USE OF THE SWAT MODEL TO QUANTIFY WATER QUALITY EFFECTS OF AGRICULTURAL BMPS AT THE FARM-SCALE LEVEL

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ABSTRACT. *Best management practices (BMPs) have been implemented on a farm-by-farm basis within the Cannonsville Reservoir watershed (CRW) as part of a New York City watershed-wide BMP implementation effort to reduce phosphorus (P) loads to the water supply reservoirs. Monitoring studies have been conducted at selected locations and at the watershed outlet on one of the farms, which spans an entire subwatershed within the CRW, with the aim of quantifying effectiveness of the BMPs installed on the farm. This study applied the Soil and Water Assessment Tool (SWAT) and a recently developed BMP characterization tool to the farm over pre- and post-BMP installation periods with the object of determining the extent to which model results incorporating all installed BMPs match observed data, and the individual impact of each of the BMPs installed on the farm. The SWAT model generally performed well at the watershed level for flow, sediment, and phosphorus simulations. Annual Nash-Sutcliffe (NS) coefficients for the components ranged between 0.56 and 0.80, while monthly NS coefficients ranged between 0.45 and 0.78. The model also performed well at the field level, with simulated in-field P loads closely matching observed data. Because the fields had various combinations of BMPs installed on them, it was difficult to separate out individual BMP impacts based on SWAT simulations. It was, however, possible to determine the effects of BMP combinations such as nutrient management plans and rotations (31% dissolved P; 25% total P). For dissolved P, integration of BMP tool efficiencies allowed individual BMP impacts to be incorporated while still maintaining the same level of representation as was obtained using model simulations. As the SWAT model is often used with little or no post-BMP data to verify simulation results, this study served to validate SWAT model suitability for evaluating BMP impacts. The BMP tool was found to suitably complement the model by providing insights into individual BMP impacts, and providing BMP efficiency data where the model was lacking.*

Keywords. *BMP effectiveness, BMPs, Phosphorus, SWAT.*

Best management practices (BMPs) have been implemented on a farm-by-farm basis within the Cannonsville Reservoir watershed (CRW, fig. 1 inset) as part of a New York City watershed-wide BMP implementation effort to reduce phosphorus (P) loads from the farms and P contributions to the water supply reservoirs. Waters within the CRW are affected by eutrophication. Agriculture, wastewater treatment plants, and urban runoff are considered the primary sources of high P levels in this reservoir (WAC, 1997; Tone et al., 1997). Excessive P loadings, though, are thought to be primarily the result of manure generated on surrounding farms. The manure is either accumulated in barnyards or applied to the land (WAC, 1997; Gitau et al., 2006).

Efforts to address this problem led to a partnership between farmers and the city, and subsequently to the development of a Watershed Agricultural Program (WAP) that is implemented by the Watershed Agricultural Council (WAC). The main goal of the program is to protect the New York City water supply while also maintaining the viability of the agricultural industry. Under the program, BMPs have been implemented on most farms within the watersheds, including cropland BMPs, such as strip cropping and crop rotations, as well as other BMPs focused on the livestock facilities areas. The latter include diversions and barnyard BMPs, such as paving, manure pack management, and filter strips (Gitau et al., 2006).

Of current concern is the need to establish quantitatively the impacts of the BMPs at the watershed scale. Previously, a number of model-based studies have been conducted with the aim of quantifying the effectiveness of BMPs within the watershed. Cerucci and Conrad (2003) used a combination of the Soil and Water Assessment Tool (SWAT; Arnold et al., 1998) and the Riparian Ecosystem Management Model (REMM; Lowrance et al., 2000) to determine the effects of riparian buffers in the Town Brook watershed, a subwatershed of the CRW. Also working in Town Brook, Gitau et al. (2004, 2006) used SWAT in combination with a recently developed BMP characterization tool (Gitau et al., 2005) and an optimization algorithm to determine optimal scenarios for BMP selection and placement at the farm and watershed levels. Other modeling studies conducted in the CRW in relation to BMPs include Cerucci and Pacenka (2003) and Tolson and Shoemaker (2004). Tolson and Shoemaker (2004) calibrated and validated the SWAT model in the Cannonsville Reservoir

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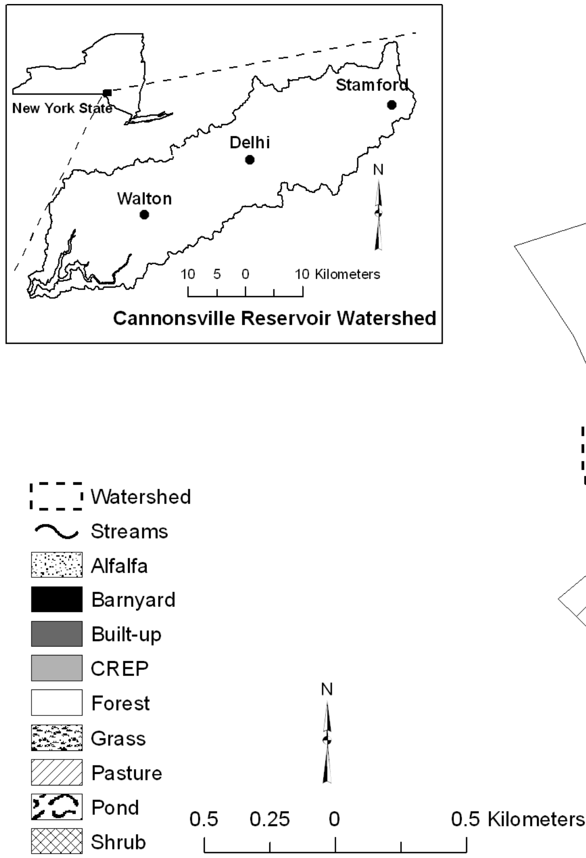

Figure 1. Study farmland location in the Cannonsville Reservoir watershed (CRW) near its Delhi station. The study farm covers an entire subwatershed within the headwaters of the CRW. Also shown is the land use as of 2005. Barnyard areas may not be visible due to their size relative to the watershed; CREP = areas under the Conservation Reserve Enhancement Program.

watershed with the object of predicting dissolved and particulate phosphorus loads from this watershed, and subsequently to analyzing the long-term effects of various phosphorus management practices. Cerucci and Pacenka (2003) compared the application of SWAT to that of the lumped Generalized Watershed Loading Functions model (GWLF; Haith and Shoemaker, 1987).

