# Carbon, Nitrogen, and Agriculture

# Improved Nitrogen Management Utilizing Ground-Penetrating-Radar: A Nine-Year Investigation

Timothy Gish, Craig Daughtry, Andy Russ, Lynn McKee, John Prueger

## Abstract

Water availability and efficient use of nitrogen are critical components of a sustainable and profitable agricultural system. Since nitrogen is typically excessively applied, considerable amounts of nitrogen may leach to and move through the subsurface to surface water resources. Our hypothesis is that knowledge of the subsurface hydrology can be utilized to reduce nitrogen applications by identifying where pathways serve as a subsurface irrigation system. This research was conducted at the U.S. Department of Agriculture–Agricultural Research Service's Optimizing Production Inputs for Economic Enhancement site in Beltsville, MD. In this study, two corn production fields about 4 ha each were studied over 9 years to evaluate nitrogen use efficiency with and without a knowledge of the subsurface water flow pathways determined using primarily ground-penetrating radar (GPR) and digital surface elevation maps. Since the depth to the GPR-identified subsurface water flow pathways typically varied along the pathway, the site has both capillary and lateral flow components. Field B received uniform applications of nitrogen with 34 kg N/ha applied at planting and then about 134 kg N/ha as sidedressing when the corn was about 60–80 cm high. The second field, field D, was under precision management receiving 34 kg N/ha at planting and then 0–134 kg N/ha as variable-rate sidedressing (same time as field B). The amount of N applied in field D, for each 8 × 8 m unit area, at sidedressing depended primarily upon the location and characteristics of the subsurface water flow pathways. Knowing where the subsurface flow channels existed allowed us to apply less N downslope along the subsurface flow pathways where they approached the surface. As a result, the precision N site generally received about 34 percent less nitrogen than the uniform N application site, yet there was no significant reduction in yields. This work demonstrates that knowledge of the subsurface hydrology can improve nitrogen use efficiency and thereby increase farm sustainability.

**Keywords:** hydrology, crop yield, precision farming

## Introduction

Sustainable agriculture is typically defined as an integrated system of animal management and crop production practices that in the long term enhance environmental quality and sustain natural resources while maintaining productivity. Although nitrogen is frequently overapplied, Keeney and Deluca (1993) showed that considerable N loss was occurring on agricultural land well before the widespread use of inorganic fertilizers. As a result, some N loss will occur regardless of agricultural management strategies. However, by improving water quality and productivity as goals, the concept of "sustainable agriculture" will require innovative solutions

Nitrogen is frequently overapplied as insurance against low yields, and that poses a risk to surface and groundwater quality. Jaynes et al. (2001) observed in tile drains (installed at 1.45 m) that nitrate leaching increased with increasing N application. In the lowest level of N applied (57–67 kg N/ha), nitrate losses in the tile drain were typically above the U.S. Environmental Protection Agency maximum contamination level of 10 mg $NO_3$-N/L. Unfortunately, at these lower N

Gish is a soil scientist, Daughtry is a research agronomist, Russ is a remote sensing specialist, and McKee is a support scientist, all with the U.S. Department of Agriculture–Agricultural Research Service, Hydrology and Remote Sensing Laboratory, Beltsville, MD 20705. Prueger is a soil scientist with the U.S. Department of Agriculture–Agricultural Research Service, National Laboratory for Agriculture and the Environment, Ames, IA. Email: timothy.gish@ars.usda.gov.

application rates, corn yields suffered and were significantly lower that the medium and high rates of N applied.

Including a nonlegume winter cover crop into the production management system has been found to reduce nitrate leaching since the cover crop reduces percolation to groundwater and utilizes nitrate that would otherwise leach to groundwater (Francis et al. 1998, Shepherd 1999). Unfortunately, when cover crop planting is delayed due to poor weather conditions the cover crop may not become established well enough to absorb significant quantities of soil water and N (Shepherd 1999). Furthermore, growth of the succeeding crop may be reduced if the cover crop has a high C/N ratio (Francis et al. 1998).

A growing crop management strategy to reduce agrichemical pollution is site-specific or precision farming. Historically, farmers have treated a field as a single unit applying the same nutrient practice to the entire field. However, since soils are inherently variable, a field can typically be divided into discrete areas, with each area managed according to its needs rather than by field averages. Birrell et al. (1996) found that much of the crop yield variability could be explained by the depth to the claypan layer. Depth to the claypan was readily measured using electromagnetic techniques (Sudduth et al. 1995), and nutrient management plans developed on the basis of claypan depth since this feature strongly influences soil water relationships for the crop (Kitchen et al. 1997).

To develop an accurate nutrient management plan, it would be useful to have reliable estimates of water and chemical movement through and along subsurface layers. Traditional methods for assessing the spatial nature of hydraulic properties include the collection of soil core and well log data (Sudicky 1986, Ritzi et al. 1994). These methods are of limited benefit for large fields as only a fraction of the field can be reasonably sampled. Additionally, it is virtually impossible to ascertain the spatial behavior of water and chemical movement using point data because the sampling density of soil core and well log data is considerably below the inherent spatial variability of soil hydraulic properties. As a result, uncertainty associated with estimating water movement where no samples were acquired can be significant.

