Determination of Critical Source Areas for Phosphorus Loss: Lake Champlain Basin, Vermont

L. T. Ghebremichael, T. L. Veith, M. C. Watzin

Abstract. *Lake Champlain, located between Vermont, New York, and Quebec, exhibits eutrophication due to continuing phosphorus (P) inputs from upstream nonpoint-source areas. To address the effects of this eutrophication and as part of total maximum daily load (TMDL) requirements, state-level P reduction goals have been established by both the Vermont and New York Departments of Environmental Conservation. Unfortunately, remedial measures undertaken thus far have been mostly based on voluntary participation by the landowners and have not been guided by a systematic technique to implement remedial measures where they could provide the greatest P loss reduction. Consequently, P reduction goals have not been achieved in most segments of Lake Champlain. The main objective of this study was to identify and quantify critical source areas (CSAs) of P loss using a model-based approach. The Soil and Water Assessment Tool (SWAT) is used for this objective. This study focuses on the Rock River watershed, which is one of the highest contributors of P to Lake Champlain. Spread over 71 km^2, the watershed is dominated by dairy agriculture and has fertile periglacial lacustrine and alluvial soils with an old tile drainage system. In this agriculture-dominated watershed, 80% of total P loss occurs from only 24% of the watershed area, signifying the need for focused remedial measures on CSAs of P loss. The identification of CSAs for P loss is expected to support the next phase of our project, which involves exploring cost-effective P management strategies with the highest potential for P loss reduction applicable to the study watershed and Lake Champlain basin.*

Keywords. *Critical source area, Lake Champlain, Phosphorus, SWAT.*

Lake Champlain has historically exhibited eutrophication problems due to continuing phosphorus (P) inputs from upstream areas (Lake Champlain Basin Study, 1979; Lake Champlain Basin Program, 2006, 2008; Meals and Budd, 1998). The 1130 km^2 lake is located mainly between the U.S. states of Vermont and New York and partly in the Canadian province of Quebec. Noxious algae blooms stimulated by excessive P inputs disrupt the lake's ecology and degrade domestic and recreational use and enjoyment of its waters. To address the excessive P loadings to the lake and as part of the total maximum daily load (TMDL) requirements of the U.S. Environmental Protection Agency (U.S. EPA) and the Clean Water Act, the Vermont and New York Departments of Environmental Conservation have specified P reduction goals for segments of Lake Champlain that do not meet water quality standards (Lake Champlain Basin Program, 2002). Over 90% of the lake segments not meeting targets are fed by nonpoint-source areas (Lake Champlain Basin Program, 2008); the majority of these lake segments are located in Vermont. Various agencies in Vermont have made substantial investments and remediation efforts to achieve P reduction goals and improve water quality in these lake segments. However, most remedial measures undertaken thus far have relied on voluntary landowner participation and have not been guided by a systematic technique to implement measures where they are most needed (i.e., where potentials for P loss reductions are the greatest and where their impacts are most cost-effective). Consequently, despite these efforts by many agencies, P reduction goals from nonpoint sources within Vermont have not been achieved. This study was aimed at identifying high-risk areas for P loss in order to provide a subset of the watershed area for focus by future efforts looking at cost-effective measures.

Due to variability in topography, hydrology, soil, and management, all nonpoint P sources do not contribute equally to water impairment. Areas within a watershed that contribute disproportionally higher losses are often called critical sources areas (CSAs). These CSAs of P loss combine (1) high soil P areas resulting from soil types and management practices (Pote et al., 1996, 1999; Sharpley, 1995; Sharpley et al., 1996), and (2) areas prone to high volumes of runoff and erosion (Pionke et al., 1997; Gburek and Sharpley, 1998). Several studies have shown the importance of focusing efforts on identification, targeting, and remediation of CSAs of P loss for effective mitigation of nonpoint-source P losses (Pionke et al., 1997; McDowell et al., 2001; Weld et al., 2001). The benefits of identifying CSAs for P losses are well recognized and drive Vermont's current and future priorities for allocating limited resources to successfully address nonpoint-source P pollution and to meet water quality

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standards required by TMDLs. Simply put, the state of Vermont is looking for data related to the extent of CSAs for P loss within priority watersheds that are identified by ongoing monitoring programs and the proportions of P loss coming from the CSAs and various other sources in the watersheds. Hence, there is a critical need for a systematic approach to identifying and quantifying CSAs for P loss at a watershed scale in order to help achieve the state's prioritization plan to reduce P and meet water quality standards. Because P loss at a watershed scale is governed by the combined effect of P source and transport factors, the approach needs to combine the complexities of hydrology, natural variability, and P source and transport factors to identify and quantify CSAs of P loss.

The main objective of this study was to identify and quantify P-based CSAs for a subwatershed of the Lake Champlain basin. Because of its globally successful applications involving TMDL analyses and conservation practice assessments, the Soil and Water Assessment Tool (SWAT; Neitsch et al., 2002) was found to be a suitable tool for this objective. SWAT is a process-based watershed model capable of simulating the complex processes of hydrology, erosion, and P loss. Results can be easily displayed spatially and further evaluated using the GIS interface with which the model is integrated. SWAT has been widely adopted in a variety of environmental applications; summaries of over 250 peer-reviewed SWAT publications can be found in Borah and Bera (2004) and Gassman et al. (2007). More specifically, numerous studies have successfully applied SWAT in identification of CSAs of surface water and P loss (Srinivasan et al., 2005; Deslandes et al., 2007; Ouyang et al., 2007; Busteed et al., 2009). These applications cover study areas in the northeast U.S., southeast Canada, central China, and south central U.S. This study used SWAT2005 with the ArcSWAT 2.1 interface, which includes a set of recently developed tools for evaluating parameter sensitivity, aiding in model calibration, and assessing input parameter and model output uncertainty.