The modeling of BMPs has also been conducted in other areas. Mostaghimi et al. (1997) and Vache et al. (2002), for example, modeled contour strip cropping using the Agricultural Non-Point Source model (AGNPS; Young et al., 1989) and SWAT, respectively. Santhi et al. (2001) modeled the impact of changes in fertilizer application rate using SWAT. Other practices that have been modeled include P reduction in feed (Santhi et al. 2001), livestock exclusion (Mostaghimi et al. 1997), tillage practices (Prato and Wu, 1991), and filter strips (Yuan et al., 2002).

One of the major drawbacks impacting modeling efforts is that there is often little or no post-BMP data, both at the watershed scale and at the field level. This makes it difficult to verify model outcomes where BMP effectiveness is concerned. Within the CRW, however, monitoring studies have been conducted in both the pre- and post-BMP periods on one of the farms (fig. 1), about 163 ha of which spans an entire subwatershed within the CRW. In particular, there has been continuous monitoring of flow, sediment, and phosphorus at locations within the watershed and at the watershed outlet, thus providing the data necessary to verify model results at both the watershed scale and the field and BMP scales. This farm-sized watershed was thus the focus of this study.

This study applied the Soil and Water Assessment Tool (SWAT) and the aforementioned BMP tool to the farm (discussed in the preceding paragraph) over pre-BMP and post-BMP installation periods with the object of determining (1) the extent to which model results incorporating all installed BMPs match observed data, (2) the individual impact of each of the BMPs installed on the farm, and (3) the extent to which model results incorporating efficiencies from the BMP tool matched observed data.

Study Area Description

The 163 ha study farm is located in Delaware County, New York, and covers an entire subwatershed within the headwaters of the 118,000 ha Cannonsville Reservoir watershed. Because the farm spans an entire watershed, both the terms "farm" and "watershed" are used in the text, depending on the context. The average annual precipitation in the region is approximately 1100 mm (15-year average). Precipitation occurs throughout the year with long-term monthly averages ranging between 60 and 117 mm. The region is characterized by low to moderate temperatures with long-term (15-year) means ranging from about –6°C (21°F) in January to 19°C (66°F) in July and August.

Elevations on the farm range between 600 and 730 m above sea level. Soils are mainly silt loams, with depths ranging from 0.5 to 1.8 m on the hillslopes and from 0.3 to 0.7 m nearer to the streams where the soils are fragipan-limited (Hively, 2004). The watershed is largely forested, covering about 50% of the land use area. The primary activity, though, is dairy farming, with pastures, corn, and hay being grown to support this industry. With regard to pollution, the major concern is P accumulation in barns and near-stream areas, as well as losses from manure-spread fields (Hively, 2004).

BMPs were implemented on the farm between June 1995 and November 1996 as part of a WAP effort in which practices were implemented on ten demonstration farms, including this study farm. Concurrently, a study was established by the New York State Department of Environmental Conservation to determine the potential effects of BMPs on phosphorus control (Bishop et al., 2004, 2005), with one of the criteria being that the farm be monitored for at least two years prior to BMP implementation. This study site, thus, presents unique opportunities from the modeling perspective in that (1) the farm is itself a watershed, thus allowing us to model at both the farm and watershed levels concurrently; (2) it is in the headwaters, thus there are no sources upstream that could confound our results; and (3) monitoring data are available in both the pre- and post-BMP periods at both the field and watershed levels, allowing us to obtain a comprehensive assessment of SWAT representation of the pre- and post-BMP periods.

SWAT Description

The SWAT model is a continuous simulation, daily time step, watershed-scale nonpoint-source pollution model. It incorporates features of several models, including the Simulator for Water Resources in Rural Basins (SWRRB; Williams et al., 1985; Arnold et al., 1990), Chemicals, Runoff and Erosion from Agricultural Management Systems (CREAMS; Knisel, 1980), Groundwater Loading Effects on Agricultural Management Systems (GLEAMS; Leonard et al., 1987), and Erosion Productivity Impact Calculator (EPIC; Williams et al., 1984; Williams, 1995). SWAT simulates runoff, stream flow, groundwater flow, and sediment and nutrient losses at locations within the watershed and at the watershed outlet (Gitau et al., 2006). The model allows a flexible discretization of the watershed, first into subwatersheds and then into hydrologic response units (HRUs) that represent unique combinations of topography, soils, and land use. These are discrete units upon which the model performs analyses. SWAT uses runoff curve numbers to predict runoff volumes from daily rainfall. Sediment yield is estimated for each response unit using the Modified Universal Soil Loss Equation (MUSLE; Williams, 1995). As described by Neitsch et al. (2002, 2005), SWAT represents P dynamics using six pools: the fresh (associated with crop residue), active (associated with humus), and stable (associated with humus) organic pools, and the solution, active, and stable inorganic pools. The model incorporates mineralization, decomposition, and immobilization in its P algorithms, partitioning P into soluble and sediment-attached forms. The model also simulates crop growth and crop uptake of P. The model contains built-in climate, soils, and crops databases from which data can be obtained in the absence of measured data. It also has a built-in weather generator that can be used to generate climate data, if these are unavailable.

Materials and Methods

This study used the Soil and Water Assessment Tool (SWAT) to characterize P losses from the study watershed at both the watershed and field levels, for the pre- and post-BMP implementation periods. Simulated losses for both periods were then (1) compared with observed data to determine the adequacy of model simulations, and (2) compared with each other to determine individual as well as overall BMP impacts. Further, BMP tool efficiencies were incorporated into a baseline scenario giving an alternate evaluation of the post-BMP scenario. Processes and procedures used are detailed in ensuing subsections.

Base Input Data

Topography data (10 m Digital Elevation Model) was obtained from the New York City Department of Environmental Protection (NYCDEP). Detailed spatial 10 m field data were available from the Delaware County Soil and Water Conservation District (DCSWCD), with field boundaries for the years 1999, 2002, 2004, and 2005. Additionally, detailed crop data were available for the years 1993 through 2005. For this study, it was of interest to model each of the fields as unique land use areas, so as to allow BMP evaluation on a field basis and so as not mask small, but potentially high P loss areas, as might be the case if the fields were lumped into their corresponding land uses. To accomplish this, georeferenced field data were used in lieu of regular land use data. Current (2005) field boundaries were used in defining the various land use units. These data were edited through digitizing to include the farm pond, roads, and barnyard areas, as well as any land use related features that might have been present in the other years but were not present in the 2005 data.

