region of Wildcat, a value slightly higher than the default of 4 was used to increase the fraction of surface runoff storage reaching the stream. ALPHA_BF is the baseflow alpha factor which describes the groundwater flow response to changes in recharge. A higher value of ALPHA_BF was used since the land has a more rapid response to recharge. CN_F is the initial SCS runoff curve number for moisture condition II. This value was changed as a percent fraction of the default value. For this case it was increased by 0.1% meaning that the soil drainage in the area was not as good as the assumed conditions in the model database. CH_KII is the effective hydraulic conductivity in the main channel alluvium. This value was set fairly high in order to represent the high loss rate due to the bed material characteristics of large sand and clean gravel. SOL_AWC is the available water capacity of the soil layer. Figure 3 depicts simulated monthly streamflow versus observed streamflow.

Table 2. Morris Results

Rank	Parameter Name	Rank	Parameter Name	Rank	Parameter Name
1	ALPHA_BF	6	SOL_AWC	11	CH_NI
2	CH_KI	7	SOL_K	12	SFTMP
3	CN_F	8	SNO50COV	13	GWQMN
4	ESCO	9	CH_KII	14	RCHRG_DP
5	SURLAG	10	OV_N		

Sediment and Nutrients Calibration

After calibrating flow, a sequential approach to calibration was performed by first calibrating sediment, then pesticides, and lastly the nutrients. Local sensitivity analysis was used to find which parameters were important for each water quality constituent. Several parameters from the .lwq file were used in calibration to account for lake processes occurring in a reservoir located in the Wildcat Creek Reservoir. This reservoir, called Kokomo Reservoir Number Two, is located about 7 km upstream of the major water quality sampling station for atrazine as well as sediment, phosphorus, and nitrogen. The sampling station is located adjacent to a water treatment plant operated by the Indiana American Water Company, which operates the reservoir’s release flows from the dam. Flow control valves at the dam are used to ensure a constant, steady flow of water of 6 MGD for the treatment plant’s creek intake pumps. Since no flow data was collected for this sampling location indicated and exact dam release flows are unavailable, parameters in the .lwq file were used. The use of the parameters in the .lwq file became very critical in the calibration of Wildcat Creek Watershed and improved results significantly.

Table 3 describe the statistics found for each of the streamflow and continuents. Both monthly and daily comparisons were made for each watershed with simulated data obtained from the SWAT runs. Monthly data were determined to be a more representative analysis for WCW since compounding factors contributed to the meaningfulness of the daily data. Factors included a lack of streamflow data at the sampling station and the sampling station’s location downstream of a reservoir dam. The results for streamflow calibration are depicted in Figure 3.

Table 3. Wildcat Creek Watershed Calibration and Validation.

		Streamflow		Sediment		Total Nitrogen		Total Phosphorus	
		Calibration (1/1999) 8/2000-7/2004	Validation (1/1997) 3/1997-7/2000	Calibration (1/1997) 7/1999-12/2002	Validation (1/1991) 8/1993-12/1996	Calibration (1/2000) 4/2002-7/2006	Validation (1/1996) 1/1998-3/2002	Calibration (1/1999) 4/2002-7/2006	Validation (1/1991) 5/1994-5/1998
Monthly	RE	16.71	29.39	1.7	-11.9751	-6.6	3.6	41.3	26.0
	BIAS	1.38	2.17	9.01E-05	0.0	-2.12E-01	9.08E-02	2.84E-02	9.10E-03
	SSE	1185.60	832.99	7.16E-04	2.10E-03	2.31E+02	1.49E+02	2.08E-01	4.77E-02
	RMSE	4.97	4.51	4.30E-03	7.90E-03	2.35E+00	1.90E+00	6.51E-02	3.29E-02
	R2	0.88	0.89	0.79	0.68	0.85	0.85	0.79	0.70
	NS	0.68	0.72	0.61	0.38	0.57	0.51	0.54	0.38
Daily	RE	-9.60	3.00	87.1	51.4	-356.4	-350.4	70.7	53.9
	BIAS	-7518.00	0.22	13.00	9.12	-3.31	-2.92	0.09	0.05
	SSE	1.86E+05	1.15E+05	1.20E+04	1.65E+04	1.45E+03	1.18E+03	0.75	0.27
	RMSE	10.53	9.59	17.79	21.70	5.44	4.96	0.12	0.08
	R2	0.84	0.84	-0.19	0.45	0.10	0.05	0.49	0.45
	NS	0.59	0.69	-6.01	-0.78	-219.60	-457.17	-0.73	-1.70

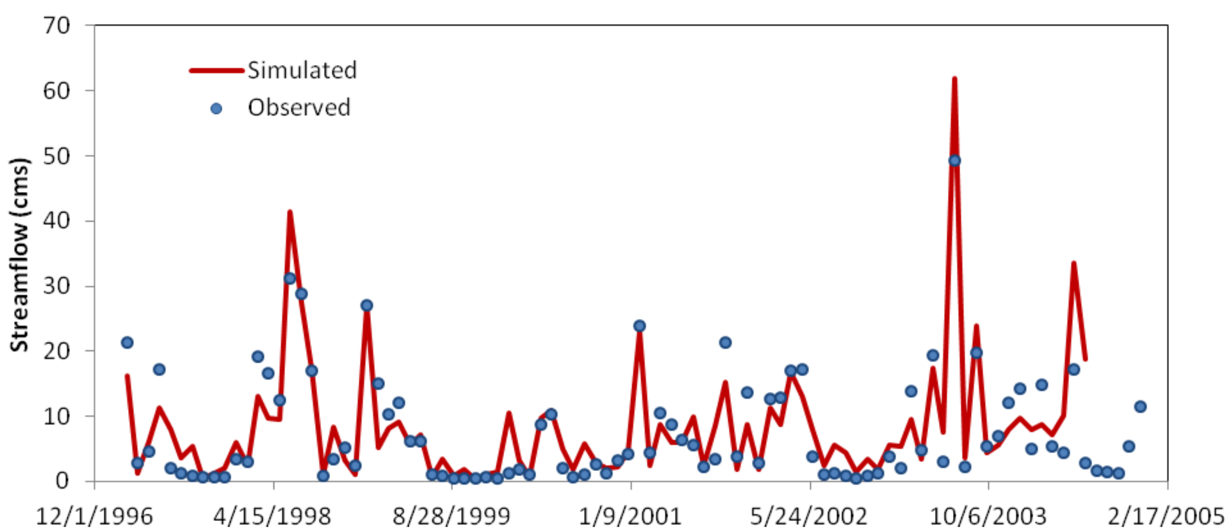

Figure 3. Simulated versus Observed Monthly Streamflow

A more elaborate investigation of pesticide calibration was undertaken to study various representations of pesticide transsport in the SWAT model and are discussed in the following section along with the incorporation of a reservoir.

Pesticide Calibration

The remaining parameters used for pesticide calibration were derived from the .lwq file which describes reservoir characteristics. The LKPST_CONC parameter identifies the initial pesticide concentration in the reservoir water. LKPST_REA identifies the reaction coefficient of the pesticide in the reservoir water which is related to the half life of the pesticide. LKPST_VOL is the volatilization coefficient of the pesticide from the reservoir. LKPST_KOC is the pesticide partition coefficient between water and sediment which can be estimated from Chapra's equation for the octanol-water partition coefficient. The LKPST_STL is the settling velocity of the pesticide sorbed to sediment while the LKPST_RSP is the resuspension velocity of pesticide sorbed to sediment. LKPST_MIX is the pesticide diffusion or mixing velocity. LKSPST_CONC is the initial pesticide concentration in the reservoir bottom sediments. PST_CONC is the initial pesticide concentration in the lake bottom sediments. PST_REA is the burial velocity of pesticide in lake bottom sediment. LKPST_ACT is the depth of the active sediment layer in the lake.

To fulfill the objective of examining how to represent pesticide application rates and dates both spatially and temporally, three different methods were explored. Since the diversity of a watershed as well as the timing and variable rates of application are common concerns associated with pesticide modeling, several approaches were taken to find the best ways to model these types of challenges. The first challenge addressed was to accurately adjust the timing of application. This was accomplished using crop planting dates from the Indiana Agricultural Statistics Service to account for the temporal application of the pesticide in the watershed. To represent this information spatially, two different methods were analyzed and compared with a simple one-time application method that many modelers opt to use due to its simplicity. These three methods, named in order of their complexity, are visually described in Figure 3.

Method I applied the total 1.48 kg/ha of atrazine on the same date for every year to all of the areas planted with corn crops. There are drawbacks to this method since this method ignores variations in both planting and application dates that may deviate due to weather conditions or farmer practices. For Method II, planting dates are segregated into 10% increments over the planting season. For each of the 10 increments, 10% of the total atrazine application rate is applied throughout the season to the areas with corn crops. For Method III, 10% increments of the planted areas were randomly segregated into groups. Each group was designated an atrazine application date throughout the planting season. These application dates were based on data describing the planting progress of corn throughout the growing season.

Atrazine was applied three days after the reported planting date at a rate based on the yearly reported rates of pesticide application in Indiana between 1996-2004 (NASS, 1998) and is summarized in Table 4. Also, tillage operations were conducted seven days before the planting date. Nitrogen and phosphorus applications were applied six days before the planting dates with a second application of nitrogen 16 days after planting. As an example for Method III, 10% of the area of planted with corn in 1997 would receive the total application rate of 1.39 kg/ha on a day within the first 10% of the planting season. This would result in a total of 0.139 kg/ha being applied to the entire watershed. When this approach was used, the actual pattern of corn planting in every season would be followed instead of using an overall average pattern of application.

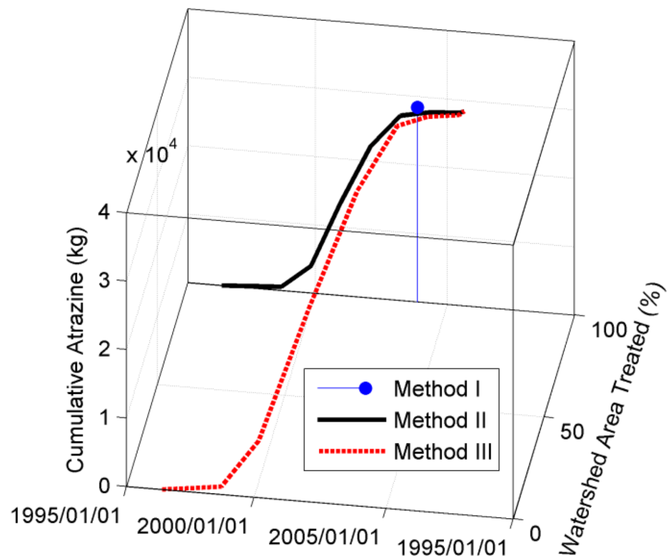

Figure 4. Graphical Representation of Each Method

Table 4. Atrazine Application Rates

Year	Application rate (kg/ha)	Year	Application rate (kg/ha)	Year	Application rate (kg/ha)
1996	1.46	1999	1.4	2002	1.41
1997	1.39	2000	1.55	2003	1.33
1998	1.41	2001	1.47	2004	1.3

The planting dates for each year are unique, which can greatly impact the timing and magnitude of atrazine releasing into the stream. The planting dates used to develop Methods II and III were regionally based on information for Northeast Indiana and Northcentral Indiana. Thus, Cedar Creek Watershed used data reported for Northeast Indiana and Wildcat Creek Watershed used data from the Northcentral Indiana database. Figure 4 explains each method in graphical form for one planting season. Method I is demonstrated by the blue dot, a onetime application for the growing season applied to the entire watershed. Method II is expressed by the black curve running along the 100% area treated plane, which shows the cumulative amount of atrazine applied for the season. Method III is represented by the orange dotted line, which increases towards to top right portion of the graph. In this method, the amount of atrazine applied varies with time and space.