Soil layers can significantly affect water movement and chemical transport because abrupt changes in texture or density across the boundary of two adjacent layers causes a discontinuity of soil pores. Research has shown that this mismatch of pore entry value and soil hydraulic conductivity can trigger funnel flow (Kung 1990 a and b, 1993; Ju and Kung 1993). Under this condition, uniform matrix flow could converge and form discrete subsurface preferential flow pathways, especially when these soil layers are inclined. Accordingly, Gish et al. (2002) identified subsurface restricting layers (typically a clay lens) using ground-penetrating radar (GPR). The depths to these restricting layers were evaluated and subsurface flow pathways identified. The subsurface flow pathways were then used to show that during a drought year, yields decreased with distance from the GPR-identified subsurface flow pathway (Gish et al., 2005). These studies indicate that with a knowledge of the subsurface stratigraphy a nutrient management plan could be developed that could reduce N inputs without a significant reduction in productivity.

The objective of this research was to determine if a multiyear nutrient management plan can be developed using knowledge of the subsurface hydrology constructed primarily with GPR data.

## Methods

### Site Description

The research site is a 21-ha agricultural production farm located at the U.S. Department of Agriculture Henry A. Wallace Beltsville Agricultural Research Center in Beltsville, MD (near 39°01'44" N., 76°50'46" W.). A variety of data including general soil properties, crop parameters, and geophysical, meteorological, and remotely sensed data are acquired annually on this site, which is identified as OPE3: the Optimizing Production Inputs for Economic and Environmental Enhancement site. One of the principal objectives of OPE3 is to determine field and catchment-scale fluxes of agricultural inputs. The site contains four fields that range from 3.6 to 4.2 ha, each draining into a 1$^{st}$-order stream and riparian wetland and each delimited with earthen berms. The soils are variable but mostly sandy, with the majority being Typic Hapludults, coarse-loamy, siliceous, mesic, and are well drained. The surface soil textures range from sandy loam to loamy sand, have an average organic matter content of <3 percent.

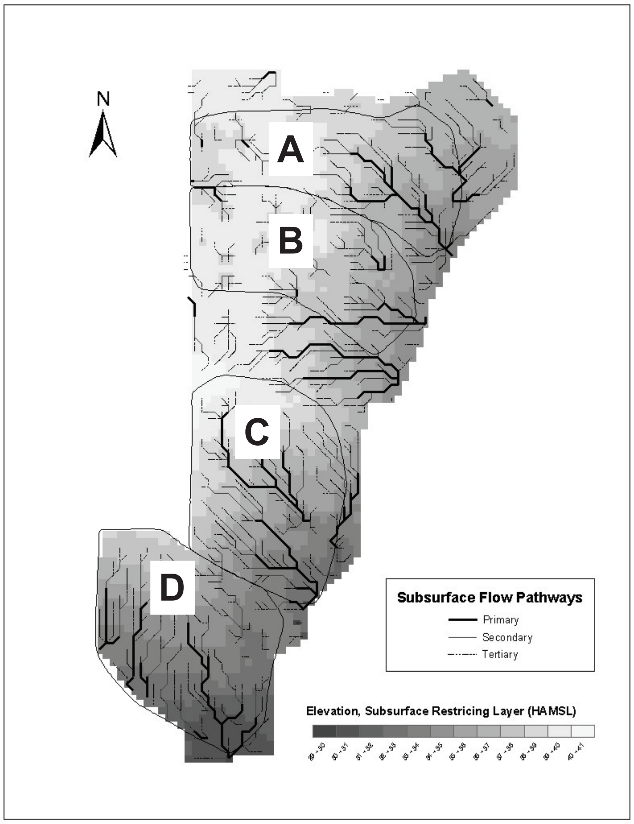


Figure 1. Depth to the subsurface restricting layers and location of GPR-identified subsurface flow pathways.

## Subsurface Flow Pathways

OPE3 field boundaries, subsurface restricting layer elevations, and the corresponding GPR-identified subsurface flow pathways are shown in Figure 1. Specifically, a subsurface interface radar system-2, with a 150-MHz antenna (Geophysical Survey Systems Inc., North Salem, NH) was used to identify subsurface reflections that could represent the depth of soil layers restricting vertical water movement (i.e., clay lenses). Over 40 km of ground-penetrating radar data were acquired for the OPE3 site, and a digital trace of the subsurface reflections were produced using RADAN Software (1999, Geophysical Survey Systems Inc.). The spatial autocorrelation of these subsurface reflections that restrict water movement for the entire research site were determined using GEO-EAS (1991, U.S. Environmental Protection Agency) and $GS^+$ (2001, Gamma Design Software) geostatistical software packages. To determine the elevation of the subsurface restricting layer, the depth of these subsurface reflections was averaged over each 8×8-m cell and was subsequently subtracted from a digital elevation map (DEM) averaged over the corresponding 8×8-m cell. The DEM was developed by analyzing real-time kinematic global positioning system (GPS) data acquired on a 5-m grid over the entire research site (Trimble, Sunnyvale, CA).