In order to accurately define the progression from the pre-BMP to the post-BMP periods, field-specific crop data from 1993 were used to provide the base land use data needed for setting up the model. Where necessary, fields with the same land use (e.g., silage corn, defined as CSIL in the SWAT database) were renamed (e.g., corn1, corn2, etc., or CSL1, CSL2 in keeping with SWAT naming conventions) so as to maintain them as unique land uses. The SWAT built-in crop database was then modified to accommodate these "new" land uses; Parameters for the new land uses were copied from the corresponding general land use as defined in the original SWAT database; thus, parameters for CSIL would be copied into the CSL1 and CSL2 entries.

Soil Survey Geographic (SSURGO) level soils data were obtained from the DCSWCD. These data are also available at the soil data mart (http://soils.usda.gov). Base climate data were obtained from the National Climate Data Center database (http://lwf.ncdc.noaa.gov/oa/climate/climatedata.html). Both precipitation and temperature data were obtained from the Delhi station (fig. 1, inset), which is closest to the watershed. Other climate data used in the model (solar radiation, relative humidity, and wind speed) were not available for the Delhi station. The SWAT model was, thus, set to generate these data using its built-in weather generator.

Definition of Hydrologic Response Units

One subwatershed, as defined in SWAT, was defined for this study. This was the same as the whole watershed, covering an area of 163 ha and encompassing a substantial portion of the study farm (fig. 1). Several authors (Bingner et al., 1997; Fitzhugh and Mackay, 2000; Jha et al., 2004; Arabi et al. 2006) have investigated the effect of watershed subdivision on SWAT prediction efficiencies. For the most part, these studies found that the level of watershed subdivision was important for SWAT sediment and nutrient simulation. However, these studies were generally focused on larger watersheds. The watersheds studied by Jha et al. (2004), for example, ranged in size between 200,000 and 1,800,000 ha. We modeled our study watershed as a single subbasin because of its size and also to more accurately represent the farm. Previous work in the CRW has shown that overall better results were obtained when such small headwaters subwatersheds were parameterized separately (Tolson and Shoemaker, 2004).

By default, HRUs in SWAT do not have a spatial reference. However, it is possible to get around this limitation by redefining soil and land use thresholds to 0%/0% (Gitau et al., 2006). Redefining HRUs in this manner precludes lumping, thus allowing for even small but critical areas to be captured. In addition, since all land uses and soils are included, it is possible to reconstruct the HRUs within a GIS framework, using the same land use and soil data that are being used by SWAT, thus giving the HRUs a spatial reference. Details of the procedure are provided by Gitau (2003). Redefining soil and land use thresholds in this manner may, however, not be suitable for large watersheds, as the number of HRUs generated would cause the model to be computationally inefficient. In this study, 0% land use and 0% soil thresholds (0%/0% definition) were used for hydrologic response unit (HRU) definition, thus further preserving all field and soil areas. A total of 161 HRUs were defined for the watershed.

HRU-Level Data Inputs

Key inputs at the HRU level were those pertaining to management, including rotations, planting, harvesting, and manure application, as well as to other BMPs installed on the watershed. Detailed rotation data for each field over the years 1995 to 2005 were obtained from the DCSWCD, while rotation data for 1993 and 1994 were determined based on information from Hively (2004). Tillage, planting, and harvesting dates (table 1) were input based on information from Hively (2004) and Dewing (2005).

Details of manure application were available from the New York State Department of Environmental Conservation (NYSDEC), including the amount of manure phosphorus spread on each field on a monthly basis, spreader capacity, the amount of phosphorus per load of manure, and for some years (1997, 1998, 2000, 2001, 2002), barn calendars giving the actual dates on which manure was spread on each field, and the corresponding number of loads of manure spread on each of the days. Additionally, information on grazing including dates, amount of manure per pastured herd per day, and the amount of P in the manure was available. This information was used in defining manure application rates and dates for each field as well as the input from pastured cows.

Other BMPs installed such as barnyard management and tile drains were also included to the extent possible, based on information from the DCSWCD. In particular, tile drains were specified for five fields that had tiles installed. Barnyards on the farm were defined in the urban land use database, with associated parameters being set to be consistent with barnyard characteristics. Table 2 summarizes the BMPs installed on the farm and how these were modeled. Additionally, HRU slopes as calculated by SWAT were replaced with actual slopes, recalculated from the DEM, consistent with information from Gitau (2003) regarding the need to recalculate HRU slopes. Soil-based parameters such as initial labile P (SOL_LABP) and the phosphorus availability index (PSP) were defined based on available soil test data.

Performance Evaluation

Flow, sediment, dissolved P (DP), particulate P (PP), and total P (TP) data for the watershed were obtained from the NYSDEC. These data were used to calibrate the model for the respective components at the watershed outlet. The model was calibrated at both the monthly and annual time step. Data were used for the periods 1 June 1993 to 31 May 1995 (pre-BMP) and 1 November 1996 to 31 October 2002 (post-BMP). The period between 1 June 1995 and 31 October 1996 was the BMP implementation period; thus, no data were collected during this period (Bishop et al., 2004). The model was first calibrated considering the whole (pre-BMP through post-BMP) period. The pre- and post-BMP periods were then separated and re-evaluated to determine the adequacy of the determined set of calibration parameters for each of the peri–

Table 1. Planting, harvesting, and grazing dates used in the model, based on Hively (2004) and Dewing (2005).[a]

Land Use	Year	Plant/Begin Growing Season	First Harvest	Second Harvest	Third Harvest	Grazing
Alfalfa	1	1 May		15 July	25 Aug.	
	2+	1 May	1 June	15 July	25 Aug.	
Corn	All	15 May	1 Oct.			
Grass	1	10 May		1 July	15 Aug.	
	2+	10 May	20 May	1 July	15 Aug.	
Grass (with grazing)	1	10 May		1 July	15 Aug.	
	2+	10 May	20 May			Graze 1 June, 15 June, 15 July, 15 Aug.
Pastures	All	1 May				Cows assumed to be uniformly spread over pasture areas
Pastures (intensive grazing)	All	1 May				Graze 10 and 25 May, 10 June, 1 and 25 July, 25 Aug., 25 Sept.