The unique challenges of Wildcat Creek Reservoir on the fate and transport of atrazine in the WCW system are also addressed. Several parameters from the lake water quality file (.lwq) and reservoir file (.res) were added in the modeling and calibration process to account for lake processes occurring in the reservoir. This reservoir, called Kokomo Reservoir Number Two, is located about 7 km upstream of the major water quality sampling station for atrazine as well as for sediment, phosphorus, and nitrogen. The sampling station is located adjacent to a water treatment plant operated by the Indiana American Water Company, which operates the reservoir's release flows from the dam. Flow control valves at the dam are used to ensure a constant, steady flow of water of 6 MGD for the treatment plant's creek intake pumps (Smith, 2009).

Since information on the exact flows being released from the dam were unavailable, the calibration of the system became very difficult. To combat this difficulty, the reservoir file was altered to represent information from the National Dam Database (ACOE, 2007) pertaining to the Kokomo Reservoir. Parameters used for calibration for the .lwq and .res files became very critical in the calibration of the WCW SWAT model and improved results significantly. Due to its importance in sediment settling and resuspension in the reservoir, the d50 of the sediment entering the reservoir was included in calibration. Five parameters used for calibration from the .lwq file proved to be the most sensitive. LKPST_REA identifies the reaction coefficient of the pesticide in the reservoir water which is related to the half-life of the pesticide. LKPST_KOC is the pesticide partition coefficient between water and sediment which can be estimated from Chapra's equation for the octanol-water partition coefficient. LKPST_MIX is the pesticide diffusion or mixing velocity. PST_REA is the burial velocity of pesticide in the lake bottom sediment. LKPST_ACT is the depth of the active sediment layer in the lake. Reasonable values for these parameters were first researched and used as a base for appropriate magnitudes of the calibrated values.

Table 5 reports both the monthly and daily values for calibration and validation of WCW with a warm-up of two years for calibration and three years for validation. These values represent the model before any consideration of the reservoir was taken into account. From Figure 5 and the statistics in Table 3, Method II and Method III clearly represent the observed data better than Method I on a daily analysis with no reservoir component for Wildcat Creek Watershed. Noting the different scales on the vertical axes for each method, it is apparent that the high peaks characterized by Method I are noticeably greater in magnitude than the model predictions made by Methods II and Methods III. The monthly evaluation in Figure 6 also shows how Method II and Method III are a better representation of the data.

Table 5. Wildcat Creek Watershed Calibration and Validation of Pesticides using different Methods with no Reservoir (calibration from 3/1997-7/2000 and validation from 8/2000-7/2004)

		Stream Flow		Method I		Method II		Method III	
		Calibration	Validation	Calibration	Validation	Calibration	Validation	Calibration	Validation
Daily	RE	3.00	-9.63	-564.81	-242.55	-246.90	-89.73	-255.68	-49.88
	BIAS	0.22	-0.79	-6.80	-5.41	-2.97	-2.00	-3.13	-1.11
	R2	0.84	0.85	0.60	0.38	0.07	0.49	0.38	0.44
	NS	0.69	0.59	-69.36	-16.40	-49.86	-15.60	-20.90	-1.55
Monthly	RE	3.00	-13.95	-411.01	-269.47	-214.03	-52.81	-185.05	-37.83
	BIAS	0.22	-1.10	2347.80	-2434.10	-1222.60	-477.03	-1057.00	-341.72
	R2	0.84	0.84	0.73	0.37	0.90	0.37	0.88	0.39
	NS	0.69	0.53	-22.84	-19.77	-7.79	-2.13	-6.50	-1.18

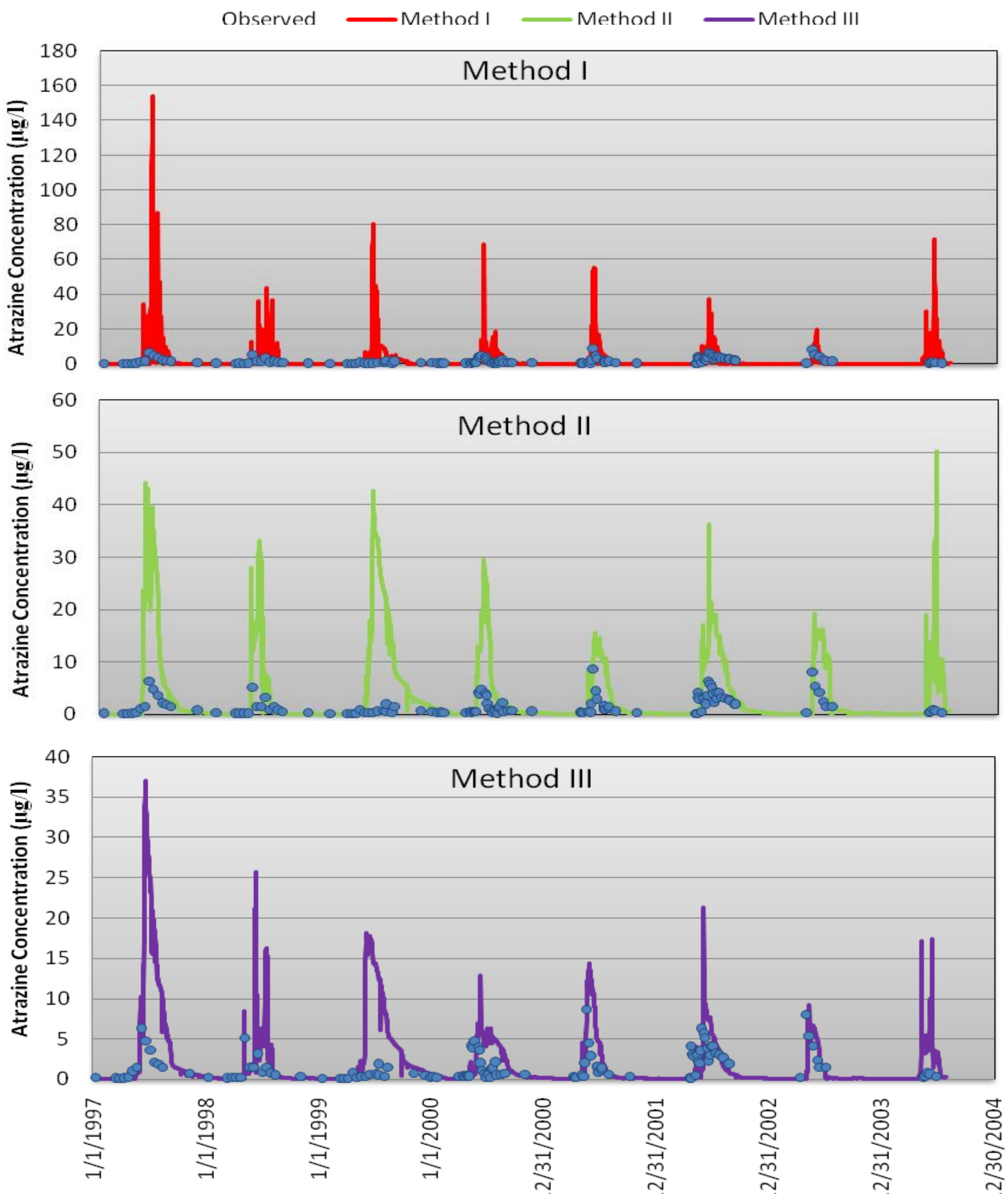

Figure 5. Wildcat Creek Watershed Daily Comparison of Methods with no Reservoir

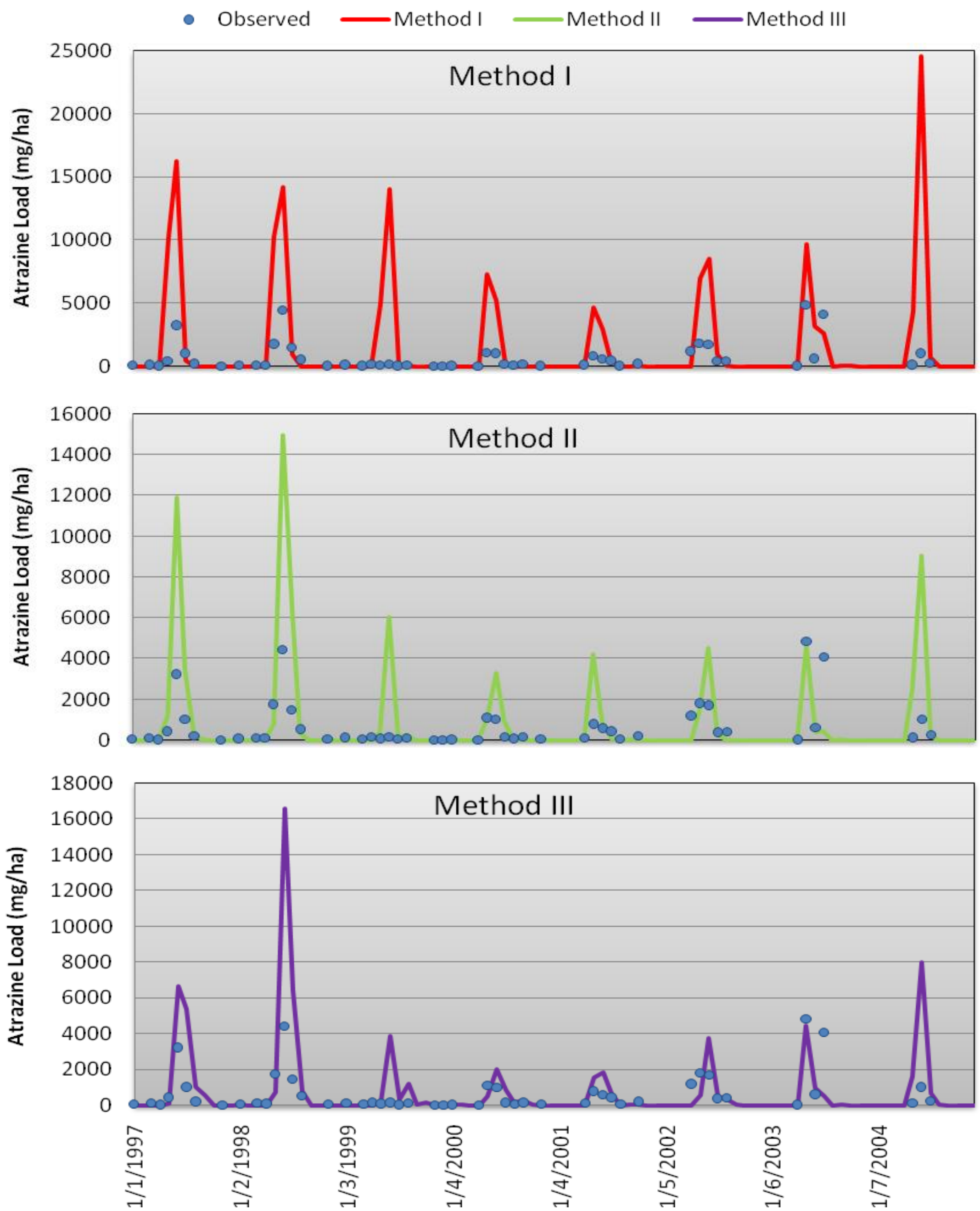

Figure 6. Wildcat Creek Watershed Monthly Comparison of Methods with no Reservoir

To gain a better understanding of the actual conditions in the WCW, the reservoir parameters were adjusted and calibrated to represent the conditions present in the watershed. The results obtained with the inclusion of the reservoir calibration are shown in Table 6 with the daily and monthly plots shown in Figures 7 and 8.