The subsurface restricting layers that have been identified with GPR reside between 1 and 4 m below the soil surface (Gish et. al. 2002). However, groundwater above these soil restricting layers can be much shallower. Thus, although the average restricting layer depth at this site is at a depth of 1.5 m, the water table may be well within 1 m of the soil surface. Although Gish et al. (2005) demonstrated that averaged corn grain yields decreased with increasing distance from the subsurface flow pathways (during a drought year) they also showed that there were areas where the restricting soil layers (and water above them) were too deep to influence soil water contents and crop yield. Additionally, since the subsurface flow pathways are three-dimensional, the depth to the restricting layer varies along the length of the GPR-identified subsurface flow pathway. Depressions along the GPR-identified subsurface flow pathway are common, and these depressions form cascading pools of water when the pathways are actively flowing (Figure 2).

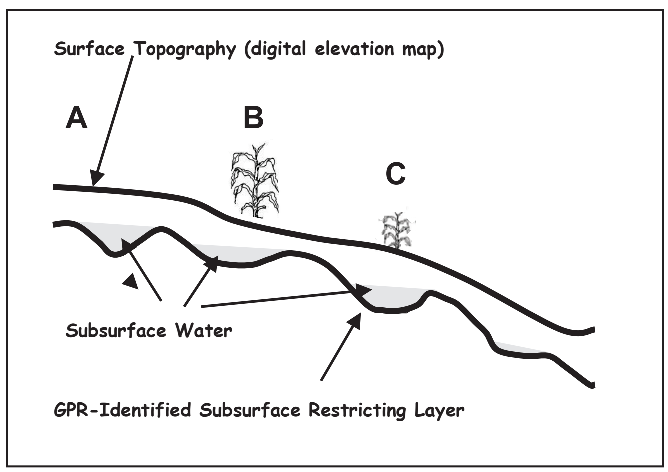


Figure 2. Schematic of a GPR-identified subsurface flow pathway with typical variations in elevation and formation of localized pools.

If there is no flow along the subsurface pathways are then water that has accumulated previously within these localized pools will behave as a local perched water table. As a result, the GPR-identified subsurface flow pathways have both lateral flow and perched water table components.

Figure 2 is a schematic that depicts the effect of the subsurface on corn growth during a drought year. Region A is at the top of the field were the subsurface flow pathways are initiated. Region B represents areas within the field were the subsurface restricting layers have formed pools of subsurface water that may provide water and nutrients to the crop root zone. Region C denotes areas within the field that are located near a subsurface flow pathway but where the pathways are too deep to affect plant growth and yield. Additionally, as more water is likely to drain into a specific GPR-identified pool, less N would need to be applied as side dressing`. In this study, The ARC-GIS (2002, ESRI) hydrologic modeling tools FLOWDIRECTION and FLOWACCUMULATION programs were applied to the raster grid of elevation corrected subsurface topography to determine the amount of water draining into each GPR-identified pool within the field.

## Nitrogen Applications

For each of the 9 years, 34 kg N/ha were banded in fields B and D during planting of corn (*Zea mays* L.). The amount of N applied during side dressing varied from year to year. During the first two years (1998 and 1999), fields B and D received the same N treatment with 134 kg N/ha applied at side dressing (see Table 1 for total N inputs). Beginning in 2000, fields B and D received different N treatments with B representing uniform applications of N and field D the precision N treatment. Side dressing of N generally occurred 4–5 weeks after planting. No data is shown for 2003 because the crop was destroyed during Hurricane Isabelle.

Table 1. Nitrogen application rates for each year.

| Year | Total N applied (kg N/ha) | | Sidedressing N (kg N/ha) | |
|---|---|---|---|---|
| | Field B | Field D | Field B | Field D |
| 1998 | 168 | 168 | 134 | 134 |
| 1999 | 168 | 168 | 134 | 134 |
| 2000 | 168 | 140 | 134 | 107 |
| 2001 | 140 | 98 | 106 | 98 |
| 2002* | 103 | 80 | 69 | 46 |
| 2004 | 172 | 109 | 138 | 75 |
| 2005 | 164 | 121 | 131 | 87 |
| 2006 | 164 | 121 | 131 | 87 |
| 2007 | 164 | 121 | 131 | 87 |

*No data for 2003 are shown as the crop was totally destroyed by Hurricane Isabelle.

The pre-side dress nitrate test (PSNT) was used from 2000 to 2004 in field B. As a result, field B received 34 kg N/ha at planting and the PSNT determined the side dressing N rate (Meisinger et al. 1992). Starting in 2005, however, PSNT values were no longer acquired and a constant side dressing rate of 131 kg N/ha was applied in field B.