[a] Plow date = 1 May. Cows are moved from pasture after 1 day and return to the same area after 14 to 30 days. Cows reduce biomass by 50% when grazing. Manure not spread on pastures when cows are grazing.

Table 2. BMPs installed on the farm and how these were modeled.

BMPs	Description	How modeled
Barnyard management	Exclusion of runoff from the barnyard and disposal of the remaining barnyard runoff in a way that minimizes its pollution potential.	Defined in urban database with parameter value adjustments.[a]
CREP	Areas earmarked for the Conservation Reserve Enhancement Program.	Land use converted to mixed forest at time program instituted, parameter adjustment to reflect transition.
Rotations	A planned sequence of annual and/or perennial crops.	Data obtained from DCSWCD[b] entered into model (Hively, 2004).
Nutrient management plans	Managing the rate, timing, and placement of fertilizers, manures and other nutrient sources to encourage maximum nutrient recycling and minimize nutrient runoff and leaching.	Data obtained from NYSDEC[c] entered into model (Hively, 2004); barn calendars available for some years.
Strip cropping	Alternating strips of corn and forage, planted across the slope	Data obtained from DCSWCD entered into model (Hively, 2004).
Tile drains	Subsurface drainage tiles.	Tiles specified in SWAT for fields with tile drains, parameters left at default values.[d]

[a] Parameter adjustments for barnyard: wash-off coefficient = 0.96 (mm^{-1}); max. solids = 450 (kg/curb km); half-life for solids build-up = 0.5 (days).
[b] Delaware County Soil and Water Conservation District.
[c] New York State Department of Environmental Conservation.
[d] Parameters for tile drains: depth = 90 cm; time to drain = 48 h; time to stream = 48 h.

Table 3. Model parameters used for calibration, listed by model component.

Parameter	Description
Hydrology	
CN2	Curve number antecedent moisture condition II
SLSOIL	Slope length for lateral flow
SMFMX, SMFMN	Snow melt factors
SURLAG	Surface runoff lag coefficient
ESCO, EPCO	Soil and plant evaporation compensation factors
DELAY	Groundwater delay
ALPHA_BF	Base flow recession factor
AWC	Available water capacity
KSAT	Saturated hydraulic conductivity
Sediment	
APM	Peak rate adjustment factor for sediment routing
USLE-C	USLE cropping factor
BIOMIX	Biological mixing efficiency
SLSUBBSN	Average slope length
Phosphorus	
PHOSKD	Phosphorus partitioning coefficient
UBP	Phosphorus uptake distribution parameter

ods. Parameters used for calibration were selected based on a sensitivity analyses by Gitau (2003) and also based on work by Tolson and Shoemaker (2004). Parameters selected for calibration are shown in table 3.

Calibrations were done manually, with model performance being evaluated at each step. Model performance was evaluated using the Nash-Sutcliffe coefficient (NS; Nash and Sutcliffe, 1970; Martinez and Rango, 1989) and the index of agreement (*d*; Willmott, 1984) as well as graphical plots.

The NS (eq. 1) is a measure of model efficiency that compares simulated values to corresponding measured values. The NS can range from $-\infty$ to one; improved model performance is indicated as the NS approaches one, while a value of zero indicates that simulated values are no better than the mean of observed values.

$$\mathrm{NS} = 1 - \left(\frac{\sum_{i=1}^{n} (Q_i - Q_i')^2}{\sum_{i=1}^{n} (Q_i - \bar{Q})^2} \right) \quad (1)$$

where Q_i is the measured value, Q_i' is the simulated value, $\bar{Q}$ is the average measured value, and n is the number of data points.

The index of agreement measures the relative closeness of predicted values to observed values and is computed as shown in equations 2 and 3:

$$d = 1 - \left(\frac{n * \mathrm{MSE}}{\mathrm{PE}} \right) \quad (2)$$

$$\mathrm{PE} = \sum_{i=1}^{n} \left(\left| Q_i' - \bar{Q} \right| + \left| Q_i - \bar{Q} \right| \right)^2 \quad (3)$$

where MSE is the mean square error, and Q_i, Q_i', $\bar{Q}$, and n are as described under equation 1. This index varies from 0 to 1.

During calibrations, parameter adjustments were made and model performance was determined at each step, until no further improvements in performance could be obtained. Model performance was considered acceptable for $0.4 \leq \mathrm{NS} \leq 0.75$, and good for NS > 0.75, based on Popov (1979) as cited by Van Liew and Garbrecht (2003), Ramanarayanan et al. (1997), and Moriasi et al. (2007). While there is currently no consensus on specific values of *d* that must be obtained for model predictions to be considered good, values of *d* close to 1 indicate good model performance. Thus, values of *d* closer to 1 were desirable.

In addition, model performance was also evaluated at the field level. In this study, georeferenced field data were used in lieu of regular land use data; thus, actual fields (and field-level data) were used to develop HRUs, as previously described. Since SWAT will give output at various levels, including the HRU level, and since our HRUs were derived from fields, it was possible to compare output at this level to data derived from field experimentation studies conducted on the farm by Hively et al. (2005) and Brown et al. (1989). Hively et al. (2005) reported DP and TP concentrations from various sites within the farm, while Brown et al. (1989) reported similar values for barnyard areas. Model performance at the field level was determined by comparing average simulated DP and TP concentrations in runoff to concentrations observed by Hively et al. (2005) and to ranges given by Brown et al. (1989). Comparisons between observed and simulated data were, however, focused on general magnitudes and ranges of the values concerned rather than on absolute values. Model performance at the field level was considered important, as this was the level at which BMPs were evaluated.

BMP Impacts

The impacts of BMPs were evaluated by compiling annual DP, PP, and TP losses (kg ha^{-1}) for all land uses (fields) for all the years. These data were then averaged separately for the pre-BMP (1993-1995) and post-BMP (1997-2002) periods. Losses were then aggregated by fields and implemented BMPs, and BMP effectiveness (percentage by which P is reduced) determined by subtracting post-BMP losses from pre-BMP losses and dividing these by the pre-BMP losses. Similarly, overall BMP impacts were determined from computing total losses (kg ha^{-1}) from the land use areas and computing effectiveness as previously described.