Table 6. Wildcat Creek Watershed Calibration and Validation of Pesticides using different Methods with Reservoir (calibration from 3/1997-7/2000 and validation from 8/2000-7/2004)

		Stream Flow		METHOD I		METHOD II		METHOD III	
		Calibration	Validation	Calibration	Validation	Calibration	Validation	Calibration	Validation
Daily	RE	16.71	29.39	-69.46	-18.45	-0.20	39.00	-12.54	34.00
	BIAS	1.38	2.17	-0.84	-0.41	0.00	0.88	-0.15	0.76
	R2	0.88	0.89	0.24	-0.07	0.03	-0.03	-0.05	-0.05
	NS	0.68	0.72	-0.39	-0.51	-0.10	-0.35	-0.19	-0.33
Monthly	RE	-9.60	3.00	-41.96	-36.20	0.85	26.46	-17.40	21.37
	BIAS	-7518.00	0.22	-379.00	-206.76	4.85	238.97	-99.37	192.99
	R2	0.84	0.84	0.61	0.76	0.74	0.67	0.76	0.70
	NS	0.59	0.69	0.07	0.49	0.52	0.37	0.43	0.43

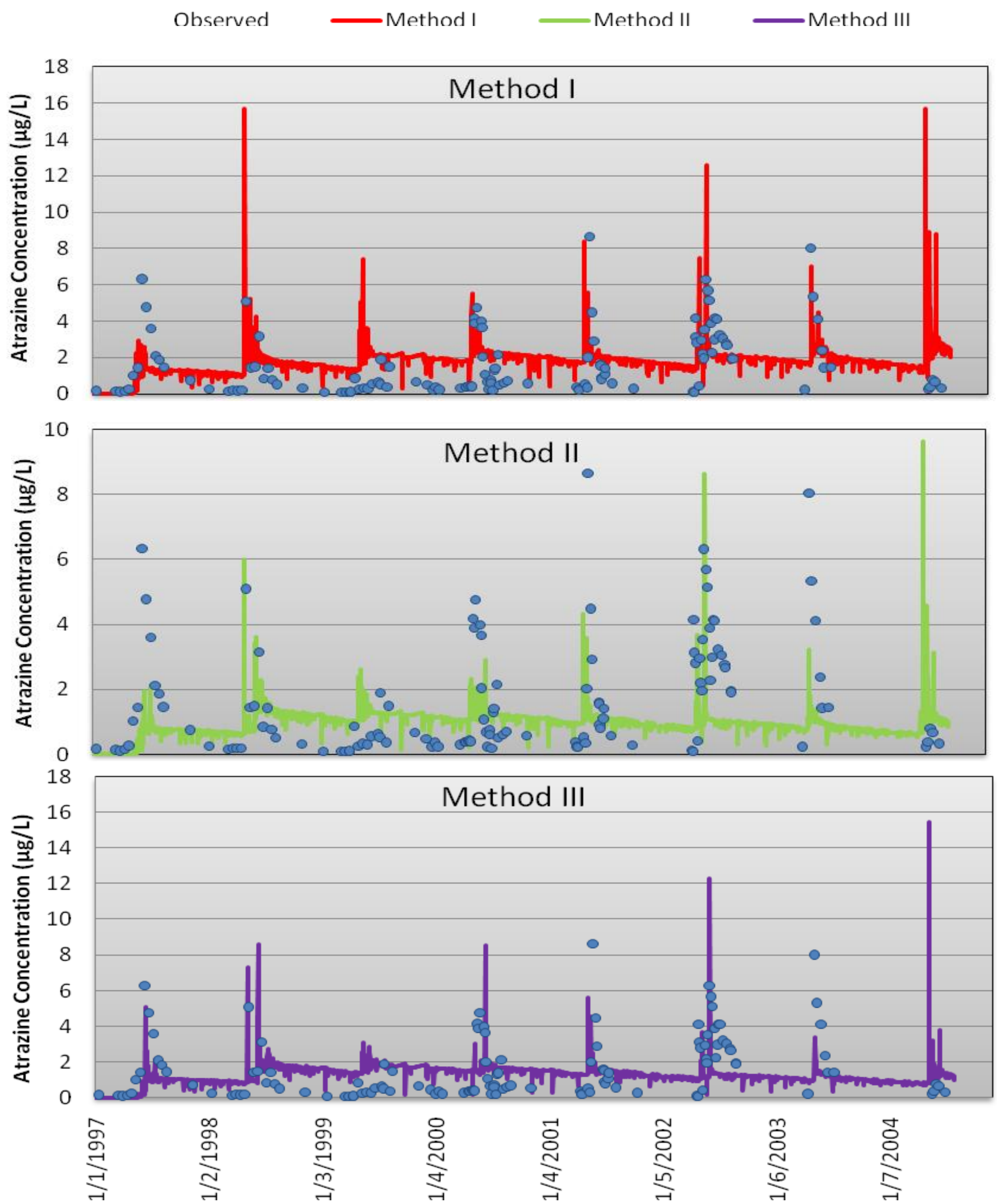

Figure 7. Wildcat Creek Watershed Daily Comparison of Methods with Reservoir

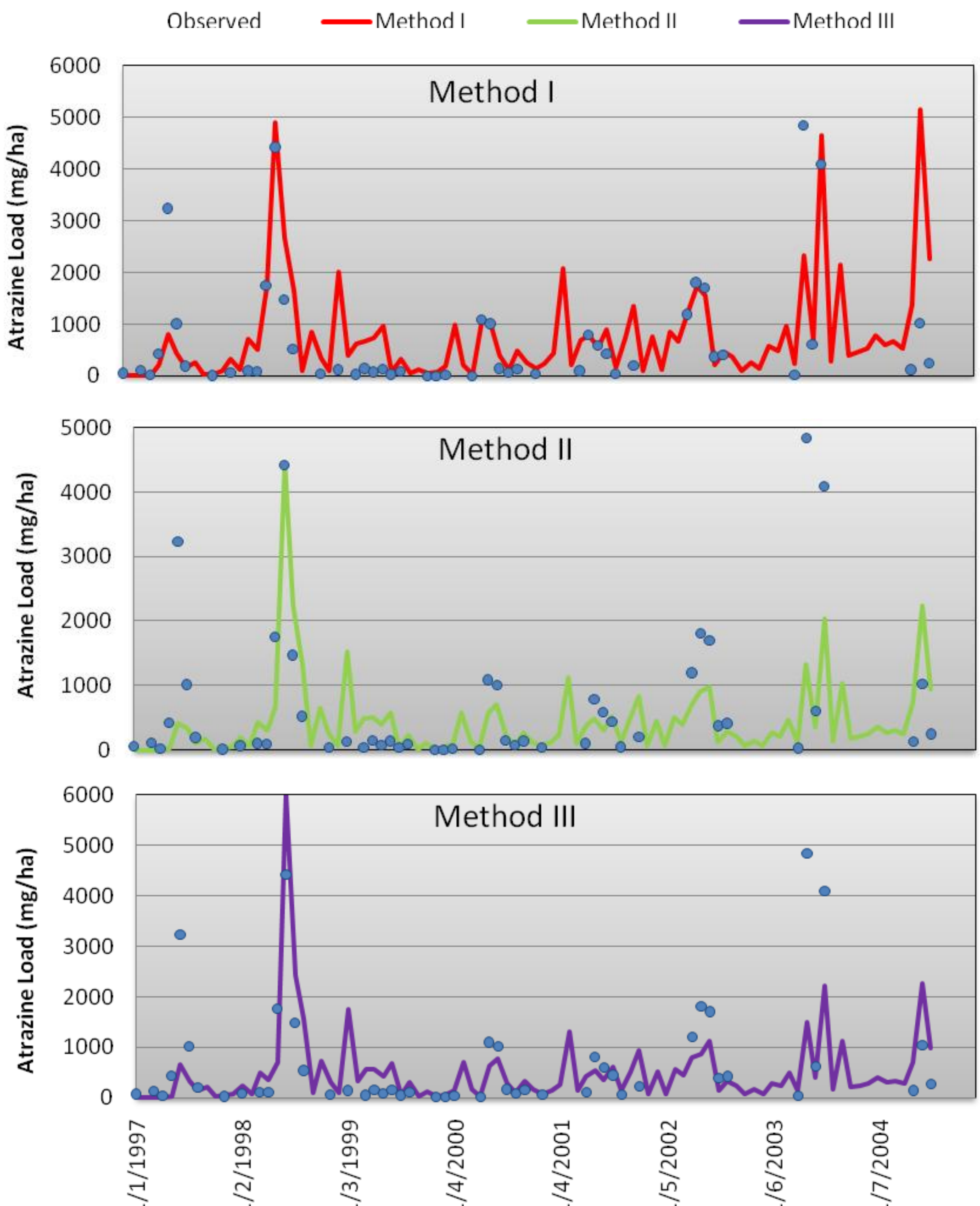

Figure 8. Wildcat Creek Watershed Monthly Comparison of Methods with Reservoir

Assessing the statistics and observing the trends in the plots of the three methods in the WCW, Method II and Method III had similar results while Method I consistently over-predicts the monthly values in the later years of reported data. Method I reports a very low NS value for the calibration period as well, indicating that the timing of simulated values created with Method I is not a good match. A distinctive assessment of the difference between Method II and Method III may not be possible for the

WCW due to the overpowering affects of the upstream reservoir. Both the magnitude and timing of atrazine releases from the reservoir's dam becomes more prominent to the downstream station's reported values than the runoff of pesticides into the reservoir. Also, any fields located in-between the 7 km reach of the reservoir's dam and the sampling station would have a much greater impact on the trends seen in the observed data and thus make the sampling station bias towards a very small portion of the entire watershed. This is evident from the comparison between the overall improvement of results with the inclusion of the reservoir and the decreased distinction between atrazine application methods.