Our project, funded by the Lake Champlain Basin Program, the Vermont Agency of Natural Resources, and several private donors, applied SWAT on the Rock River watershed in Vermont. The Rock River watershed is an agriculturally dominated watershed draining into the Missisquoi Bay on the northeastern side of Lake Champlain. This bay does not meet the TMDL-specified target for P loading. Based on P monitoring data gathered to identify troubled subbasins within the Lake Champlain basin, the Rock River watershed was found to contribute relatively large P losses per unit area (Smeltzer and Simoneau, 2008) and was established as a high-priority area for watershed management activities.

In this article, outputs of SWAT sensitivity analysis, model calibration, and validation are discussed for runoff, erosion, and P loss. Temporal SWAT predictions of hydrology, sediment, and total P loss in the Rock River watershed are also presented. Finally, the quantity and extent of CSAs of P loss resulting from the model analysis are determined and presented.

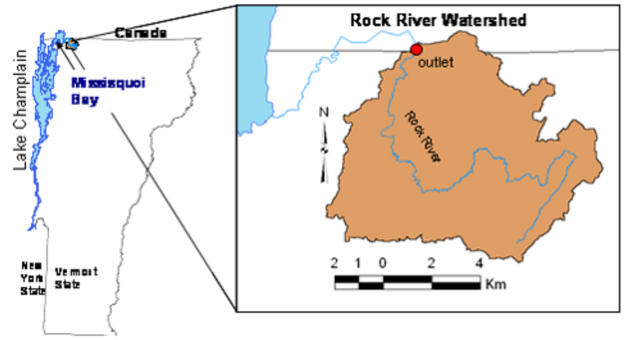


Figure 1. Location of the Rock River watershed, Missisquoi Bay, and Lake Champlain at the U.S./Canada border.

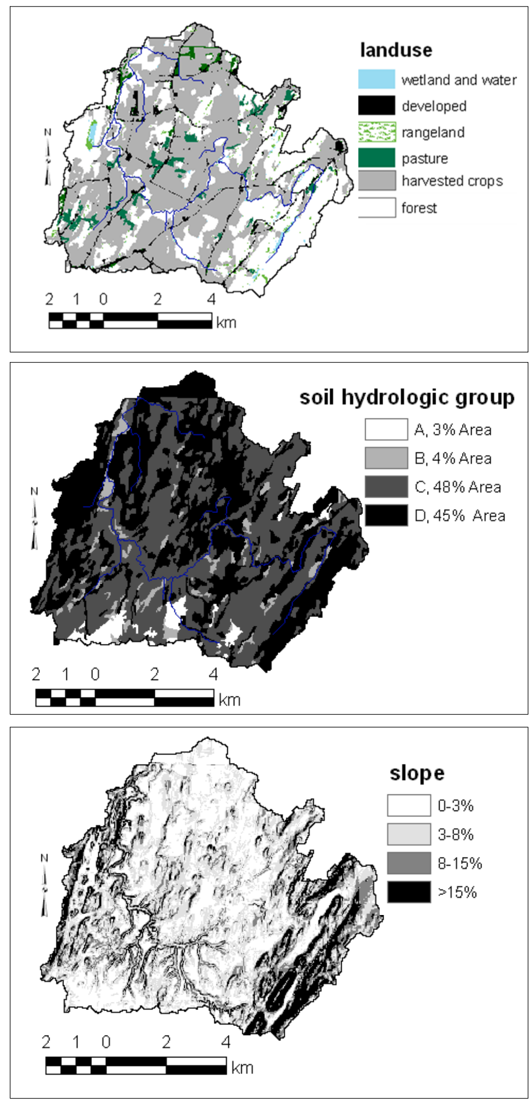


Figure 2. Slopes, land use, and soils of the Rock River watershed, Vermont.

Materials and Methods

Study Watershed Description

Rock River, located in the northwestern corner of Vermont (fig. 1), flows northward into Missisquoi Bay, a northeast arm of Lake Champlain. The river is monitored at the location where it crosses from the U.S. into Canada. The Rock River watershed, modeled in this study, encompasses 71 km^2 of rural land, primarily in Franklin County, Vermont. The watershed has an average elevation of 101 m and is relatively flat, with about 68% of its slope ranging from 0% to 8% (fig. 2). The climate is humid with average annual precipitation of 1100 mm. Land use in the Rock River watershed consists of 55.4% harvested crops (corn, small grains, and rotational hay), 3.1% permanent pasture, 6.1% developed (buildings, roads, and farmstead), 34.4% forest, 0.4% rangeland, and 0.6% wetland and water bodies (fig. 2). Currently, about 90% of corn fields and 75% of grass fields in the watershed are estimated to overlie old tile drainage systems. Soils are of glacial origin, dominated by silt loams or silt clay loams, with about 48% and 45% classified under hydrologic soil groups C and D, respectively (fig. 2). These fertile periglacial lacustrine and alluvial soils support an intensive and increasingly consolidated dairy farming industry.

Based on Vermont's farm size categorization, a farm with 0 to 199 cows is considered a small farm operation (SFO), 200 to 699 cows is a medium farm operation (MFO), and more than 700 cows constitute a large farm operation (LFO) (VAAFM, 2006, 2007). In the Rock River watershed, 89%, 8%, and 3% of farms are categorized as SFOs, MFOs, and LFOs, respectively, with 79% of the cows in the watershed owned by SFOs. The average farm size in Franklin County is 75 ha, with about 50% of all farms owning fewer than 40 ha (USDA-ERS, 2009). Although SFOs may have higher animal density per unit farm land than other operations, EPA Concentrated Animal Feeding Operation regulations do not require them to implement nutrient management plans. By not taking advantage of programs, such as nutrient management planning, that are aimed at preventing pollution, SFOs are likely to be a significant source of nutrient loss to streams.