Incorporating BMP Tool Efficiencies

For this study, detailed data were available for simulating BMPs as needed, and for verifying the accuracy of the output. This is, however, not often the case. Additionally, there are some BMPs that are either not defined or only defined in part (such as filter strips) within SWAT. For these reasons, the direct incorporation of potential BMP effectiveness-based data from the BMP tool was investigated. The BMP tool was developed in Microsoft Access based on effectiveness data reported in the literature (Gitau et al., 2005). The tool is underlain by a database that contains data on BMP effectiveness (defined as the percentage by which P is reduced) in reducing DP, PP, and TP as well as other BMP characterization information. The tool, thus, provides literature-based estimates of BMP effectiveness, which can either be obtained as average values or based on site soils and slopes. Values from the tool represent the average effectiveness of each BMP over its expected lifetime.

To apply the effectiveness values, a BMP-specific reduction factor (R = {100 – effectiveness}/100; Gitau et al., 2004) was first calculated. The reduction factors calculated were then used as multipliers applied to SWAT-simulated annual loads to estimate reduced loads. For example, by definition, an effectiveness value of 40% for TP implies that the BMP can reduce TP by 40%; thus, 60% of the initial load would still be leaving the field. The reduction factor calculated in this case would be 0.6. For a SWAT-simulated annual load of 100 g, the reduced load would then be estimated as 60 g (0.6 × 100). For this study, tool-based BMP efficiencies were applied to baseline (no BMP) P losses in the post-BMP period, obtained by running SWAT through the pre- and post-BMP periods using only the pre-BMP setup. Resulting annual loads were then compared with observed data and tested for performance as previously described.

Results and Discussion

Parameter values as obtained based on existing data and on model calibrations are presented in table 4. Figure 2 shows monthly plots of simulated stream flow, sediment, DP, PP, and TP in comparison to observed data following calibrations.

Table 4. Pre-adjusted and calibrated model parameter values in comparison to default values.

Parameter[a]	Parameter Values: Default	Calibrated	Units
CN2	Varied[b]	× 0.85	
SLSOIL	Varied[c]	25	m
SMFMX	4.5	1.6	mm H_2O/°C-day
SMFMN	4.5	1.4	mm H_2O/°C-day
SURLAG	4	0.1	days
ESCO	0.95	0.5	
EPCO	1	0.5	
GW_DELAY	31	4	days
ALPHA_BF	0.048	0.6	days
AWC	Varied[d]	× 1.5	m m^{-1}
KSAT	Varied[d]	× 2	mm h^{-1}
APM	1	1.5	
USLE_C			
Corn	0.2	0.5	
Grass	0.003	0.008	
Forest	0.001	0.002	
BIOMIX			
Forest	0.2	0.8	
CREP[e]	0.2	0.6	
SLPSUBBSN/			
Forest	25	50	m
Corn	25	30	m
PHOSKD	175	250	m^3 Mg^{-1}
UBP	20	10	
PSP[f]	0.2	0.3	
SOL_LABP[f]			
Corn	5	26	mg kg^{-1}
Grass	5	46	mg kg^{-1}
Pasture	5	12.5	mg kg^{-1}
Forest	5	8	mg kg^{-1}

[a] CN2 = curve number antecedent moisture condition II; SLSOIL = slope length for lateral flow; SMFMX, SMFMN = snow melt factors; SURLAG = surface runoff lag coefficient; ESCO, EPCO = soil evaporation and plant evaporation compensation factors, respectively; DELAY = groundwater delay; ALPHA_BF = base flow recession factor; AWC = available water capacity; KSAT = saturated hydraulic conductivity; APM = peak rate adjustment factor for sediment routing; USLE-C = USLE cropping factor; BIOMIX = biological mixing efficiency; SLSUBBSN = average slope length; PHOSKD = phosphorus partitioning coefficient; PSP = phosphorus availability index; UBP = phosphorus uptake distribution parameter; SOL-LABP = initial labile phosphorus concentrations.
[b] Varied by land use and hydrologic soil group.
[c] Varied by HRU.
[d] Varied by soil type and soil layer.
[e] Areas under the Conservation Reserve Enhancement Program.
[f] Values were adjusted prior to model calibrations based on existing soil test data.

Based on figure 2, the model simulated stream flow very well and simulated sediment and phosphorus with reasonable accuracy. For both DP and TP, however, the model performed better in the post-BMP period as compared to the pre-BMP period. This better performance in the post-BMP period was also evident from an analysis of annual phosphorus loads (fig. 3) and computed performance statistics (table 5). While both the NS and *d* statistics were computed, only the NS is shown in table 5. Across the board, values of *d* ranged from 0.80 to 0.97 for the combined periods, from 0.68 to 0.94 for the pre-BMP period, and from 0.85 to 0.98 for the post-BMP period. This indicated an overall good model performance