2.5. SUMMARY AND CONCLUSION

In order to obtain an acceptable calibration of WCW, the modeling of pesticide fate and transport as well the incorporation of reservoirs were important factors. Numerous methods for the representation of pesticides in SWAT are available for exploration beyond the three discussed in this research and other methods may prove to be a better fit. Also, a more thorough sensitivity analysis study that includes the various reservoir and lake water quality parameters with a variety of methods such as FAST, Morris, and Sobol would be beneficial to obtain a better understanding the tendencies of the watershed. Future examination of uncertainty analysis for both the streamflow and water quality parameters would add another layer of confidence of the accuracy of the created model.

Observing these different methods, it can be ascertained that Method II and Method III represent the atrazine trends more accurately the Method I on a consistent basis. This is likely due to several factors including the fact that Method II and Method III incorporate the actual application dates based on historical crop progress reports. Most farmers take weather patterns into account when deciding when to plant crops or apply pesticides. This was accounted for by using planting dates for each year as well as visually assessing the rain patterns after the planting dates and varying the application dates of atrazine depending on potential wash off rain events. Also, since most farmers do not apply atrazine on the same days across the watershed, this variation in decision making by the farmers is represented in Method III. By spatially and temporally varying the application of atrazine, a good representation was created.

Each watershed has very unique characteristics and cannot be evaluated based on a blanket criterion for all watersheds. Nuances and peculiarities for each watershed must be taken into account. By understanding the characteristics of each watershed and carefully selecting solutions that represent the watershed's individual distinctiveness allows for the creation of an improved model. The challenges, whether it is the physical makeup of the area and the availability of well documented historical data must be addressed.

For the Wildcat Creek Watershed, the placement of the reservoir with respect to the collection of data points was an important factor in developing an improved model calibration. A thorough understanding of both Eagle Creek and Cedar Creek Watershed needed to be made in order to select the best methods for representing and assessing the data collected in this region.

Future improvements can be made in the understanding of and solutions for challenges associated with modeling pesticides. Other methods to describe the applications of pesticides need to be developed that can more accurately describe the actual trends in pesticides. More intensive reporting of atrazine application by farmers could also aid in creating a better model.

SECTION 3. OPTIMIZING TRADEOFFS BETWEEN POLLUTION REDUCTION AND ECONOMIC COST

3.1. THEORETICAL CONSIDERATIONS

3.1.1. GENETIC ALGORITHM (GA)

A genetic algorithm (GA) was employed to derive optimal watershed management plans generated from six setups of objective functions. Genetic algorithms belong to the evolutionary class of artificial intelligence (AI) techniques. GAs are based on natural selection of chromosomes from a population for mating, reproduction of offspring by crossover, and mutation to ascertain diversity. Each chromosome string in the population corresponds to a solution for the problem at hand, with each variable being represented by a gene (a specific position in the string). The values of the genes, known as allele, can be binary, real-valued, or character-valued.

The main benefit of GAs is their ability to use accruing information about an initially unknown search space in order to favor ensuing searches into useful subspaces. GAs differ from conventional non-linear optimization techniques in that they search by maintaining a population of solutions from which better solutions are fashioned, rather than making incremental changes to a single solution to the problem (Karahan et al., 2007). Since GA's are not intended to examine all possible solutions, its convergence to an optimum cannot be guaranteed regardless of how long the algorithm searches. However, it has been shown that the GA converges to near optimal solutions for a variety of problems (Venkataramanan et al., 1995). Efficiency of the algorithm depends on the optimization parameters (i.e. crossover and replacement) and the convergence criterion. The higher the number of individual evaluations for converging at the optimum, the less efficient is the procedure. The values of the optimization parameters are problem dependent, and can be determined by performing a sensitivity analysis.

The GA is a well-suited optimization technique for searching for spatially optimal watershed management plans, because unlike gradient-based methods, it does not require linearity, continuity, or differentiability either for the objective and constraint functions or for input parameters. Binary representation of individual management actions provides additional capacities for incorporation of producers' willingness to comply with the watershed plan.

In the GA-based search algorithm for watershed planning, each optimization string corresponds to a specific watershed management scenario. The length of each string corresponds to the total number of individual management actions that are considered in optimization. The alleles are binary values, with "1" or "zero" indicating that the corresponding management action "to be" or "not to be" implemented.

3.2. METHODOLOGY

3.2.1. 5.4.2 ECONOMIC COMPONENT

To achieve the second objective of evaluating the economic approach, several elements must be assessed. The economic component of the proposed planning tool is comprised of two models: a model to estimate the total watershed cost of management practice implementation, and another to estimate the total on-site benefits of each management practice. The total cost of implementation of watershed plans is evaluated by establishment, maintenance, and opportunity costs of the practices selected (Arabi et al., 2006; Bracmort et al., 2004). Establishment costs include the cost of installation of management practices as well as 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 lifetime of practices as a result of investing the establishment and maintenance costs by purchasing saving bonds. For each individual management action, the total cost (*C*) is evaluated by the following equation:

$$C = c_0 + c_0 r_m \sum_{t=1}^{t_s} \left[1 - \frac{(1+i)^{-t}}{i}\right] \tag{1}$$

where c_0 is the establishment cost, i is the interest rate, and r_m is the ratio of maintenance cost to establishment cost. The total watershed cost of a watershed plan is computed by summing the costs of individual management actions in the plan from Equation (1).

The economic benefits (net return) of management plans to producers are determined by evaluation of benefits of individual management actions at each site. These are benefits accrued by producers from changes in agricultural production due to new management practices in their respective fields. On-site benefits are estimated in the model as the long-run change in producer profits that result from implementing management actions:

$$B = \sum_{t=1}^{t_s} [\pi_r(X, t_s, m) - \pi_r(x, t)] \tag{2}$$

where B is the on-site benefits over the long-run (t_s); x is the state of the given field at time t and represents landscape characteristics; t_s is the design life specified for development of the management plan in years; m is the management plan implemented at the site; and π_r is annual net return from crops in crop rotation for year t that account for the effects of agricultural activities such as tillage and/or fertilizer and pesticide application.

3.2.2. COST DATA

Research on representative input values for the variables in these equations was conducted. Mandatory information for these equations included the costs of installation for each management practice and the cost of maintaining these practices. These price values were obtained from estimated payment schedules for eligible management practices implemented under the Environmental Quality Incentives Program (EQIP) (NRCS-USDA, 2007). A summary table of these values is presented in Table 7. Research indicated that the cost of the pesticides and nutrients were not included in the estimated EQIP values. Information from Indiana's Farming of Maximum Efficiency (MAX) Program reported information on cost data for prices of Anhydrous Ammonia, Nitrogen (00-15-00), and Aatrex from 2002 (Kck et al., 2002). An average cost of \$0.29/kg was obtained for nutrient applications and a value of \$6.06/kg was used for pesticide (Aatrex) applications. The maintenance costs associated with each management action are shown in Table 7 as well.

3.3. OPTIMIZATION COMPONENT

The optimization of watershed management plans is deemed to be an intractable problem because of the large number of fields, even within small watersheds. Using functions *B*, *C*, and *P* to represent, respectively, onsite benefits and/or net annual return, total watershed cost, and pollutant loads associated with the watershed plan represented by function *m*, the following formulation in a general form is proposed:

Table 7. Estimated Management Practice Cost (IN EQIP, 2007)

Management Practice	Cost	Unit	Maintenance Cost
Grade Stabilization Structures	$ 1,700.00	per structure	5%
Grassed Waterways	$ 4,200.00	per hectare	4%
Field Strips	$ 0.56	per meter	4%
Bank Stabilization	$ 70.00	per meter	4%
Parallel Terraces and Field Borders	$ 0.56	per meter	3%
Field Borders	$ 0.56	per meter	2%
Nutrient Management	$ 30.00	per hectare	1%
Pesticide Management	$ 17.00	per hectare	1%
Residue Management	$ 35.00	per hectare	1%
No Till	$ 35.00	per hectare	0%

Maximize $Z = z(B, C, P)$ (3)

Subject to transition constraints:

$$B = b(x, t, t_s, m)$$
$$C = c(x, t, t_s, m) \quad (4)$$
$$P = p(x, t, t_s, m)$$

Environmental (water quality) constraints:

$$P_{m,s} \leq P_{t,s} \quad (5)$$

Economic (total watershed cost) constraint:

$$C \leq C_t \quad (6)$$

where Z is the objective function to be maximized; x is state of the given watershed at time t and represents landscape characteristics; t_s is the design lifespan specified for development of the management plan in years; s represents the temporal scale for which the maximum pollutant loads are computed in day, month, or year; $P_{m,s}$ is a vector of maximum pollutant loads estimated by the NPS model (SWAT) simulations for temporal scale s over the design lifespan t_s in kg/ha; $P_{t,s}$ is the total maximum pollutant load specified by regulatory agencies for temporal scale s in kg/ha; C_t is the maximum available budget for implementation of the management plan in dollars.

In Equation (4), p is the mathematical relationship in the NPS model that is used for representation of hydrologic and water quality processes; c is from Equation (1); and b represents mathematical formulation of the farm-scale economic model. Identification of a versatile mathematical relationship between net benefit (P), cost (C), and pollutant loads (Y) in Equation (3) is one of the tasks of this research. To assess the full range of approaches available on the Pareto front, six cases will be assessed. The following figure describes the availability of these cases. Point A describes the objective function that will converge on the minimum cost while being constrained to a particular water quality standard. Point C depicts an objective function that will converge upon the minimum pollutant load within a specified budget. Point B shows an objective function that considers both goal attainments of lowering cost and lowering pollutant loads within the feasible region bounded by the constraints. These three general formulations can be described in various ways for use with the genetic algorithm. The following six cases examine different setups for evaluation of optimizing the tradeoffs between cost of implementation and the reduction in pollution loads. Since the genetic algorithm technique requires a value to be maximized, several objective functions were negated in order to reach a minimum pollutant load.

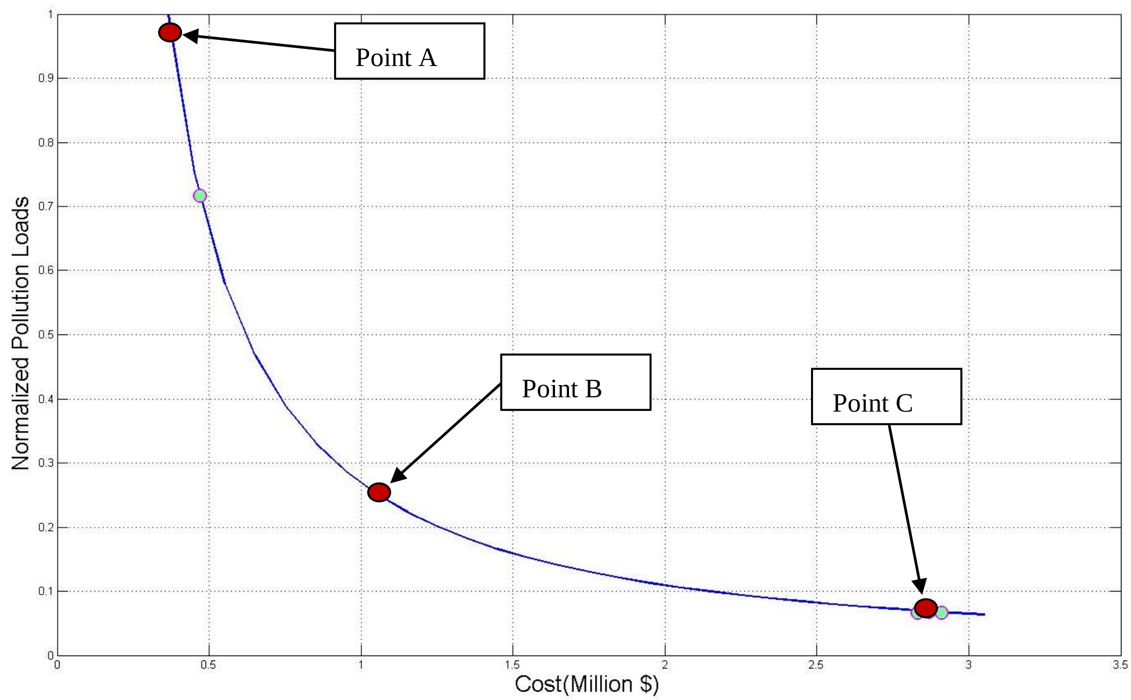

Figure 9. Pareto Front

Specifically, the following six formulations for the objective function (OF) will be examined:

OF 1: Maximize $Z_1 = B$ (7)

This objective function will inspect the values needed for maximizing the benefits of implementing management practices.