Nitrogen side dressing on field B occurred on the same dates as field D for all years. From 2000 to 2004, field D received a side dress N prescription based on the subsurface hydrology and PSNT values. For example, in areas corresponding to regions A and C in Figure 2, the N rate prescribed by the PSNT values were applied. However, in regions within the field that correspond to region B in Figure 1, no nitrogen was applied at side dressing, regardless of PSNT values. Beginning in 2005, PSNT values were no longer acquired, so the N side dressing rate was determined by subsurface hydrology alone. Regarding the subsurface hydrology, the amount of N applied at sidedress was determined in an algorithm that accounted for several factors: (1) the proximity of the nearest GPR-identified subsurface flow pathways; (2) the depth to these subsurface flow pathways; and (3) the amount of land draining into the GPR-identified pools (depicted in Figure 2). Briefly, using Figure 2 as an example, areas within the field that correspond to region A, where the subsurface flow pathway initiated (no convergence of subsurface flow), or region C, where the pathways were located too deep (>3 m), the highest rate of about 134 kg/ha was applied at side dressing. In general, as the regions within the field approached a subsurface flow pathway (vertically or laterally), N application amounts were reduced linearly until the within-field region was within 1 m of the subsurface flow pathway, indicating that no N would be applied at side dressing.

## Yield Monitoring

Corn grain yields for all 8 years were acquired with a yield monitor (AgLeader 2000, Roswell, GA) interfaced with a differential GPS. Yield data were processed to eliminate measurement errors resulting from harvester detours around field instrumentation and other obstacles. The spatial autocorrelation of corn grain yields were determined using GEO-EAS packages. To make direct comparison of yield data to the GPR-identified flow pathways, the GEO-EAS (1991, U.S. Environmental Protection Agency) and $GS^+$ (2001, Gamma Design Software) geostatistical software yield data was then kriged at 8×8 m. In general, corn grain yield values were collected every 1.4 m in the row direction.

## Results

### Field Comparisons

Fields B and D have nearly identical soil textures in the top 0.3 m with an average sand content ranging between 61 and 63 percent. Surface slopes are about 1 percent greater in field D than field B, but the depth of the restricting layer (orthogonal to the soil surface) is similar, about 1.5 m.

For the first two years of this study, fields B and D received the same tillage and agrichemical treatment and as such generated similar yield responses. In 1998, both fields generated a corn grain yield of 3.8 Mt/ha. Although 1998 had precipitation below normal, 1999 was a severe drought (Table 2). As a result, field B generated a corn grain yield of 1.3 Mt/ha while field D generated a yield of 1.5 Mt/ha. Since soil properties, depth to the subsurface restricting layers, and even yields over two years are nearly identical, a direct comparison of the subsequent yield data should be appropriate.

Weather conditions varied a great deal for the next eight years, with total rainfall amounts (from planting to plant senescence) ranging from 0.6 to 3.3 m. During this time, yields in the uniform N treatment varied from 3.4 to 7 Mt/ha. Meanwhile, corn grain yield varied from 3.6 to 7.4 Mt/ha for the precision N field. Figure 3 compares the corn grain yield in both fields for all years except 2003, which was never harvested due to being destroyed during Hurricane Isabelle.

Statistical analysis revealed that there was no significant difference in corn grain yields between the two fields even though the precision N field (D) received much less N at sidedressing. Although both field received 34 kg N/ha at planting, averaged sidedressing on field B was 120 kg N/ha compared to only 79 kg N/ha on field D. As a consequence, field D received about 41 kg/ha less N with no significant reduction in yield, a reduction in sidedress N of over 34 percent.

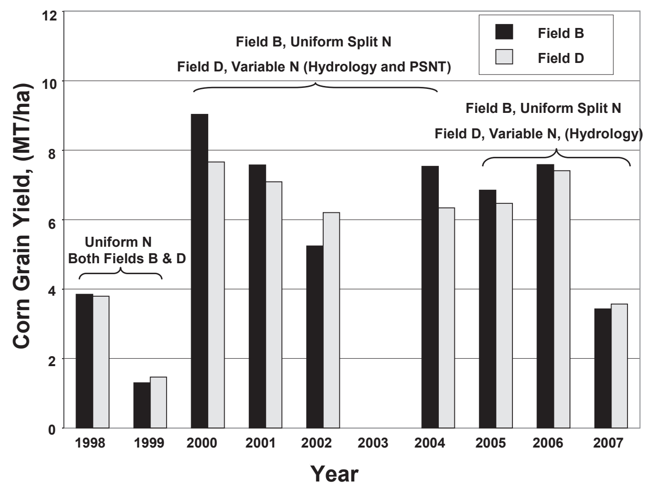


Figure 3. Yield comparison between uniform side dressed N (field B) and precision side dressed N (field D).

Table 2. Rainfall and yields.

| Year | Rainfall* (m) | Corn grain yield (Mt/ha) | |
|---|---|---|---|
| | | Field B | Field D |
| 1998 | 1.1 | 3.8 | 3.8 |
| 1999 | 0.6 | 1.3 | 1.5 |
| 2000 | 2.9 | 9.0 | 7.7 |
| 2001 | 3.1 | 7.6 | 7.1 |
| 2002† | 1.6 | 5.2 | 6.2 |
| 2004 | 3.3 | 7.5 | 6.3 |
| 2005 | 2.6 | 6.8 | 6.5 |
| 2006 | 3.4 | 7.6 | 7.4 |
| 2007 | 1.0 | 3.4 | 3.6 |

*Rainfall reported here was measured from the day of planting until plant senescence.
†No data for 2003 are shown as the crop was totally destroyed by Hurricane Isabelle.