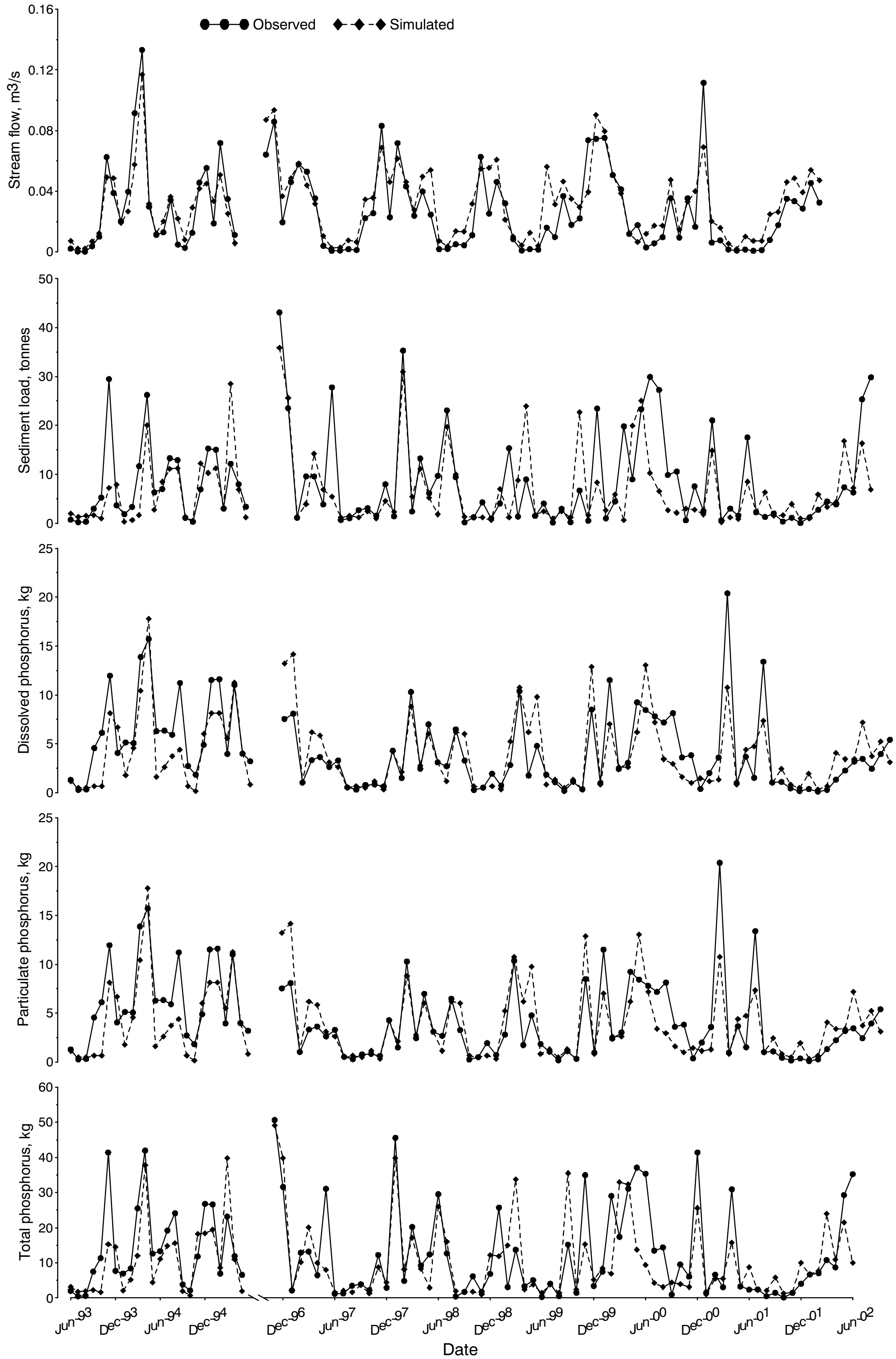

Figure 2. Comparison of calibrated monthly stream flow, sediment ,and phosphorus with observed data in the pre-BMP (June 1993 to May 1995) and post-BMP (Nov. 1996 to June 2002) periods.

for the calibrated components, while also showing better performance for the post-BMP than for the pre-BMP period.

These results indicated a need to review the calibration parameter set for the pre-BMP period. A separate simulation was thus set up, for the pre-BMP period, which had the parameter set from the previous (pre- and post-BMP) calibration as its initial dataset. On re-calibrating the pre-BMP period, it was found that changing the phosphorus partitioning coefficient from calibrated value 250 to 175 $m^3\ Mg^{-1}$ for the pre-BMP period was sufficient to improve model simula-

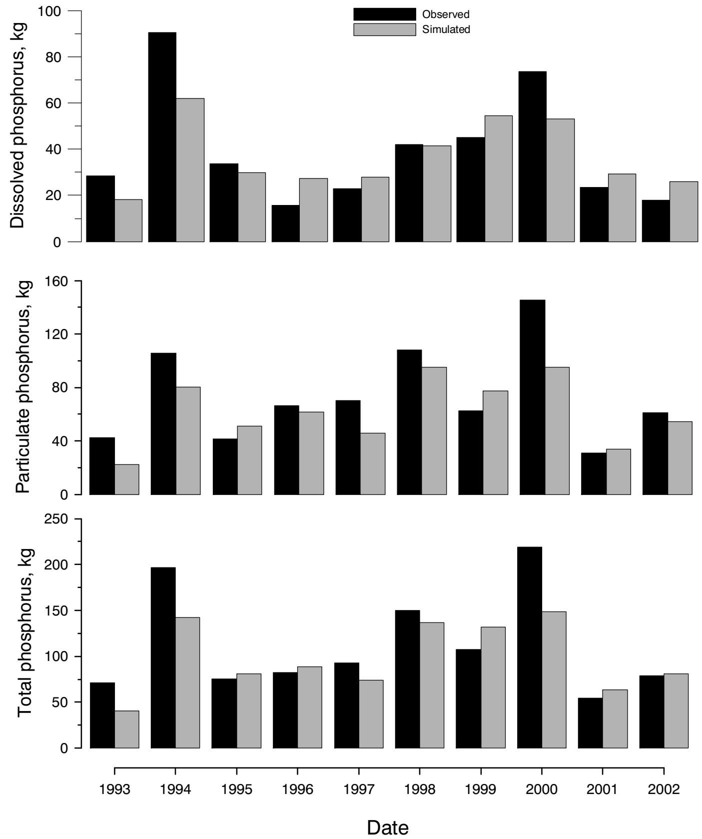

Figure 3. Simulated and observed annual phosphorus loads at the watershed outlet over the whole simulation period.

Table 5. Nash-Sutcliffe coefficients for combined and individual pre- and post-BMP periods.

	Monthly			Annual		
	Combined	Pre-BMP	Post-BMP	Combined	Pre-BMP	Post-BMP
Stream flow ($m^3 s^{-1}$)	0.78	0.86	0.72	0.80	0.83	0.80
Sediment load (tonnes)	0.26	0.40	0.23	0.70	0.77	0.66
Dissolved P (kg)	0.43	0.19	0.46	0.41	-0.05	0.70
Particulate P (kg)	0.40	0.26	0.43	0.59	0.57	0.57
Total P (kg)	0.45	0.38	0.47	0.56	0.36	0.66

Table 6. Performance statistics for dissolved, particulate, and total phosphorus simulation in the pre-BMP period following a change of the phosphorus partitioning coefficient.