OF 2: Maximize $Z_2 = -C$ (8)

This objective function will inspect the values needed to minimize the cost of implementing management practices.

OF 3: Maximize $Z_3 = -(C - B)$ (9)

This objective function will evaluate the minimization of costs minus benefits of management practice implantation.

OF 4: Maximize $Z_4 = -\sum\left[{}^{P}/_{P_0}\right]$ (10)

where P_0 is the vector of pollutant loads for the existing base condition. This objective function will evaluate the minimization of normalized pollutant loads.

OF 5: Maximize $Z_5 = \sum \left[{(P_0 - P)}/{P_0} \right]$ (11)

This objective function will evaluate the maximization of the aggregated normalized pollutant load reductions.

OF 6: Maximize $Z_5 = B/C$ (12)

This objective function will evaluate the maximization of the benefits associated with pollution reduction to the cost of installing management actions.

As a case study of the performance of this model, Wildcat Creek Watershed was analyzed for 500 generations with a string of 50 runs. A 10% goal reduction of atrazine loads for Wildcat Creek into the Kokomo reservoir was developed in a management plan. By reducing average annual pesticide concentrations from the reported 3.31 µg/L to 3.0 µg/L (EPA MCL), this goal could be achieved.

Since the pesticide atrazine is a contaminant of concern in Wildcat Creek, the focus of the management practices and the target water quality value will be scrutinized for this particular scenario. The management practices taken into consideration include filter strips, parallel terraces, pesticide management, residue management, and no till practices. The landuses considered for the application of these management practices include pasture/hay and row crops.

3.4. RESULTS

An assessment of the usefulness of an evolutionary algorithm like the genetic algorithm was accomplished using a simplified watershed set up for Wildcat Creek of four sub-basins with a total of four HRUs. This was evaluated with both a full enumeration method and the genetic algorithm. The full enumeration method evaluated the possible combinations of BMPs, which for three selected sub-basins and four HRUs with one sub-basin-level BMP and three HRU level BMPs resulted in a total of 8192 runs. Using the benefit to cost ratio as the objective function for optimization of BMPs in the simplified watershed, the full enumeration was run 8192 times to cover the possible range of solutions. The same set up of inputs was used in running the genetic algorithm. As shown in the Figure 10, the genetic algorithm converged to the optimal solution within 210 runs, less than 2.6% of the runs for the full enumeration to complete the fully exhaustive combinations of runs. Although the best solution for the full enumeration method was reached around 2800 runs, this solution could not be considered the optimal point until all runs were complete. This evidence suggests that the genetic algorithm is a very useful tool in converging to an optimal set of solutions with much fewer runs and thus, converges more quickly.

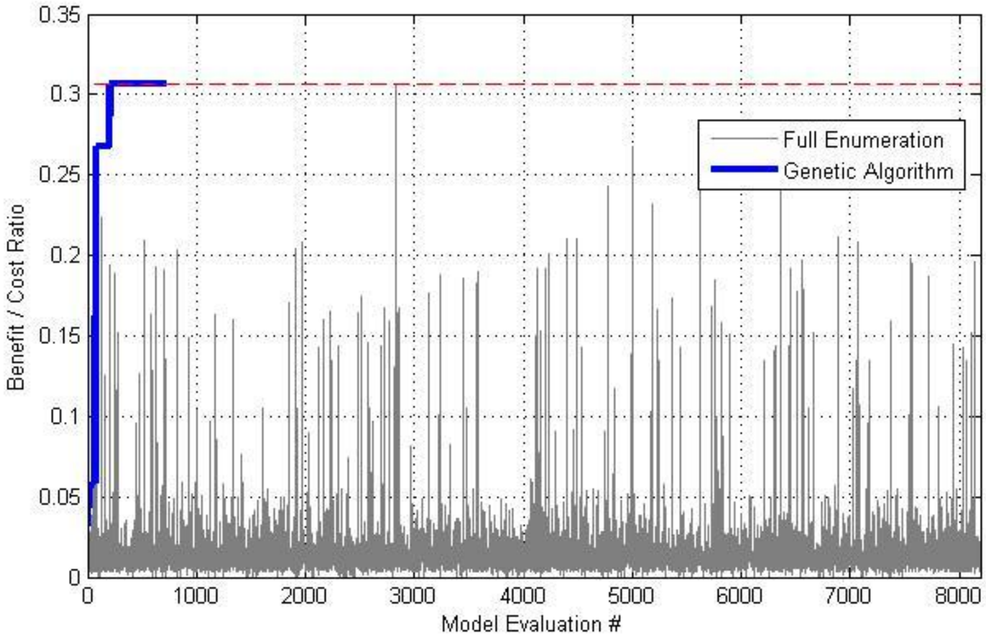

Figure 10. Full Enumeration versus Genetic Algorithm Optimization of Simplified Wildcat Creek Watershed

With the understanding of the efficiency of the genetic algorithm method of optimization, the evaluation of each objective function with the fully defined set of 19 sub-basins and 146 HRUs with an expanded range of BMPs can be computed more quickly to more timely results. On average, 8 days were required to complete 500 generations with a string of 50 for each generation (25,000 total simulations) with the genetic algorithm.

The results for each objective function are shown in Figures 11-16. The bold blue line indicates the best solution from each generation while the gray circles indicate the value obtained for each simulation.