SWAT Model Base Inputs and Representations

Baseline input data used to represent the Rock River watershed in SWAT (topography, soil map and properties, and land use maps with their sources and resolution) are described below, along with information about climatic and hydrological data. Topography data (1:50,000 scale Digital Elevation Model, DEM) were obtained from the Vermont Center for Geographic Information (VCGI) and the Canadian Digital Elevation Data (CDED) geobase. Soil Survey Geographic (SSURGO) level soils data were obtained from the USDA Natural Resources Conservation Services (USDA-NRCS) soil data mart. Land use inputs were developed by combining several data sources: 30 m land cover data from the 2001 National Land Cover Dataset (NLCD), the USDA Farm Service Agency (FSA) Common Land Unit (CLU) GIS layer, and digitized active farmsteads. The first two layers were obtained from the University of Vermont spatial analysis lab, and the third was generously provided by the Vermont USDA-NRCS office. The 30 m land cover layer available for this study watershed represents agricultural land use as either closely grown crops or row crops without identification of specific crop types. The CLU layer identifies specific crops at the field level. The CLU layer, which covers most of the agricultural areas in the watershed, was developed via farm owners who participated in conservation programs and allowed sharing of their farm data. Wherever possible, CLU field boundaries of crop fields and digitized farmsteads were used to update the general NLCD land cover data, and the appropriate SWAT land cover type was used. For agricultural areas without CLU field boundaries, and hence without specific crop type, the general NLCD land cover data were used, and SWAT land cover types "agricultural land – generic" and "agricultural land – row crops" were selected to represent closely grown crops and row crops, respectively. As a result, modeled areas of agricultural land uses were 17.2% corn, 25% hay, 3.1% permanent pasture, 0.5% farmstead, 11.7% row crops, and 1.5% closely grown crops.

Climate data were obtained from National Weather Service (NWS) Cooperative Observer Stations in Enosburg, St. Albans, and South Hero, Vermont, and from Canadian government data from Philipsburg, Quebec (Ministère du Développement durable, de l'Environment et des Parcs – MDDEP). All these stations are located outside the watershed boundary, but they surround the study watershed with distances ranging from 10 to 30 km. Both precipitation and temperature data were obtained from these stations. The weather generator within SWAT was used to generate the other climate data needed: solar radiation, relative humidity, and wind speed. Measured stream flow, sediment, and P data at the watershed outlet were obtained from MDDEP, Canada, for 2001 through 2008.

SWAT allows a watershed to be divided into subbasins based on topographic criteria and user-defined streams. A 10 m DEM of the Rock River watershed was used to define stream networks, and a USGS digitized streams layer was used to confirm that the modeled streams closely matched USGS data. In this study, the watershed was divided into ten subbasins representing the main tributaries. Within each subbasin, SWAT hydrologic response units (HRUs) were defined based on combinations of SSURGO level soil types, four slope groups, and field-level land use. This resulted in a total of 5,577 HRUs for the watershed. The slope groups (0% to 3%, 3% to 8%, 8% to 15%, and >15%) were purposely selected to match slope categories used in a variety of farm planning purposes. For crops with available field boundaries, HRUs were defined by distinctly coding individual fields and thus maintaining the spatial location of the crop fields. By distinctly coding individual fields, amounts of runoff and associated sediment and P loadings for each crop field can be extracted and, most importantly, spatial locations of the crop fields are maintained for further analysis in determining of CSAs of P loss.

SWAT Management Data Inputs

Key SWAT inputs pertaining to management include planting, tillage, harvesting, grazing, and fertilizer and manure applications, as well as tile drainage practices. To maintain privacy for those farms with well documented, field-level data and to incorporate less documented fields, management inputs were based on typical practices specific to crop type (personal communication with H. M. Darby, agronomist, University of Vermont Extension – Northwest Region, Saint Albany, Vermont, 2009). Crop rotation was not represented in the model because specific information on crop rotation related to the 2003 CLU crop data layer was not available. This will have some limitation on the study, particularly in the year-to-year analysis of modeling results.

Due to the shorter growing season for corn grain, corn in the study area is harvested as silage and utilized as a feed supplement in livestock production. Typically, corn is planted between May 1 and June 15 and harvested between mid-September and early October. Based on these data, May 10 and September 30 were used as corn planting and harvesting dates, respectively. Corn fields with heavy soils are generally plowed in the fall (October to November) and harrowed in the spring before planting. Other more well-drained soils are chisel-plowed in the spring and harrowed afterwards. Most farms use a low rate of P fertilizer as starter when planting corn. The rates are usually between 45 and 90 kg of phosphate per hectare.

Grass hay produced for livestock feed in this study area is predominantly orchardgrass, with some timothy and bluegrass, and mixed with alfalfa or clover legumes. New seedlings of hay are typically planted during the first two weeks of May. Typically, harvests occur at the end of May, end of June, mid-August, and sometimes a cutting in late September. Based on these data, May 1 was set in the model as the beginning date for grass growing, and June 1, July 1, and August 15 were set as hay harvest dates. Based on similar data, grazing generally occurs on pasture lands starting around May 10 and continues until about November 1. These data were represented in the model using appropriate model parameters.

Manure quantity in the watershed was estimated based on animal numbers obtained from University of Vermont Extension and Vermont Agricultural Agency and on typical livestock manure production rates (*ASAE Standards*, 1998). Manure application on corn fields in this region typically occurs in spring and occasionally in fall. Although manure application rates depend on individual nutrient management plans, application rates for corn average 55 kg ha^{-1} in both spring and fall. Spring applications are generally incorporated within 24 h, while fall applications are incorporated within 7 days. Overall, the quantity of manure applied to grass fields on an annual basis is equivalent to the amount applied to corn, except the amount is split into three applications after each hay harvest. This information was used in defining manure application rates and dates for each crop in the model.

Rating Curve for Continuous Observed Data

Unlike stream flow, which was recorded continuously using automated gauge meters, measured data for both sediment and P were available only as discrete data. These data were grab samples taken mostly during low or moderate flow conditions. Because SWAT predictions of sediment and P are provided as continuous daily and/or monthly outputs, it was desirable to use a continuous set of observed data for model calibration and validation. Various rating curves for generating continuous "observed" datasets from available discrete data were evaluated. For sediment, of the various rating curves tested against the 69 measured data points, a simple linear relationship was found to provide the best fit between measured sediment concentration and stream flow (fig. 3). This regression had an $R^2 = 0.49$ and tested significant overall (F-test = 61.2, $p < 0.001$) and individually for both the constant (t-test = 2.7, $p = 0.01$) and the dependent variable of stream flow (t-test = 7.8, $p < 0.001$). Hence, a continuous set of "observed" daily sediment concentration data was generated using this rating curve and daily flow data. This continuous observed data was then used for calibration.