## Conclusions

Corn grain yields from two nitrogen application treatments were compared for 9 years at the OPE3 site in Beltsville, MD. The uniform N treatment received 34 kg N/ha starter N at planting and the bulk of the N at sidedressing, 4–5 weeks after planting. The precision N treatment also received 34 kg N/ha starter N at planting, with the bulk of the N applied at sidedressing. However, in the precision treatment, the sidedressed N was determined primarily as a function of subsurface hydrology. Corn grain yields varied significantly over the nine years, in part because of the amount of rainfall received.

Over the nine years there was no difference in corn grain yields between the two treatments even though the precision N treatment received 34 percent less N at sidedressing. This research indicates that knowledge of the subsurface hydrology determined with ground-penetrating radar can be useful in reducing N inputs without having a detrimental effect on yields.

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# Water, Energy, and Carbon Flux Observations from Agricultural Research Service Watersheds and Agro-Ecosystem Experimental Sites

Joseph Alfieri, John Baker, Gerald Flerchinger, Rebecca Phillips, John Prueger, Russ Scott, Howard Skinner, Keirith Snyder, Bill Kustas, Danny Marks, Jerry Hatfield, Dave Goodrich, Jeff Herrick

## Abstract

Several Agricultural Research Service watershed locations and long-term experimental/monitoring sites have been measuring water, energy, and carbon fluxes using eddy covariance techniques. Several sites have been collecting flux data for the last 5–10 years, while other locations have only recently started a monitoring program. The measurement sites from east to west include corn in Beltsville, Maryland, at the OPE3 watershed; pasture and switchgrass fields near State College, Pennsylvania; corn and soybean rotation in the Walnut Creek and South Fork watersheds near Ames, Iowa; corn and soybean rotation near St. Paul, Minnesota; grassland near Mandan, North Dakota; grassland and shrubland sites at the Jornada Experimental Range near Las Cruces, New Mexico; riparian, grassland, and shrubland in Walnut Gulch watershed and San Pedro river basin near Tombstone, Arizona; grassland and savanna sites in the Santa Rita Experimental Range near Tucson, Arizona; a riparian site near Reno, Nevada; and high elevation shrubland and forest sites in Reynolds Creek watershed near Boise, Idaho. This presentation provides an overview of the measurements conducted at these sites and comparisons of energy flux partitioning, water use, and net carbon exchange during the growing season. In addition, there will be a discussion of possible future multi-location research projects and inter-comparison studies involving the eddy flux measurements and ancillary data.

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*Alfieri, Baker, Flerchinger, Phillips, Prueger, Scott, Skinner, Snyder, Kustas, Marks, Hatfield, Goodrich, and Herrick are research scientists with the U.S. Department of Agriculture, Agricultural Research Service. Alfieri and Kustas, Bldg 007 Rm 104 BARC-W, 10300 Baltimore Ave., Beltsville, MD 20705. Email: joe.alfieri@ars.usda.gov, bill.kustas@ars.usda.gov. Baker, 439 Borlaug Hall, 1991 Upper Buford Cir., St. Paul, MN 55108. Email: john.baker@ars.usda.gov. Flerchinger and Marks, Ste. 105, 800 Park Blvd., Boise, ID 83712. Email: gerald.flerchinger@ars.usda.gov, daniel.marks@ars.usda.gov. Philips, 1701 10th Ave. SW, Box 459, Mandan, ND 58554. Email: rebecca.phillips@ars.usda.gov. Prueger and Hatfield, 2110 University Blvd., Ames, IA 50011. Email: john.prueger@ars.usda.gov, jerry.hatfield@ars.usda.gov. Scott and Goodrich, 2000 E. Allen Rd., Tucson, AZ 85719. Email: russ.scott@ars.usda.gov, dave.goodrich@ars.usda.gov. Skinner, Bldg 3702, Curtin Rd., University Park, PA 16802. Email: howard.skinner@ars.usda.gov. Snyder, 920 Valley Rd., Reno, NV 89512. Email: keirith.snyder@ars.usda.gov. Herrick, Rm 250, 2995 Knox St., Las Cruces, NM 88003. Email: jeff.herrick@ars.usda.gov.*

# Integrating Watershed- and Farm-Scale Models to Target Critical Source Areas While Maintaining Farm Economic Viability

Lula T. Ghebremichael, Tamie L. Veith

## Abstract

Nonpoint source pollution from agriculture and the effects best management practices for mitigation are commonly evaluated based on hydrologic boundaries using watershed models. However, management practice effectiveness is affected by which of the feasible practices are actually selected, implemented, and maintained. It is increasingly recognized that alternative management practices to mitigate nutrient losses from agricultural watersheds are applied at the field and farm levels and are usually selected and maintained at the farm level. To be successful, watershed- and farm-scale models must be combined in such a way that environmental concerns, such as identification and mitigation of critical source areas, are addressed while farm production systems are maintained or improved. This study develops a modeling framework for integrating watershed- and farm-scale models that is based on experience from numerous location-specific studies at both scales in the northeastern United States.