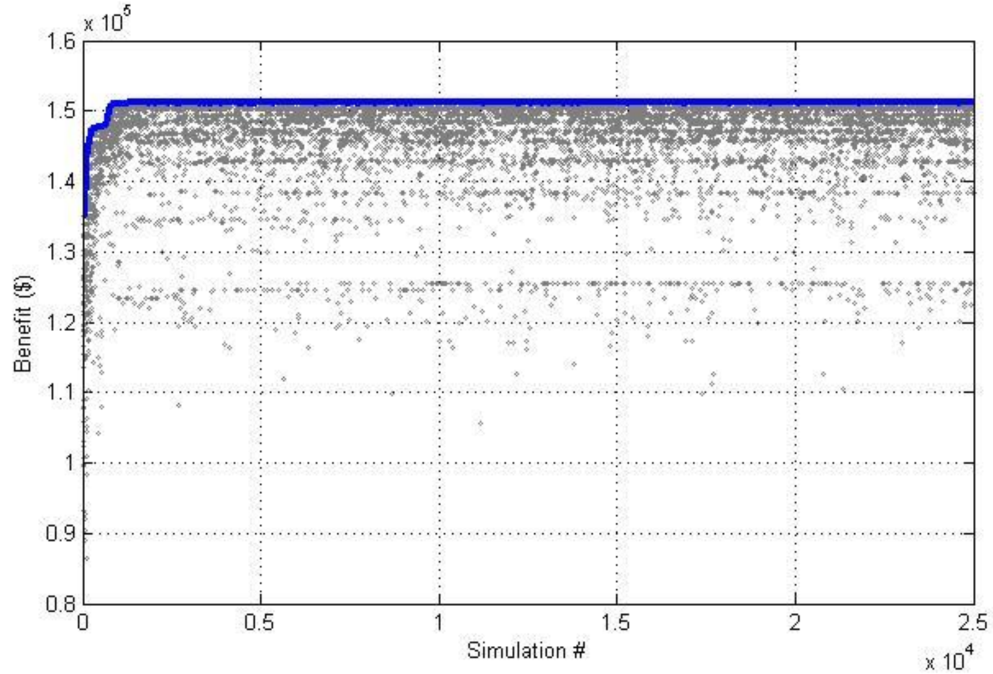

Figure 11. Objective Function 1- Maximizing Benefit

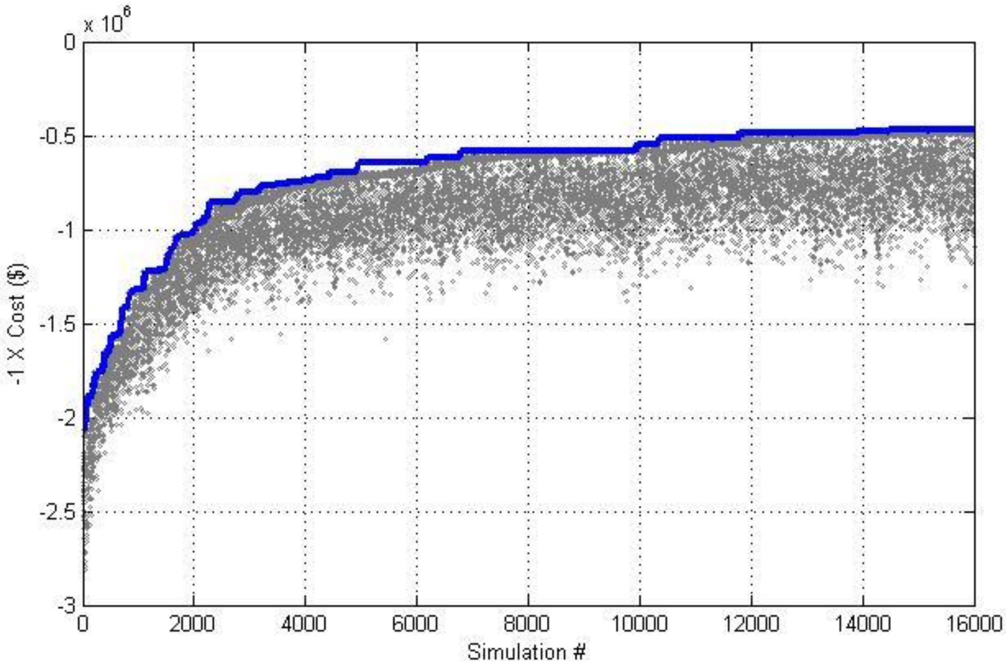

Figure 12. Objective Function 2- Minimizing Cost

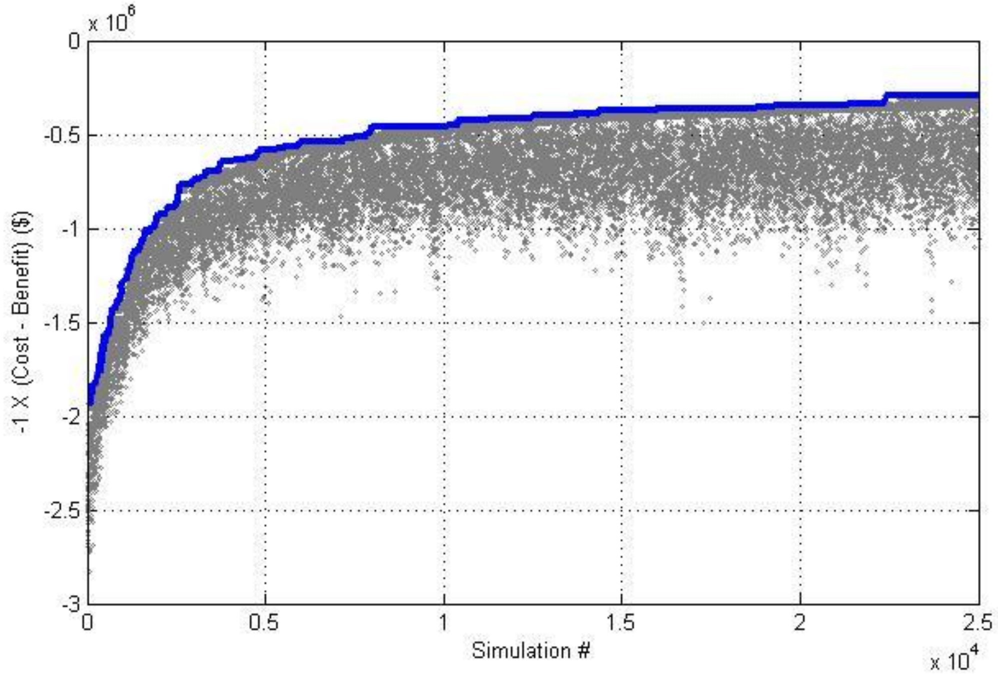

Figure 13. Objective Function 3- Minimizing cost minus benefit

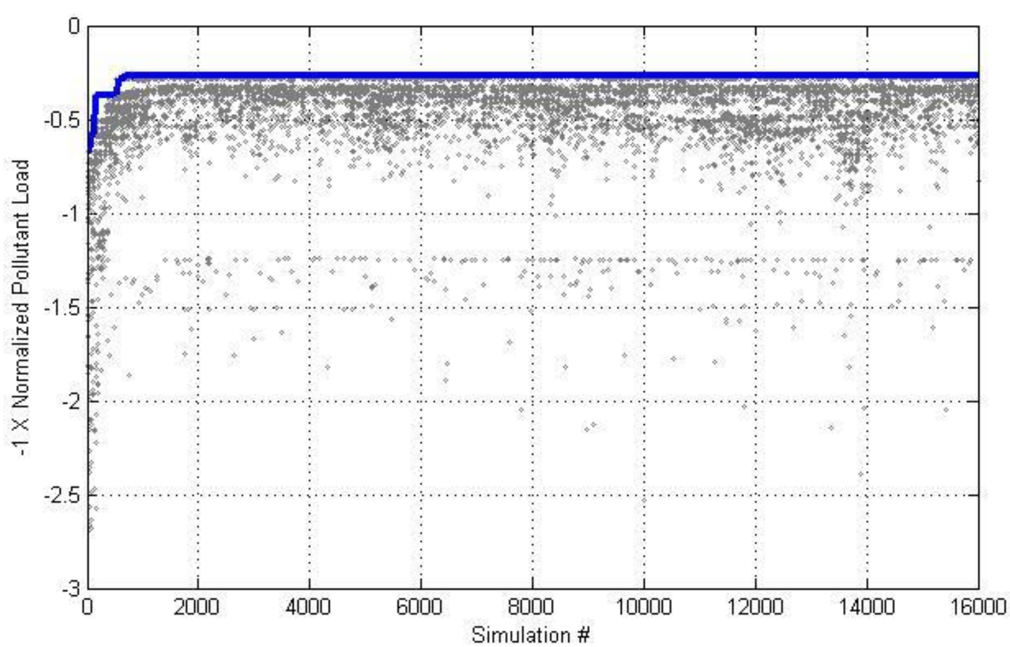

Figure 14. Objective Function 4- Minimizing normalized pollutant load

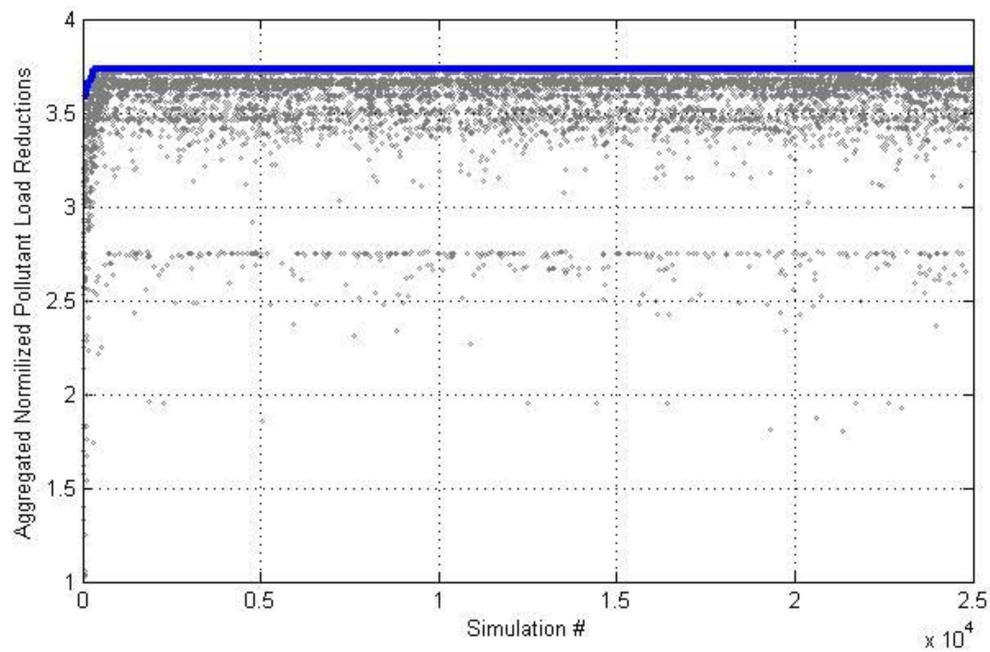

Figure 15. Objective Function 5- Maximizing aggregated normalized pollutant load reductions

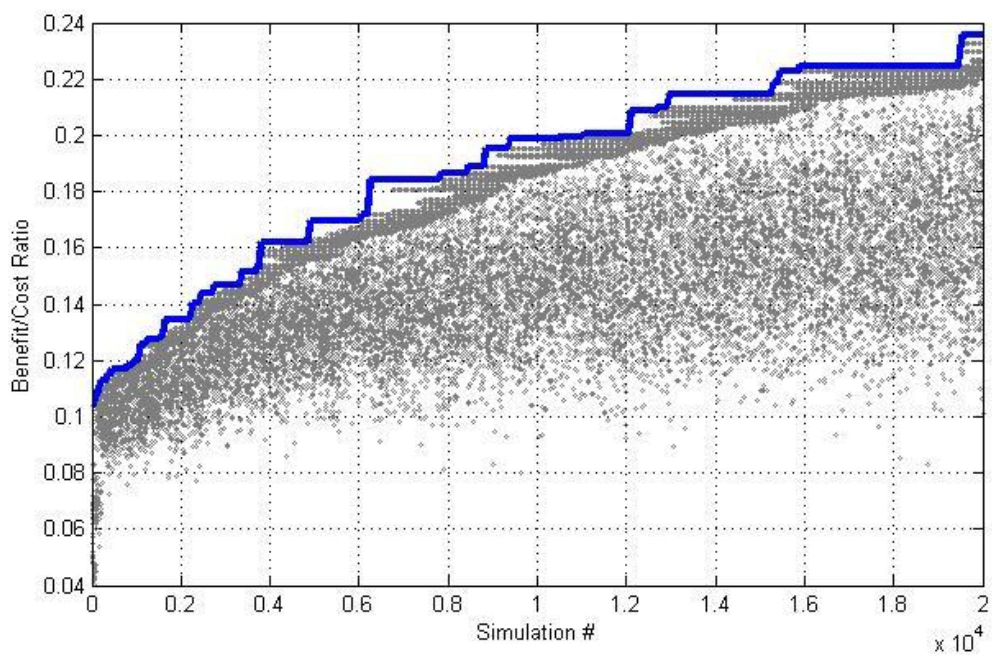

Figure 16. Objective Function 6- Maximizing benefit to cost ratio

Comparing the above simulations, it can be ascertained that an optimal solution can be obtained in a reduced number of simulations, especially for the objective functions involving benefits or pollution reduction considerations. Objective functions 1, 4, and 5 all converge to an optimal solution with 1000 simulations. When cost was considered in objective functions 2 and 3, an asymptotic behavior was not as noticeable. This may be due to using a cost constraint set to infinity since sufficient data on budgets for management plans were unavailable. If a budget were set, these functions could converge more quickly to an optimal solution.

Each of the objective functions ran produced the set of optimal results for the HRUs or reach segments which required a particular management action to obtain this optimal result. These results were compiled in GIS to visually show the areas in which actions need to be implemented. These results are shown in Figure 18-23 for each objective function.