Similarly, 97 total P concentration data points and corresponding stream flow data were fit to a linear rating curve with $R^2 = 0.52$ (fig. 3) and F-test = 87 ($p < 0.001$). The variables were again individually significant as well: constant t-test = 8.6 ($p < 0.001$) and stream flow t-test = 9.3 ($p < 0.001$). The continuous set of daily "observed" total P concentration data generated using the rating curve and stream data was used to estimate monthly total P load, which was later used for model calibration. For both sediment and P, predictions

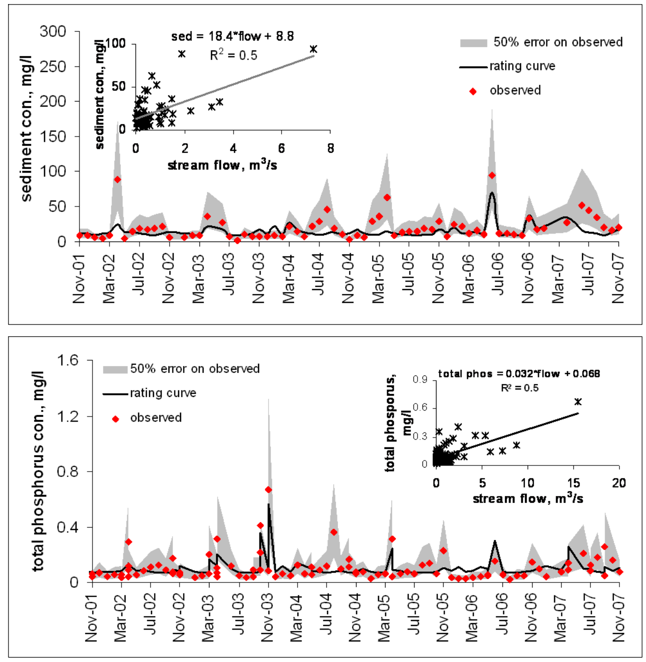


Figure 3. Rating curves and estimated uncertainty bounds of sediment and total phosphorus grab samples from the outlet of the Rock River watershed, Vermont.

were manually calibrated from 2001 through 2004 and validated from 2004 through 2007.

Measurement uncertainty for both sediment and total P was estimated at 50% because they were grab samples (Harmel et al., 2006). This uncertainty was considered in calculating goodness-of-fit for the rating curves using the method described by Harmel and Smith (2007). For sediment, the Nash-Sutcliffe coefficient (NS) doubled from 0.48 to 0.93; for total P, the NS increased from 0.51 to 0.94.

Parameter Sensitivity Analysis and Calibration Selection

Sensitivity analysis was used in this study to determine the sensitivity of model outputs to changes in the values of model input parameters. By identifying input parameters that are sensitive, the number of parameters included in the calibration process can be reduced, and more effort can be focused on determining best values for the most sensitive input parameters. Because of the relatively large number of input parameters that may be involved in calibrating hydrology, compared to sediment and P, sensitivity analysis was performed only on hydrology. Hence, 26 parameters that may potentially influence hydrologic predictions were included in the sensitivity analysis using the ranges of variation provided in the SWAT default range settings (table 1). The SWAT sensitivity analysis was performed using two objective functions: (1) the sum of squared residuals difference between daily simulation flows of the original run and the run with changed parameter values, and (2) the sum of squared residuals difference between daily observed and simulated flows at the watershed outlet.

The SWAT simulation was run from 1997 through 2007. The first four years were used as a warm-up period to ensure proper initial model conditions, including (among others) soil moisture, aquifer water levels, and crop growth. Using observed data (October 2001 to October 2007) from the wa-

Table 1. Hydrologic input parameters included in daily SWAT sensitivity analysis for the Rock River watershed, Vermont.

Parameter	Description	Model Process	Default Value	Variation Range	Calibrated Value
Cn2	SCS runoff curve number for moisture condition II	Runoff	Land use and soil dependent	±25%	-10[a]
Esco	Plant evaporation compensation factor	Evapotranspiration	0.95	0-1	0.63[b]
Gwqmn	Threshold depth in shallow aquifer required for return flow to occur (mm)	Groundwater/ soil water	0	±1000	750[c]
Timp	Snow pack temperature lag factor	Snowmelt	1	0-1	0.11[b]
Sol_Awc	Available water capacity (mm mm^{-1} soil)	Soil water	Soil dependent	±25%	-14.9[a]
Sol_Z	Soil depth	Soil water	Soil dependent	±25%	-1.4[a]
Blai	Leaf area index for crop	Crop/infiltration	Plant dependent	0-1	0.45[b]
Gw_Revap	Groundwater “revap” coefficient	Evapotranspiration/ groundwater	0.02	±0.036	-0.025[c]
Ch_K2	Effective hydraulic conductivity in main channel alluvium (mm h^{-1})	Channel losses	0.5	0-150	53.17[b]
Alpha_Bf	Baseflow alpha factor (days)	Groundwater	0.048	0-1	0.45[b]
Smtmp	Snow melt base temperature (°C)	Snowmelt	0.5	±25%	-3.19[a]
Surlag	Surface runoff lag coefficient	Runoff	4	0-10	0.30[b]
Biomix	Biological mixing efficiency	Soil water	0.2	0-1	--
Canmx	Maximum canopy index	Evapotranspiration	Plant dependent	1-10	--
Sol_K	Soil conductivity (mm h^{-1})	Soil water	Soil dependent	±25%	--

[a] Default values multiplied by this percentage value.
[b] Default values replaced by this value.
[c] Default value increased by this value.

tershed outlet, the model was then calibrated and validated for stream flow. The autocalibration tool in SWAT was used for calibrating daily stream flow predictions from October 2001 to October 2004. Model predictions were validated from October 2004 to October 2007.