	NS		*d*	
	Previous	Re-calib.	Previous	Re-calib.
Monthly				
Dissolved P (kg)	0.19	0.50	0.73	0.87
Particulate P (kg)	0.26	0.26	0.75	0.76
Total P (kg)	0.38	0.47	0.78	0.84
Annual				
Dissolved P (kg)	-0.05	0.60	0.51	0.87
Particulate P (kg)	0.57	0.58	0.89	0.86
Total P (kg)	0.36	0.62	0.78	0.87

tions of both DP and TP in the pre-BMP period (table 6). The phosphorus partitioning coefficient provides a comparison of soluble P concentrations in the soil to those in surface runoff, and is defined as the ratio of soluble P concentrations in the top 10 mm of the soil to that in surface runoff. Based on information from Sharpley et al. (2002), the partitioning coefficient differs with land use and can range from about 40 m^3 Mg^{-1} for cultivated areas to about 200 m^3 Mg^{-1} for grass. The improvements obtained in model performance were, thus, thought to be attributable to improved representation of land use changes within the watershed, as there had been more area in cultivated crops in the pre-BMP period (18% in 1993 vs. 1% in 2002) and more pastures and grass in the post-BMP period (30% in 1993 vs. 43% in 2002). The partitioning coefficient was then expected to have a lower value in the pre-BMP period than in the post-BMP period, consistent with information from Sharpley et al. (2002). Further analyses were thus conducted using outputs combined from separate model runs of the pre- and the post-BMP periods.

Field-Level Performance

Figure 4 shows a comparison of DP and TP concentrations in runoff based on SWAT model simulations in comparison to observed data as reported by Hively et al. (2005). Values obtained through simulation were aggregated by generalized land use by calculating area-weighted averages for each land use. In general, simulated DP and TP concentrations corresponded well to observed data, based on figure 4. For barnyards (omitted from fig. 4 because of the magnitude of losses from these areas), simulated DP and TP were 4.1 and 16.1 mg

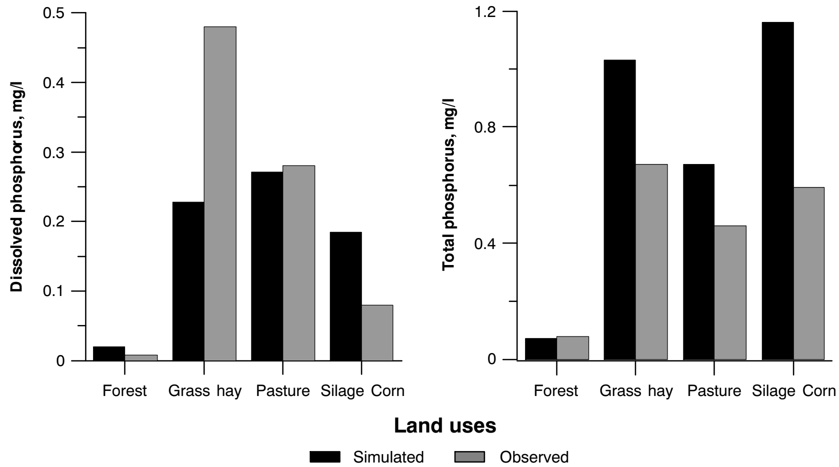

Figure 4. Comparison of simulated and observed (Hively et al., 2005) phosphorus runoff concentrations summarized by the various land uses.

L^{-1}, respectively. These compared well with observed concentrations of 11.9 and 13.7 mg L^{-1}, respectively, documented by Hively et al. (2005) and were within the ranges of 2 to 15 mg L^{-1} and 7 to 30 mg L^{-1}, respectively, documented by Brown et al. (1989). In general, simulated and observed data were comparable with regard to both absolute losses and order of magnitude. Thus, the SWAT model could be said to perform well at the field level.

BMP Impacts

Impacts of BMPs as determined from analyses of model outputs are shown in table 7. As shown in this table, the BMPs were able to reduce DP losses by between 15% and 41% and TP losses by between 2% and 52%. However, an increase of 192% in TP losses was observed, this being associated with strip cropping, for which a corresponding increase of over 500% was observed in simulated PP losses. This was thought to be because corn was included within the strips in 1995 through 1998; the associated field had been in alfalfa in the immediate pre-BMP period (1993-1994), thus leading to increased sediment and therefore PP and TP losses from this field. Efficiencies determined for tile drains show their impacts on losses in surface runoff. It should be noted, however, that benefits derived from tile drains may be counteracted by losses occurring through tile drainage discharge. For this reason, the WAC has recently removed tile drains from its list of BMPs (Bishop et al., 2005). Overall, BMPs could reduce DP losses by an average of 32%, PP losses by an average of 13%, and TP losses by an average of 21% based on the simulations. It was, however, difficult to separate out individual BMP impacts based on SWAT simulations, as BMPs had been implemented on the fields in various combinations (for example, nutrient management plans and crop rotations) and had thus been represented as such within the SWAT model.

Table 7. BMP effectiveness as determined from SWAT model simulations.

	BMP Efficiencies (%)[a]		
	DP	PP	TP
Barnyard management[b]	15	23	21
CREP	39	73	52
Rotations, nutrient management plans	31	-7	25
Rotations, nutrient management plans, strip cropping, tile drains	36	2	4/27[c]
Strip cropping[d]	23	-574	-192
Tile drains[d]	41	-20	2
Overall	32	13	4/21[c]

[a] Negative values indicate increases in pollutant losses.
[b] Barnyard management impacts estimated by incorporating efficiencies from Gitau et al. (2005).
[c] Represent values with/without year 2002 data.
[d] Effects calculated for affected fields and include rotation and nutrient management practice effects.

Incorporating BMP Tool Efficiencies

As previously discussed, it was of interest to this study to evaluate the possibilities of incorporating BMP tool-based efficiencies in evaluating post-BMP scenarios. This was particularly with regard to determining their use in situations where available post-BMP data were insufficient for BMP evaluations, as well as for integrating BMPs not included in the model. In light of the challenges encountered in determining individual BMP impacts based on model runs, the use of the BMP tool in providing estimates of individual BMP impacts was also evaluated.