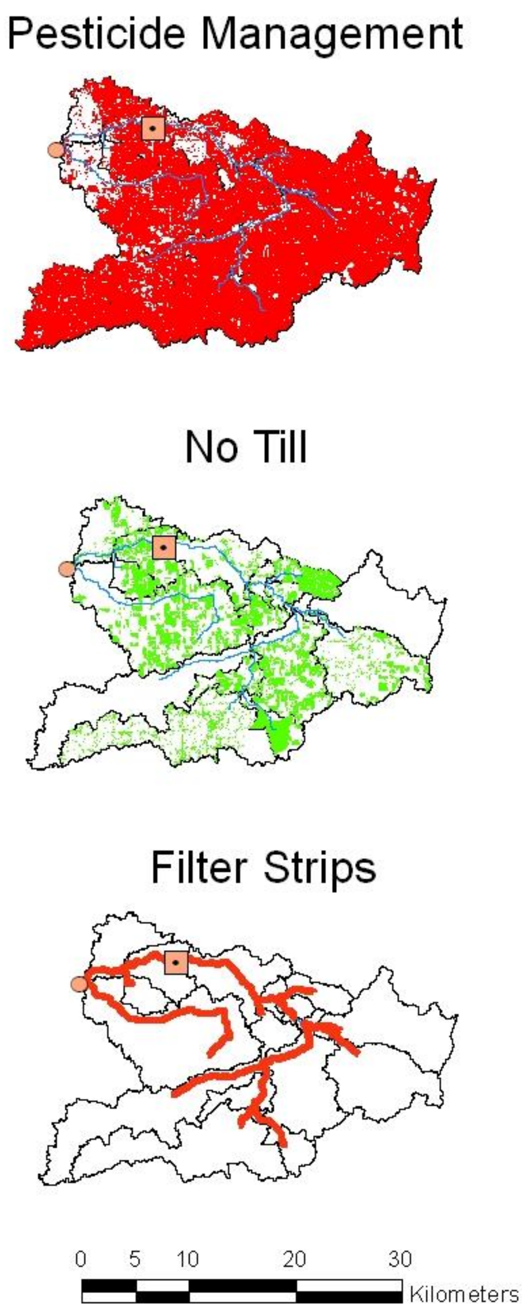

Figure 17. Objective Function 1- Maximizing benefit

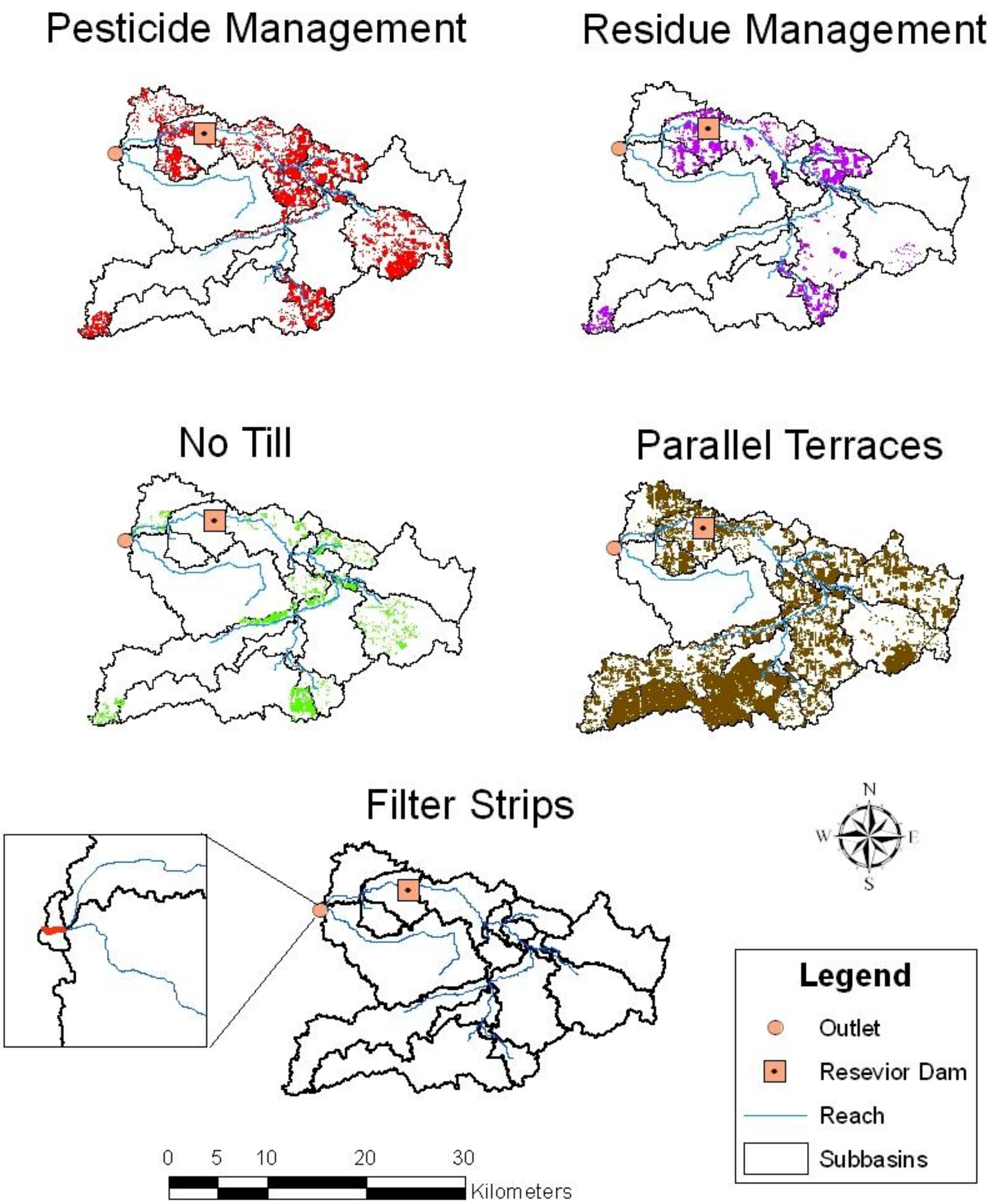

Figure 18. Objective Function 2- Minimizing cost

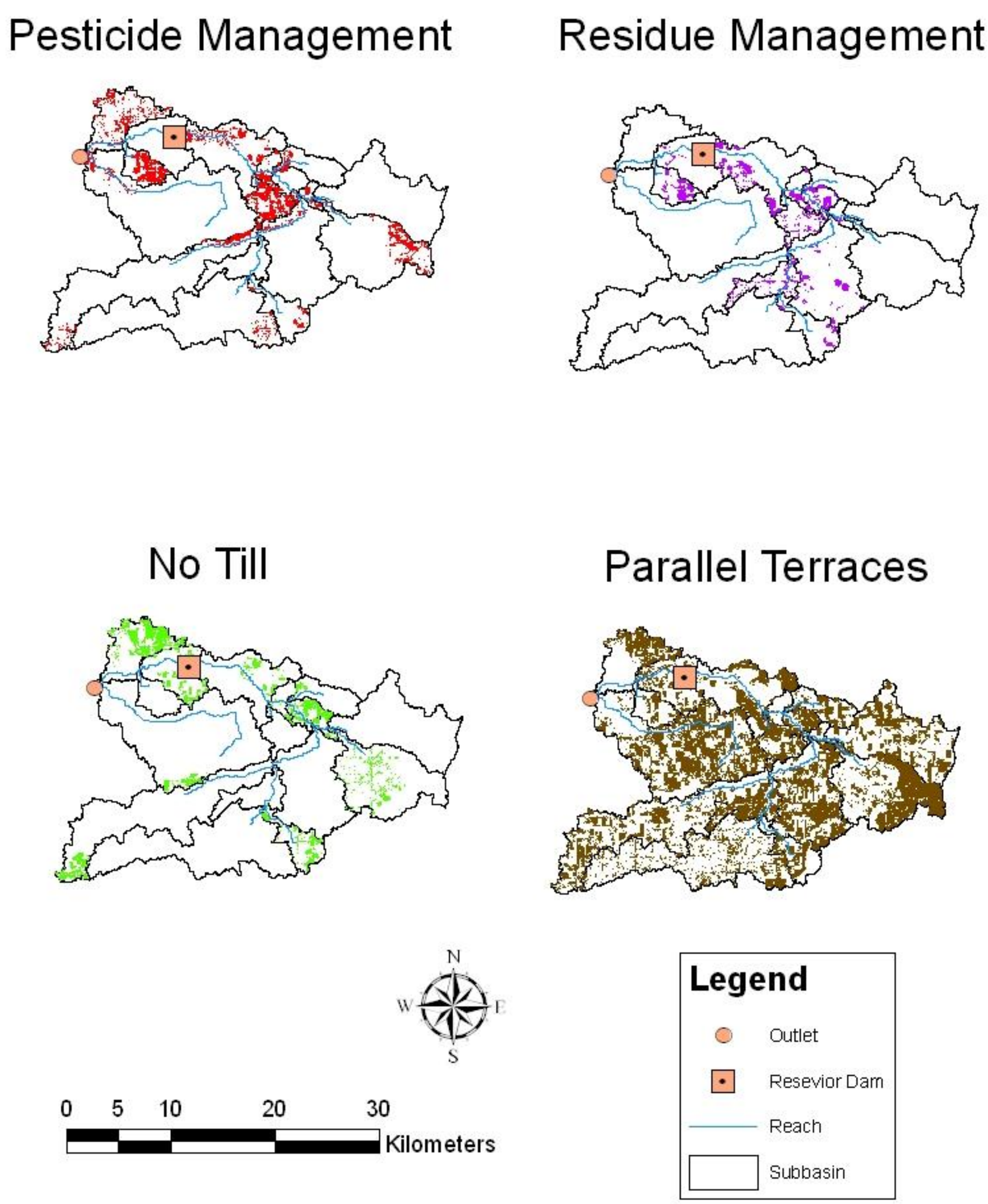

Figure 19. Objective Function 3- Minimizing cost minus benefit

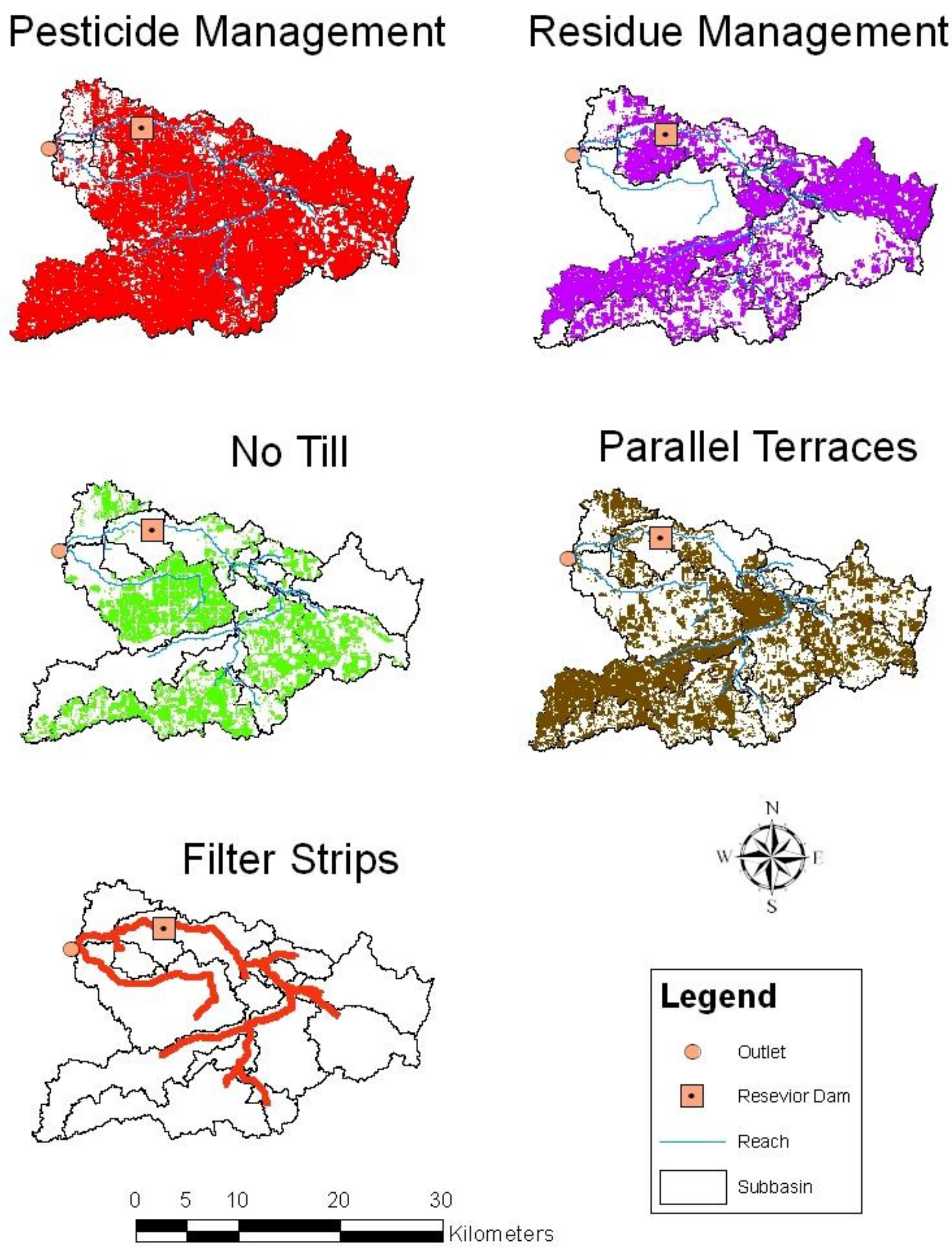

Figure 20. Objective Function 4- Minimizing normalized pollutant load

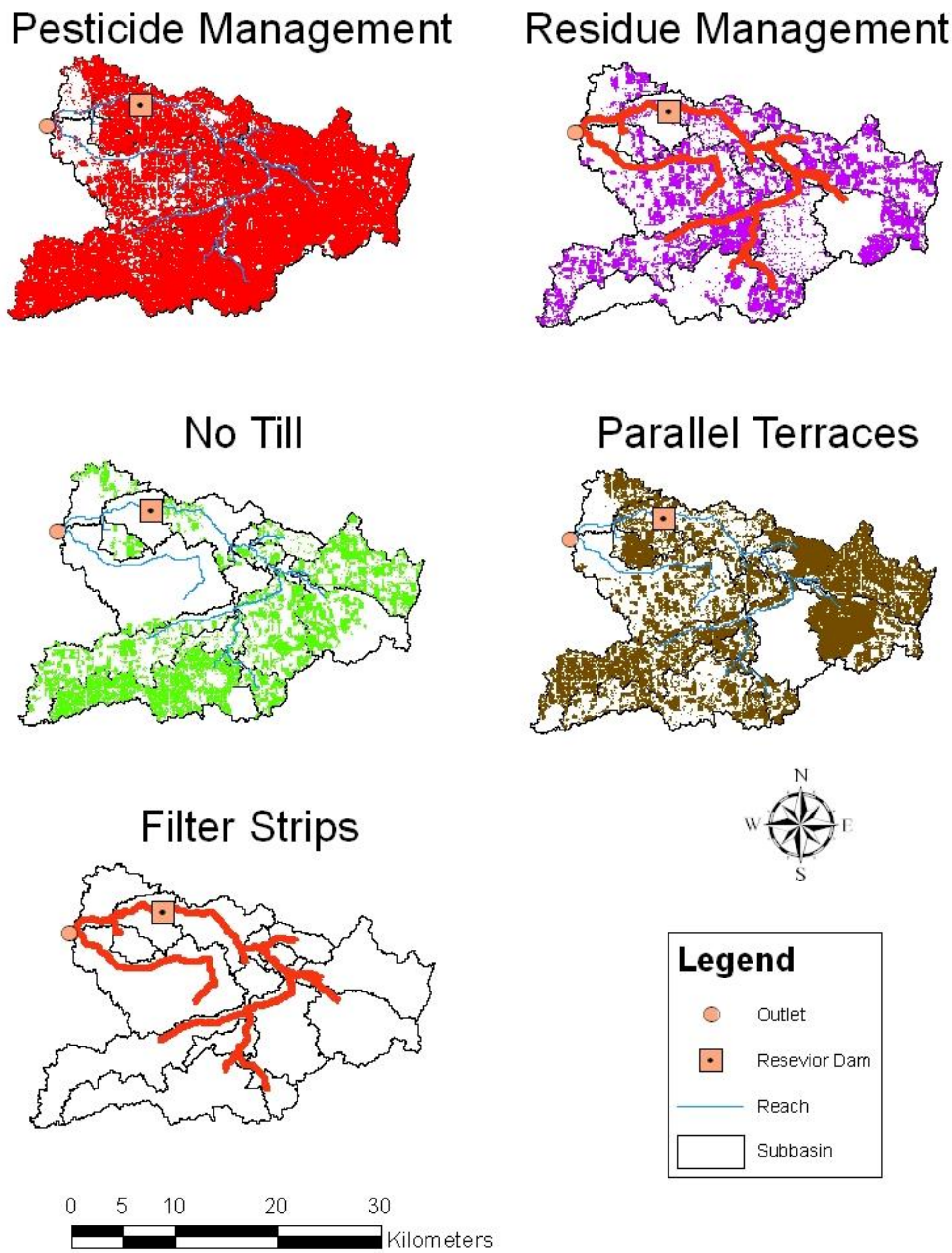

Figure 21. Objective Function 5- Maximizing aggregated normalized pollutant load reductions

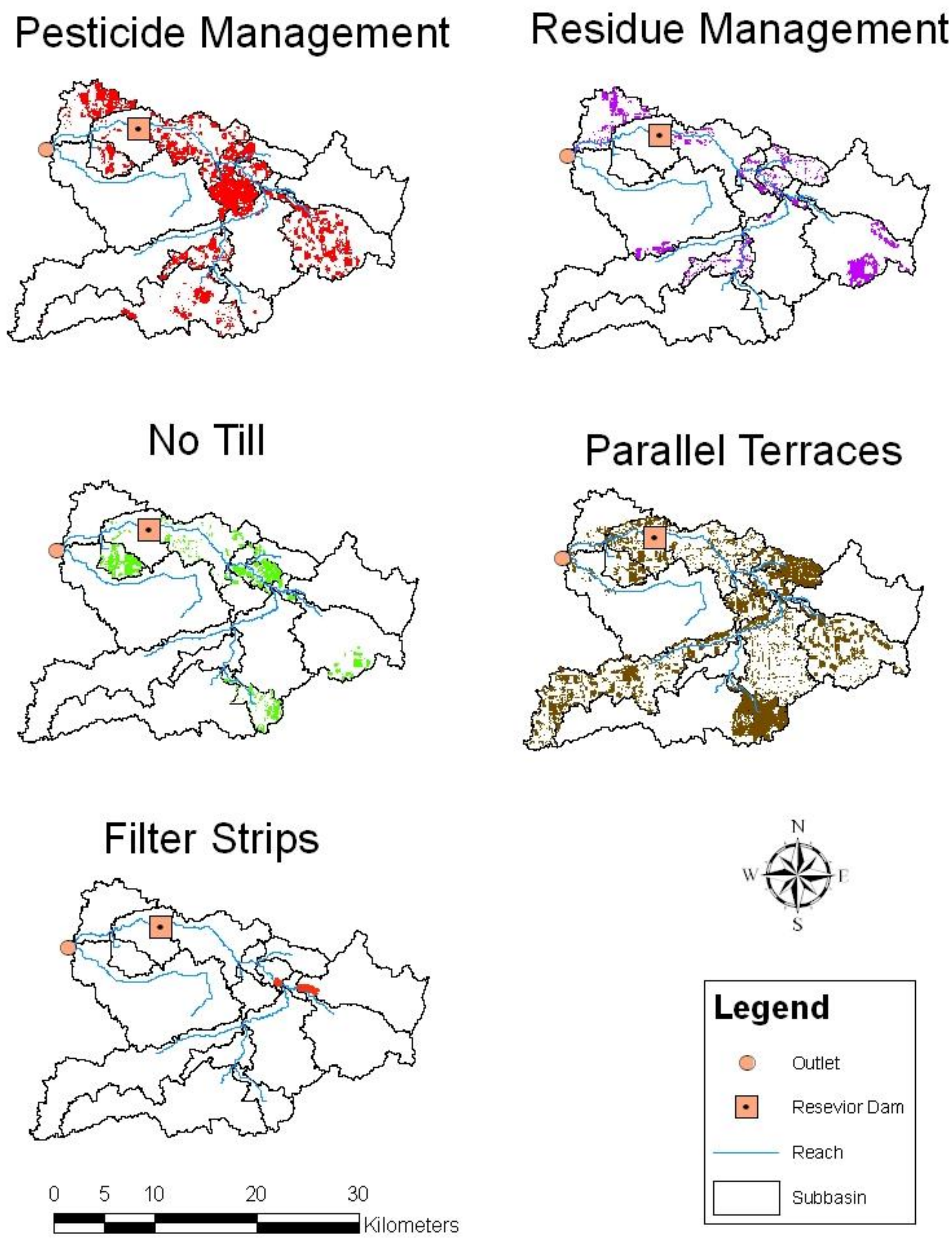

Figure 22. Objective Function 6- Maximizing benefit to cost ratio

Observing the figures, tradeoffs between maximizing benefit and minimizing costs are apparent. Objective functions that consider only the benefit and reduction in pollution (Objective Functions 1,4,5) more intensively use management practices. On the other hand, objective functions that consider only cost have significantly less implementation of BMPs (2). Considering both the benefits and cost with Objective Function 3 shows that a compromise between the two goals can be reached. Also, it is evident from the maps that prioritization of management actions in the watershed based on sub-basins can be an effective strategy. In many cases, entire sub-basins have no management actions implemented which may be due to the physical characteristics noticed in Figure 2. Comparing the use of an optimizing tool such as the genetic algorithm to localized targeting of management practices, it is evident that both objectives of reducing pollution loading in area streams and minimizing costs can be achieved on a more holistic scale.

3.5. CONCLUSIONS

By applying the optimization tool using multiple objective functions to Wildcat Creek Watershed, a variety of optimal choices for management plans were identified based on multiple constraining criteria. The flexibility of the objective functions allows the decision maker to exercise professional judgment in the selection of the best management practices. Within the constraints of the objective functions, the judgment criteria for decision makers varies based on the priorities of the managing group whether the focus is on increasing water quality or maximizing production.