The sensitivity analysis identified six influential hydrological parameters. Runoff curve number (Cn2), available water capacity (Sol_Awc), and plant evaporation compensation factor (Esco) were found to be among the most sensitive parameters affecting surface runoff. Similar findings were reported in previous studies (Cryer and Havens, 1999; Eckhardt and Arnold, 2001; White and Chaubey, 2005). Of the parameters that affect groundwater flow, the threshold depth of water in the shallow aquifer required for return flow to occur (Gwqmn) was found to be the most sensitive parameter. The importance of this groundwater parameter is not surprising because baseflow contributes the majority of the stream flow in this region. Snowmelt process parameters, such as snow pack temperature lag factor (TIMP) and snowmelt base temperature (Smtmp), were also identified as very sensitive parameters. This was expected in this cold region where snowmelt is an important component of hydrology. A sensitivity analysis of SWAT hydrological parameters performed in a southeastern Canada watershed, located in the same region as the study watershed, also found snowmelt TIMP and Smtmp parameters among the most sensitive parameters (Levesque et al., 2008).

Using mean values obtained from sensitivity analysis results, parameters that are more likely to affect model outputs and errors were identified. The sensitivity analysis tool evaluates parameter sensitivity by calculating mean values of the difference between the objective function of output values of the simulation runs before and after changing the value of a parameter. Of the 26 input parameters, only twelve had mean sensitivities greater than 0.4. Many of these parameters were expected to be sensitive based on the model process they affect and the watershed characteristics. Changing the values of these parameters has a greater impact on stream flow predictions than changing the parameters with lower mean values. Hence, they were included in the stream flow model calibration process. Calibrated parameter values for the best solution are presented in table 1.

Determination of Critical Source Area

SWAT predictions on an HRU level were selected to perform analysis in determination of CSAs of P loss. In this study, an HRU represented an area in a subbasin that contains a unique combination of land use, soil type, and slope range. An important consideration taken during the process of HRU formation was that crop fields were distinctly represented to avoid lumping of similar land use, slope, and soil combinations within a subbasin into one HRU. By avoiding lumping of HRUs, especially for crop fields, the amounts of runoff and associated sediment and P loadings for each crop field can be extracted and, most importantly, the spatial location of the crop fields can be maintained for further analysis in determination of high P loss areas. After completion of the model calibration and validation processes, the magnitudes and locations of runoff, sediment, and P losses from the HRUs were analyzed spatially. Analyses of runoff and sediment were important steps in determining CSAs of P loss because P loss predictions in the model are governed by runoff and sediment transport factors in addition to P source factors. To determine CSAs of P loss, a threshold value of P loss rate, above which losses can be considered too high, was used to discriminate HRUs with higher P loss rates. Additionally, two graphs were developed to demonstrate the percentage of watershed area corresponding to the amount and percentage of total P and sediment losses. For both graphs depicting total P and sediment, HRUs were ranked from high to low based on their SWAT-predicted loss rates, and cumulative total P and sediment loads were plotted along with loss rates. This type of graphic analysis is useful in determining a cost-effective target level for mitigating P and sediment losses.

RESULTS AND DISCUSSION

CALIBRATION AND VALIDATION OF SWAT SIMULATIONS

Stream flow was calibrated using the autocalibration tool in SWAT from 2001 through 2004 on a daily basis. Model performance was assessed using descriptive statistics and graphical representations for measured and simulated runs. The widely used Nash-Sutcliffe coefficient (NS; Martinez and Rango, 1989) and the time series plots of simulated versus observed data were compared (fig. 4). Model predictions were then validated using the same performance measures from 2004 through 2007. Results for daily and monthly stream flow predictions gave NS values of 0.60 and 0.74 for the calibration period and 0.60 and 0.70 for the validation period, respectively. A review of the watershed-level, water quality modeling literature indicated that values of NS > 0.50 are generally considered satisfactory with median monthly NS values of 0.79 for stream flow across the reviewed calibration literature (Moriasi et al., 2007). Overall, daily and monthly predictions obtained for stream flow were considered acceptable for this project. Additionally, annual predicted and observed total annual flow rates were 38 and 31 $m^3 s^{-1}$ for the calibration period and 41 and 42 $m^3 s^{-1}$ for the validation period, respectively. Compared to the observed data, the model slightly overestimated annual stream flow amounts with an error of 18% overprediction during the calibration period, but reasonably matched during the validation period. Closer inspection revealed that 5% of this error occurred during the summer months (25% of the simulation period), in which there was very little precipitation. This is as expected, considering that SWAT has been shown to overpredict during low flows (e.g., Van Liew et al., 2007). Here, the autocalibration tool incorporated in SWAT was helpful, and it needs to be commended in helping achieve these results with minimal time spent.

Because tile drainage is an important aspect of farming in this study watershed, predicted flow through tiles was also assessed. The model predicted drainage through the tiles only during March, April, and May, with the majority in March and April and very little during the month of May. The predicted timings and magnitudes of the flow could not be directly verified due to unavailability of measured tile drainage data. However, field observations in the watershed indicate that flow from tiled crops, particularly corn, is highest during March after the soil thaws and during April and May following spring rains; it then decreases as the growing season progresses. Hence, the overall representation of tile drainage in the model was considered reasonable. Field-based efforts of gathering and analyzing tile drainage data would enhance the understanding and modeling of tile drainages and how they impact the amount of runoff and movement of P in this study region. Given time and resources, such a field-based tile drainage monitoring and modeling study may be doable; however, it was beyond the scope of this study.