Figure 5 shows DP, PP, and TP loads as computed by applying tool efficiencies to the post-BMP period in comparison to observed data. From the figure, the application of BMP tool efficiencies for DP gave an overall reasonably good output, with a NS = 0.54 being obtained, comparable to NS = 0.69 obtained through calibration. Additionally, the annual plot obtained using BMP tool efficiencies for DP was comparable to that obtained through calibration (fig. 3). For PP and TP, however, BMP impacts appeared to be overestimated when BMP tool efficiencies were used; thus, simulated PP and TP loads were far lower than corresponding observed loads in the post-BMP period (fig. 5). This was possibly attributable to the increases in PP and TP losses resulting from the introduction of corn onto previously pastured strips (as previously discussed), and thus the observed negative impacts of contour strip cropping. This behavior is atypical of what is documented in the literature as the expected impact of contour strip cropping, and thus the apparent overestimation of BMP impacts by the BMP tool.

General Discussion

When simulations were conducted for the combined pre- and post-BMP periods, model performance was excellent for stream flow and adequate for sediment and phosphorus. With

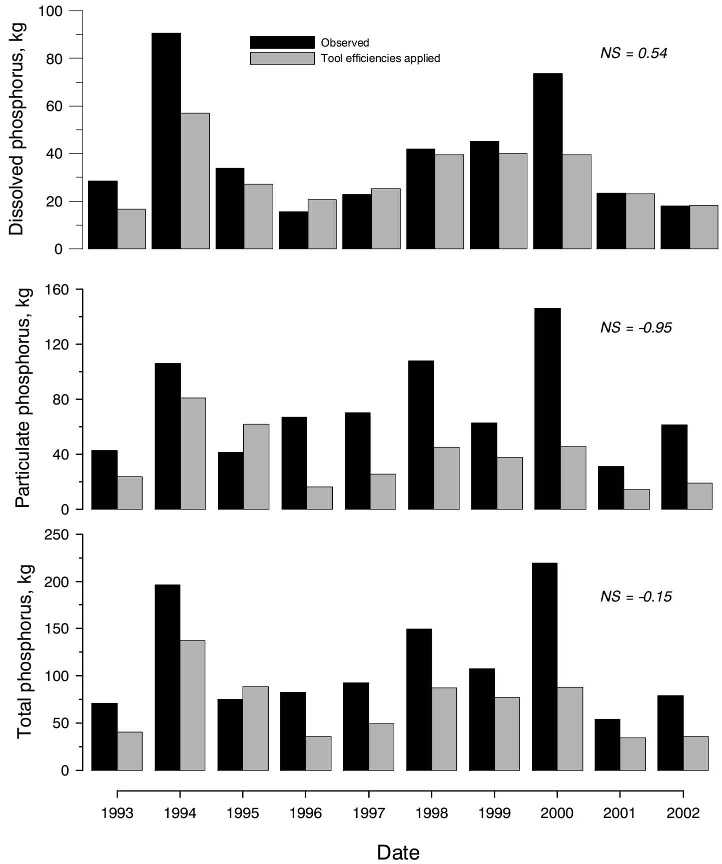

Figure 5. Comparison of DP, PP, and TP as computed by applying tool efficiencies (post-BMP period) in comparison to observed data.

this setup, the model performed much better in the post-BMP than in the pre-BMP period, especially with regard to sediment and phosphorus simulations. The model performed appreciably better in the pre-BMP period when this period was run separately, and the phosphorus partitioning coefficient was adjusted to reflect more cropland than grass in the pre-BMP scenario as compared to the post-BMP scenario. As only the phosphorus partitioning coefficient needed to be changed to improve model performance, this study suggests that there is a need to offer more flexibility in specifying the parameter within the SWAT model. The model currently allows only one value of the parameter for the whole watershed. This parameter would be better defined as one that can be specified independently for the various land uses, consistent with suggestions for future work documented by Gitau (2003) and Arnold and Fohrer (2005).

There are other areas in SWAT for which added flexibility in inputs would be desirable. For example, tile drains are set up as a single management input; thus, there is no flexibility in terms of modeling a scenario in which tile drains are introduced within the simulation period, without splitting the simulations. A similar situation occurs with regard to simulating land use changes. While time-based changes in agricultural and forested land uses are readily modeled by specifying the crop as needed, modeling a change from agricultural or forested land use to urban land use is not as straight forward. While this change can be modeled by setting up a new simulation, it would be more realistic, and possibly more accurate, if the model allowed this change to be specified in a continuous manner.

Summary and Conclusions

This study applied SWAT and a recently developed BMP characterization tool to a New York dairy farm, which spans an entire subwatershed within the headwaters of the larger CRW. The model was applied over pre- and post-BMP installation periods with the object of determining the extent to which model results incorporating all installed BMPs match observed data, and the individual impact of each of the BMPs installed on the farm. The SWAT model has often been used to investigate BMP impacts without sufficient post-BMP data to verify the results. For this study, pre- and post-BMP data were available in sufficient detail, both at the watershed outlet and within the fields, to allow an investigation into the adequacy of SWAT for simulating BMP impacts. This study found that the SWAT model could adequately represent pre- and post-BMP periods, both at the watershed outlet and for in-field losses, when compared with observed data. Based on SWAT simulations, the BMPs installed on the watershed were found to reduce DP by an average of 31%, PP by an average of 13%, and TP by an average of 21%, consistent with findings from observed data.

In this study, the impacts of the BMPs installed on the watershed were determined successfully. The impacts attributable to individual BMPs could, however, not be quantified based on SWAT model simulations, as the BMPs existed in various combinations within the fields. Determination of individual BMP impacts is important for identifying the BMPs that really have or are likely to have an impact, and thus in determining which BMPs need to be on the watershed at the same time, as well as where the BMPs would be best placed in order to have the most impact (Gitau, 2003; Gitau et al., 2006). In this regard, efficiencies from the BMP tool were found to adequately represent BMP impacts on DP. Tool efficiencies, however, overestimated PP and TP impacts of the BMPs as installed on the study farm.

This study found that the SWAT model could justifiably be used in simulating BMP impacts at both the farm and watershed scales. Additionally, BMP tool efficiencies could be used to complement modeling efforts by providing insights into individual impacts of BMPs, as well as data on BMPs not included directly in SWAT.

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