**Keywords:** critical source area, model scale, net profit, phosphorus balance

## Introduction

Targeting critical source areas (CSAs) of pollution for best management practices (BMPs) is important in successfully controlling nonpoint source pollution (Walter et al. 2000, McDowell et al. 2001, Weld et al. 2001). Critical source areas are relatively small proportions of a watershed that contribute disproportionately high pollutant loads to nearby streams (Gburek and Sharpley 1998, Pionke et al. 2000). Many studies have demonstrated the potential of watershed-based simulation models and geographic information systems (GIS) in assessing pollutant losses from CSAs and associated BMP effectivenesses (Zollweg et al. 1996, Secchi et al. 2007, Busteed et al. 2009). Watershed-scale models, simulating pollutant transport to water bodies, commonly involve representations of complex watershed systems based on hydrologic boundaries. These models use input data of physical landscape properties taken from geodatabases (e.g., digital elevation models [DEMs], soil maps, property lines, and land cover data). Despite the environmental potentials for watershed-scale tools to aid in targeting, these tools are limited in practical application by conservation specialists for on-farm CSA delineation and BMP targeting. A few of the challenges can be mentioned.

First, information acquired from these tools is not easily transferred into simplified forms suitable for interpretation by conservation specialists involved with practical aspects of pollution control. Transferring CSA-related findings obtained from hydrologic-scale models to individual farms in a multi-farm and multi-owner watershed remains particularly challenging. Second, BMP evaluations made by watershed models are based primarily on environmental performance, without considering economic and environmental feasibility at the farm-system level. Third, most watershed model tools lack a detailed representation of farm system changes (i.e., labor, resources, and animal feed availability) that are core influencers of farm sustainability and water quality conditions.

To use these tools for practical applications in delineating CSAs and targeting on-farm BMPs, a framework is needed that (1) transfers CSA-related findings obtained from complex models into forms that can be applied at a field level and then into farm-level plans, (2) evaluates farm-scale CSAs and associated mitigation measures with regard to their feasibility and

Ghebremichael is an assistant research agricultural engineer with Pennsylvania State University. Veith is an agricultural engineer with the U.S. Department of Agriculture–Agricultural Research Service, Pasture Systems and Watershed Management Research Unit, Bldg. 3702 Curtin Rd. Both at University Park, PA 16802. Email: tamie.veith@ars.usda.gov.

economic aspects, and (3) incorporates farm systems and farm-level plans into watershed-based tools to assess their effects on the quality of larger water bodies. This study discusses and demonstrates a comprehensive modeling framework that meets these needs by integrating watershed- and farm-level assessments. Integrating the two scales allows environmental concerns to be addressed while the farmers' production systems are maintained or improved. The framework is demonstrated by combining portions of previous studies from the northeastern United States that used the Soil and Water Assessment Tool (SWAT, Neitsch et al. 2002) and the Integrated Farm System Model (IFSM, Rotz et al. 2011).

## Modeling Framework

The modeling framework (Figure 1) aids in the design of environmentally targeted BMPs in agricultural watersheds such that they are also economically viable at the farm level. The watershed-level assessments are driven by the environmental quality goal, while the farm-level assessment is primarily driven by the farm sustainability goal. The framework applies a tiered approach in identifying CSAs at a watershed scale and in planning targeted BMPs at both watershed and farm scales. In task 1, CSAs of pollution that should receive higher priority for potential BMPs are identified. Then, in task 2, potential BMPs needed to treat these CSAs are evaluated at a watershed scale with respect to their potential for preventing water pollution. Both tasks use a hydrologic watershed-level water quality model such as SWAT. CSA data obtained from the watershed model are simplified into a form applicable at the field-level and then into farm-level plans. When modeling is performed with known field boundaries and land ownership, CSAs can be specifically located, and key land owners can be encouraged to participate in targeted nonpoint source pollution control programs. Otherwise, CSA characteristics identified from the model can be developed as a reference; then, by performing field surveys or farm-by-farm assessments, farm fields can be checked against the reference for similarity in characteristics. Once these farm fields are identified, task 3 applies a whole-farm model, such as IFSM, to assess farm-specific feasibility and the economic and environmental effects of implementing the CSA BMPs identified in task 2. Task 3 also incorporates a farm-level assessment that includes farmers' inputs in the process of planning effective CSA BMPs. Finally, task 4 goes back to the watershed level to evaluate the collective effects of farm-level BMPs on the water quality of streams and water bodies fed by the watershed. In addition, some farm factors that are important at a local farm scale (such as labor availability and animal rations), but that are not easily represented at the watershed scale where broader hydrologic processes are modeled, are reevaluated for their effect on watershed-level water quality by integrating farm-scale results across farms.