Sediment and total P predictions obtained by manually calibrating the model are also presented in figure 4. For sediment, daily and monthly NS values were 0.4 and 0.7, respectively, for the calibration period and 0.4 and 0.6, respectively, for the validation period. Although daily sediment concentration predictions were difficult to match to observed data, monthly sediment concentrations predictions were reasonably close to the observed data. It is also important to mention that manual calibration was involved mainly with changing two influential parameters related to peak flow rate adjustment factors for sediment routing in main and tributary channels (PRF and ADJ_PKR, respectively). The main reason for manually calibrating these two parameters was that they are not among the parameters available for selection in the SWAT autocalibration tool. No better solutions were located using sediment-related parameters available for selection in the tool. Field visit observation confirmed the existence of a variety of streams for which remedial strategies had been already implemented, including stone and grassed waterways, small-sized sediment basins, and back road stream stabilization. These may substantially contribute to slowing the water flow and controlling sediment movement in the streams, but they were not explicitly specified in the model. Overall, sediment predictions acquired by manual calibration were satisfactory for the objective of this study. We recommend that future work in enhancing the SWAT autocalibration tool either expands the list of selectable parameters for sediment prediction or provides flexibility for model users to include parameters that may not be on the list. This will help facilitate a proper calibration of the model's sediment processes, a necessary step in predicting P loss as prediction of P is governed by the accuracy of predictions of both sediment and runoff.

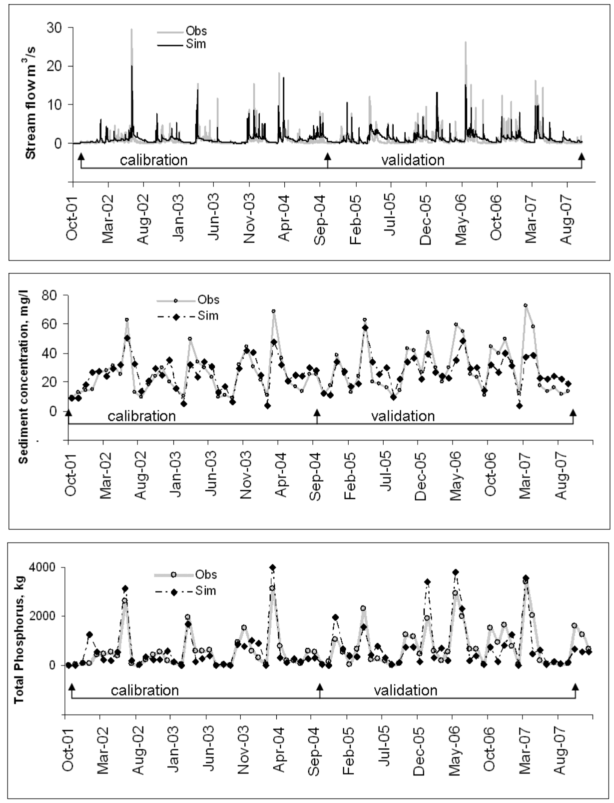


Figure 4. Simulated (Sim) versus observed (Obs) daily stream flow, monthly sediment concentrations, and monthly total phosphorus loads during SWAT calibration and validation periods at the outlet of the Rock River watershed, Vermont.

For total P, only monthly load predictions were compared to the observed data. Based on this comparison, NS values for monthly total P load predictions were 0.7 and 0.6 for the calibration and validation periods, respectively. Total P loads tended to be slightly overpredicted for some months and underpredicted for other months (fig. 4). SWAT-predicted, eight-year average annual loads were 9400 kg of total P and 43,100 tonnes of sediment at the watershed outlet. Overall, SWAT prediction of total P load at the outlet of the watershed were satisfactory, with only 2% error of overprediction for calibration and 10% error of underprediction during validation. Considering the uncertainty involved in predicting runoff and sediment, which in turn are used in predicting total P loss, and the uncertainty of input data related to P application and management (typical planting and tillage dates, manure application rates and times, and others), the overall accuracy of total P load predictions is reasonable for our study objective aimed at identifying CSAs for P loss. It is also worth noting that, as with sediment, model predictions of total P were compared against the observed P values described previously, which in turn were generated from grab samples of P and stream flow that have inherent uncertainty in their collection and analysis (Harmel et al., 2006).

Critical Source Areas for P Loss

As widely accepted and previously noted in this article, CSAs for P loss are affected by the combined effect of P source and P transport factors. The P source factors include variations in soil type and field-specific management practices, such as fertilizer and manure applications, tillage, and harvest practices. The modeling setup in this study watershed was designed to capture these variations on a field-by-field basis. For instance, the variations due to specific soil type and properties were captured by using detailed soil data as input in the model. With regard to variations in field-specific management practices, however, due to the limited information recorded, this study reflects only typical management practices specific to crop type. Also note that the use of typical management practices, such as manure application rate, tillage type and timing, and harvest timing, was acceptable for the objective of this article because most farmers plan and schedule farm activities based on specific crop type. Having said that, P source and P transport variations within fields of the same crops but differing in the underlying soil and slope properties were captured in the modeling process.

Although only 30% of the watershed is row cropped, over 50% of both sediment and total P loss came from corn land, while another 25% and 20%, respectively, came from other row crops (table 2). Spatial maps were generated to demonstrate average annual surface runoff, and sediment and total P loss rates predicted from unique response units (HRUs) for the seven-year simulation period (fig. 5). These spatial maps depict average annual predictions of overland flow and sediment and total P generated from HRUs.

Table 2. Watershed area, sediment load, and total P load by land use type in the Rock River watershed, Vermont.