Many avenues of research can be expanded from the base of ideas presented in this study. There is an opportunity of an interface to be created which can analyze a user's primary goals and concerns to develop the best objective function to be used for optimization of management practices. Different decision makers, ranging from a government agency to a farmer, can have varying opinions on the weight of importance of different factors. Also, more refined development of estimates for the cost for management practices and onsite benefits characteristic of the watershed under analysis is open for extended work. The incorporation of social acceptance of these criteria is also helpful in developing recommendations for watershed management plans.

SECTION 4. CONCLUSIONS

While agricultural practices that cause nonpoint source pollution such as runoff of sediment, nutrients, and pesticides are harmful to the area surface waters in the watershed, actions can be taken to minimize these harmful effects. The use of computer generated models can be used to determine the optimal amount and application timing of pesticides resulting in reduced pesticide loading from the watershed. Also, evaluations of management practices can help to reduce the cost of practices while maintaining crop yields. This altered but improved practice would be beneficial to the farmer since cost would be reduced. Watershed managers would deal with lower pollutant loadings and thus reduce the need for continued treatment and maintenance cost. Educating decision makers and farmers to utilize the improved evaluation techniques available through optimization modeling will lead to better use of limited fiscal resources available for watershed BMPs while improving water quality and improving pesticide, nutrient and soil management techniques.

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