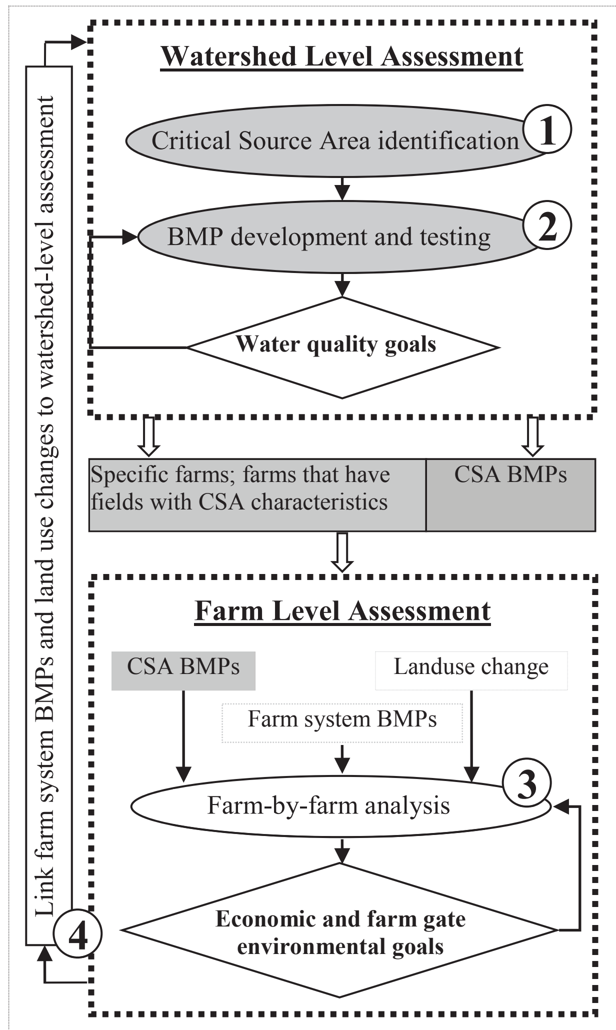


Figure 1. Modeling framework integrating watershed-level (shaded) and farm-level (unshaded) assessments.

Integrating watershed- and farm-level assessments ensures not only that targeted water pollution preventive managements planned at a watershed scale can be linked to farms, but also that farmers' management decisions and BMPs can be tied more directly to downstream pollution of the streams and water bodies. The modeling framework is a comprehensive system approach that incorporates multiple objectives of water quality and farm profitability at appropriate hydrologic and management scales. It can be used to guide implementation of targeted strategies that are both environmentally and economically sustainable.

## Typical Application

The modeling framework demonstration draws from previous studies of a 163-ha watershed that encompasses a single 102-cow dairy farm (R-farm). Various watershed- and farm-scale modeling studies have been done in the R-farm watershed to address phosphorus (P) related water quality problems while maintaining the farmer's economic viability.

### Task 1: Identify CSAs for Targeting

When using SWAT to model a watershed, the hydrologic response units (HRUs), which are composed of distinct soil, land use, and slope combinations, become the building blocks of the CSAs. HRUs must be transferred to the field level to be used for practical application because the field is the smallest scale recognized by farmers and planners at the ground level. Gitau and Gburek (2005) provide an example of the most direct way to link HRU predictions to specific fields. In SWAT, they used field-distinct land use and detailed field-level management input data to represent the R-farm watershed. With each field uniquely coded and represented by several HRUs, they then calibrated SWAT with respect to streamflow, sediment, and total P (TP) losses and identified variable TP losses by HRU within the fields (Figure 2A).

In this paper, field-by-field based average TP losses were estimated by calculating area-weighted averages of the HRU-based TP losses within each field (Figure 2B). Because these model predictions are field specific and ownership of the fields is known, these predictions can be directly used in planning targeted remedial strategies for this farm. However, when crop fields are in rotation, the rate of TP loss from a particular field may vary from year to year depending on the type of crop and associated management (see graphs for 1993, 1994, 1995 in Figure 2). Therefore, it is important to recognize these year-to-year spatial and temporal variations when interpreting model outputs for practical use.

In many cases, watershed modeling efforts involve land use input data that may not be field specific and (or) management input data that reflect typical practices obtained from extension personnel or other agencies working with farmers. Even when field-specific data are available, the number of fields in larger watersheds may be too large to identify the owners explicitly and represent them in the model. In these cases, it may be necessary to extract important information from modeling outputs regarding specific landscape characteristics, including land use, soil types, and slope, that are likely to result in CSAs. When farm fields and land uses with characteristics similar to these modeled CSAs are identified, they can be selected as priority fields for further analysis and targeting.

### Task 2: Evaluate Watershed-Level BMPs

Once priority CSAs for targeting are identified, the next step is to assess and prioritize BMPs needed to remediate each CSA based on the BMPs relative effectiveness toward meeting pollution reduction goals. For example, when a no-till management practice was imposed on all corn and alfalfa fields from 1993 to 1995, SWAT predicted a 15 percent reduction in TP losses compared to the baseline condition (no-till; Figure 3). In addition, the watershed-level SWAT prediction for converting corn to grass (Ghebremichael et al. 2008) reduced TP losses by 9 percent from the baseline (no-corn; Figure 3). This process of BMP analysis continues with as many individual BMPs and combinations as possible until the target water quality goal is achieved.

### Task 3: Evaluate Farm-Level CSAs and BMPs

For environmentally-sound measures to be potentially implemented by farms, they have to be feasible for both their practical and economical aspects. Task 3 uses IFSM, a farm-scale model, to assess how BMPs designed at the watershed level affect different factors of the farm production system and its profitability. This analysis should be performed on selective farms identified as critical in Tasks 1 and 2.