Land Use	Watershed Area (%)	Sediment Load (%)	Total P Load (%)
Closely grown crops	1.5	5.0	4.0
Corn crops	17.2	52.0	58.0
Development (building, road)	5.6	12.0	6.0
Farmsteads	0.5	3.0	1.0
Forests and rangeland	34.8	1.0	0.4
Hay crops	25.0	1.4	8.7
Pasture	3.1	0.4	2.0
Row crops (other than corn)	11.7	25.0	20.0
Wetlands and water bodies	0.6	0.1	0.0

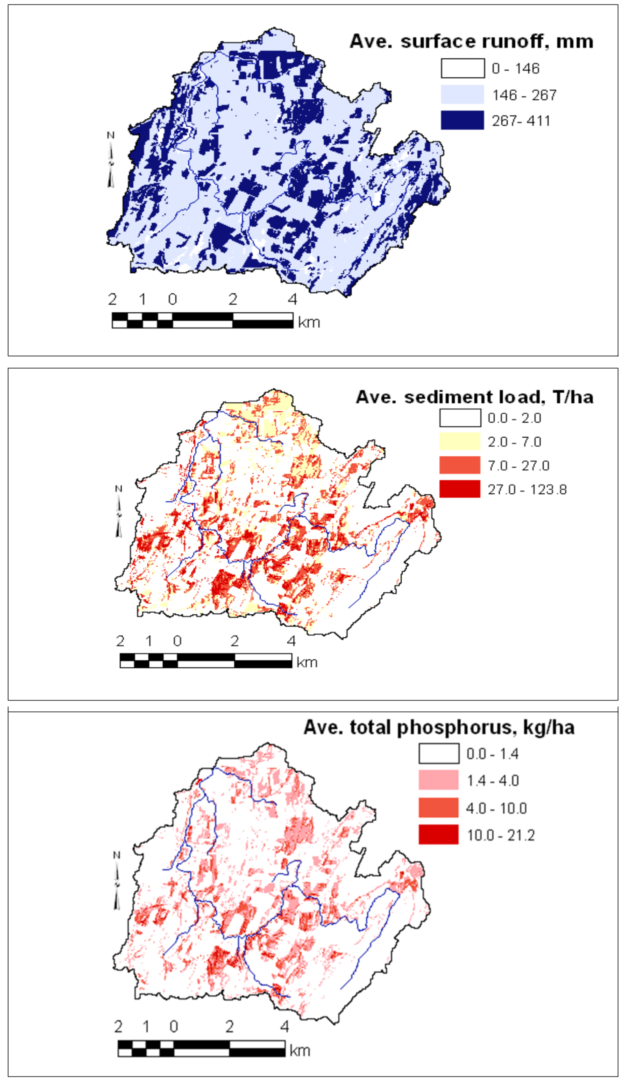
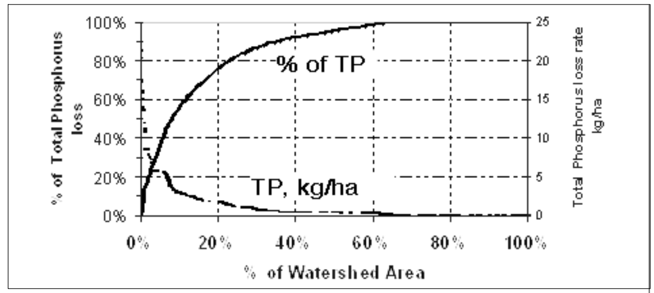


Figure 5. Average annual runoff, erosion, and total phosphorus loss in the Rock River watershed, Vermont, as simulated in SWAT from 2001 through 2007.

As shown in figure 5, surface runoff, and sediment and total P losses vary spatial in accordance with the unique response units (HRUs) comprised of different land use, soil, and slope combinations. Areas shaded with darker color represent larger runoff, sediment, and total P loss predictions, while lighter-colored areas represent smaller predictions of runoff, sediment, and total P. As expected, most surface runoff was generated on soils with low infiltration rate, such as soils in hydrologic groups C and D. In addition, developed land use with low permeability and corn fields were among the largest surface runoff contributors in the watershed. Results confirmed that, primarily, land use and soil combinations govern surface runoff from the landscape. SWAT uses a curve number (CN) method, which is based on the area's hydrologic soil group, land use and cover, and hydrologic conditions, in estimating runoff volume. Once runoff is generated, slope governs the amount and timing of runoff to the stream. The amount of sediment loss from the landscape, besides the runoff, affects the amount of P that is potentially delivered to the stream. As shown in the map depicting the spatial variations of total P loss (fig. 5), larger total P losses correspond to areas with larger sediment and runoff losses. This is most likely because most of the P losses occur via surface runoff (Sharpley et al., 1994), with the majority of total P loss in areas dominated by cultivated land occurring in a sediment-bound, particulate form (Gburek et al., 1996; Fraser et al., 1999). Such spatial data obtained from SWAT demonstrates the model's ability to generate results that are easily transferable to maps and eventually to the ground where planning takes place. This type of spatial representation of areas with higher P loss (or CSAs for P loss) can be used as a guiding map in planning targeted remedial strategies on these CSAs within the watershed. Note that these spatial maps were based on the 2003 CLU crop data layer; hence, careful consideration must be taken when interpreting these results directly on the ground for different crop production years. Due to crop rotations, some fields may be in different crop year than what is represented in the model. Hence, interpretation of the analysis presented in this report must include these considerations.

The maps presented in figure 5 show spatially different ranges of runoff, sediment, and total P losses. For runoff, runoff predictions were classified simply into three ranges to show areas with high, medium, and low runoff. However, it is important to establish threshold values of sediment and P loads for determining CSAs for the respective pollution levels. Threshold loads are values above which losses can be considered too high; these values can be established based on literature, load reduction goals such as TMDLs, soil productivity goal levels, and/or numerical water quality standards. In this study, the threshold value for total P was determined by combining the tolerable soil loss (T) levels for soils in the study watershed (5 to 7 tonnes ha^{-1}) with a suggested upper threshold of 2 kg ha^{-1} total P loss (Sharpley and Rekolainen, 1997). As a result, a total P threshold value of 1.4 kg ha^{-1} was selected to take into consideration both T levels and high P loss values. The location and extent of CSAs of P loss with P loss rates above the threshold values is shown in figure 5.

Additionally, the graphs in figure 6 demonstrate the percentage of watershed area corresponding to the amount and percentage of total P and sediment losses. For both graphs depicting total P and sediment, HRUs were ranked from high to low based on their SWAT-predicted loss rates, and cumulative total P and sediment loads were plotted along with loss rates. Depending on the availability of resources and specific water quality goals, different threshold rates of total P loss can be selected for targeting areas with high P loss risk. Based on the previously selected total P threshold (1.4 kg ha^{-1}), about 24% of the upland watershed area was predicted to produce about 80% of the total P loads (fig. 6). A similar study of CSA identification in five Oklahoma watersheds also reported 34% of total P originated from only 5% of the land area (White et al., 2009). In this study, the same 24% of the watershed area also contributed 91% of the total sediment loads. The majority of these areas were predicted to have sediment loss rates greater than 7 tonnes ha^{-1}, the highest T factor value for soils in the study watershed; others had sediment loss rates ranging from 4 to 7 tonnes ha^{-1}. The soil T factor is a broadly used criterion in land resource management for making sure



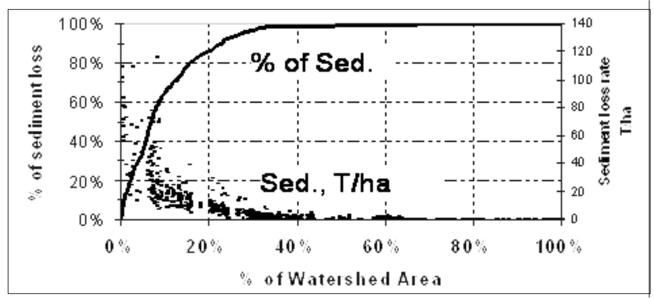


Figure 6. SWAT-predicted rates and percentages of total phosphorus (TP) and sediment losses as compared to area percentage of the Rock River watershed, Vermont as simulated from 2001 through 2007.

that erosion levels do not compromise soil productivity. From the results, some areas with sediment loss rates lower than their respective soil T factors produced larger P losses, indicating that areas with sediment losses less than T may still be of concern with regard to water quality pollution related to P. In summary, this kind of analysis provides decision makers with excellent information on the location of CSAs and their predicted quantities of P loss under current management practices. This provides one method for limited resources to be allocated more efficiently, i.e., reducing a high-priority watershed to a fraction of that area via CSAs, which can then be targeted based on cost-effectiveness of appropriate management practices to achieve a maximum P loss reduction for a minimum cost. Although not included in this study, costs of management strategies can have significant implications in making decisions on choices of management strategies and water quality tradeoffs. Hence, the cost of management practices need to be included in the task of exploring cost-effective management practices with the highest potential of reducing P loss.

Of the 24% watershed area producing higher than 1.4 kg ha^{-1} of total P loss rate, areas of corn, agricultural row crops, farmstead, and developed land (building and roads) constitute 13%, 8%, 0.3%, and 3%, respectively (table 3). Sparse ground cover, erosive soil types, steep slopes, and readily available P contributed to these high total sediment and total P losses. As shown from the detailed output for corn (table 3), magnitudes of total P and sediment loads differ for corn fields that are managed similarly due to difference in soil type and slope. Soils of hydrologic groups C and D and with higher slopes make corn and row crop fields susceptible to runoff, erosion, and P loss. In addition, these fields typically also have larger amounts of readily available P than do other land uses due to applications of manure and P fertilizer. Although not explicitly presented here, in addition to the high P loss rate, corn fields for potential implementation of management strategies can be further selected based on their closeness to

Table 3. Characteristics, by land use, of the portion of the Rock River watershed, Vermont, for which total P loss rates are above the threshold value of 1.4 kg ha^{-1}.

Land Use	Soil Hydrologic Group	Slope Group (%)	Area (%)	Total Sediment Load (%)	Total P Load (%)
Corn crops	D		7.9	25.6	27.2
	C	>15, 8-15, 3-8	4.3	18.8	21.9
	B	>15, 8-15, 3-8	0.6	3.4	3.3
	A	>15, 8-15, 3-8	0.2	0.4	0.5
		Subtotal:	13	48	53
Row crops	D	>15, 8-15, 3-8	2.8	11	6.7
	C	>15, 8-15, 3-8	5	16.3	11
	B	>15, 8-15	0.2	0.8	0.4
	A	>15, 8-15	0.1	0.4	0.3
		Subtotal:	8	28.5	18.5
Farmstead	D	>15, 8-15, 3-8	0.1	0.5	0.2
	C	>15, 8-15, 3-8	0.2	0.6	0.5
	A	8-15	0.02	0.05	0.03
		Subtotal:	0.3	1.1	0.7
Developed land	D	>15, 8-15, 3-8	1	5	2
	C	>15, 8-15	2	7	4
	B	8-15, 3-8	0.1	0.7	0.2
	A	8-15	0.02	0.05	0.05
		Subtotal:	3	13	6.9
Total			24	91	80

streams. Corn fields with higher P loss rates that are close to streams are likely to have higher potential and immediate threat of P loss. Thus, they are recommended to receive higher priority for control management than corn fields farther from the stream but otherwise of similar characteristics.

Conclusion

SWAT was justifiably used in identifying and quantifying CSAs for P losses in the Rock River watershed, in which about 60% of the watershed is agricultural. To generate maps representing these CSAs for P losses that are spatially transferable to the ground, however, care should be taken during the process of HRU generation to purposely design HRUs that depict the desired scale of representation and objectives of a specific project. Overall, results in this study indicate disproportional runoff, sediment, and P loss impacts from various fields of the same land use due to differences in soil and slope. Findings emphasize the benefits of using a systematic methodology, such as SWAT, to identify the areas with higher risks for pollution. This study found that 80% of total P loss occurred from only 24% of the watershed area. Such model-based identification of the high P loss risk areas is expected to help managers and planners in the Rock River watershed in implementing management strategies with limited resources. For example, management strategies, such as cover crop and minimum tillage, can be applied to CSA corn fields instead of across all corn fields in the watershed.

Insights and findings on the characteristics of CSAs identified in this study watershed can be employed in other similar watersheds in the Lake Champlain basin to help achieve the established in-lake water quality standards. The next steps to this effort will be to add uncertainties to the SWAT predictions and to assess cost-effectiveness of potential management practices. Knowing the degree of uncertainty associated with the model outputs may be a vital component in the decision-making process of targeting the most cost-effective conservation practices.

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