Strategies evaluated at a watershed level for their environmental benefits need to be reevaluated at the farm level. For example, a farm-level evaluation of the watershed-level strategies of no-till corn fields and of converting corn land to grass production was developed for the R-farm, which is the only farm within the R-farm watershed. Using IFSM, Ghebremichael et al. (2007) predicted negative economic consequences to the R-farm when corn land was converted to grassland. Although the strategy reduced TP loading at the watershed level, IFSM predicted a $68/cow/yr decrease in farm profit (Table 1).

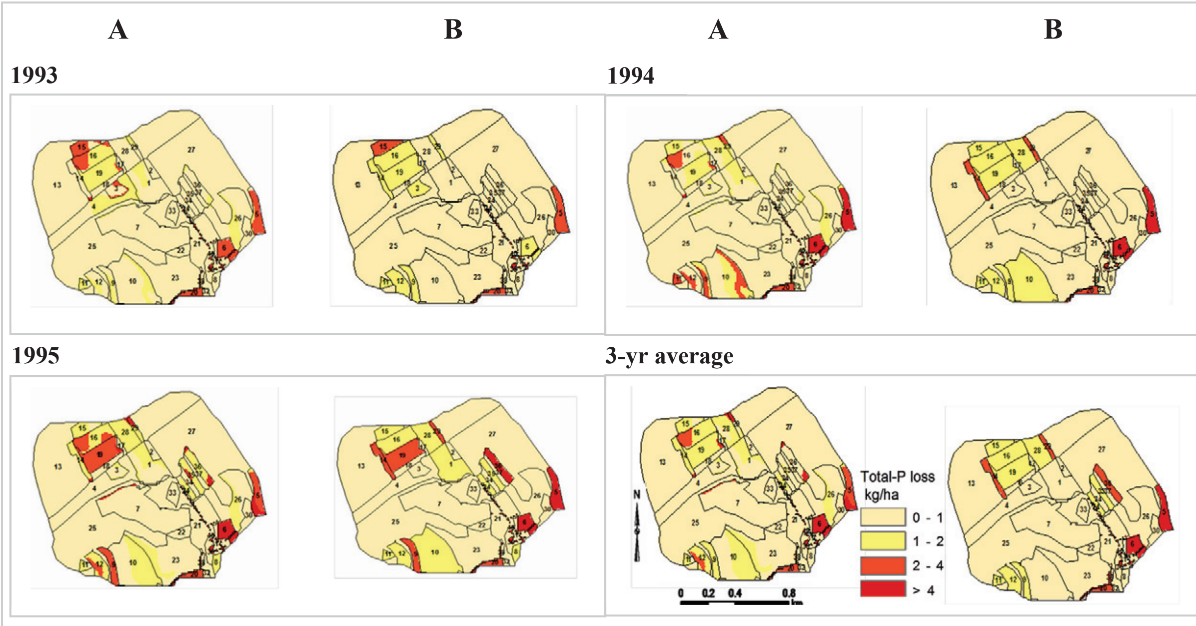


Figure 2. Predicted average total-P losses for the R-farm watershed (A) by hydrologic response units (HRUs) as output by SWAT (Gitau and Gburek 2005), and (B) by fields, calculated as the HRU weighted averages.

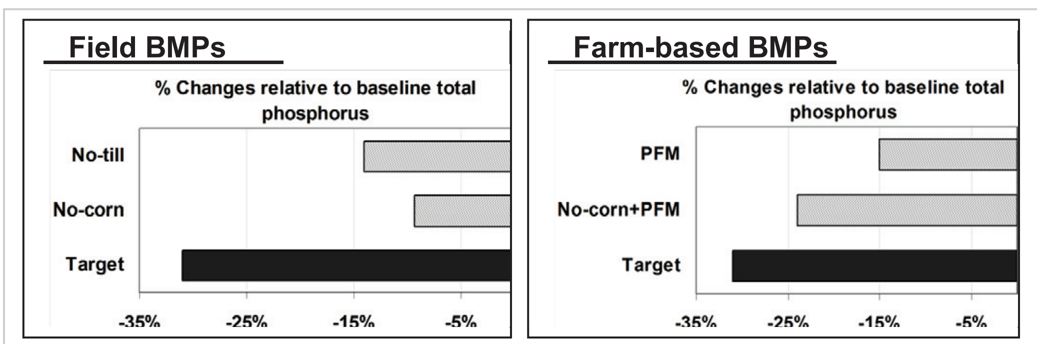


Figure 3. SWAT-predicted effectiveness for two management practices for the R-farm watershed compared with a 31 percent target phosphorus reduction from the baseline. (PFM, or Precision Feed Management, reduces dietary phosphorus and increases forage productivity and utilization.)

Table 1. IFSM-predicted outputs for a baseline scenario and alternative management scenarios for the R-farm.

| | Baseline[2] | Change in value[1] as compared to baseline | | | |
|---|---|---|---|---|---|
| | | No-corn[2] | No-till[3] | PFM[2] | PFM + No-corn |
| Environmental aspects of the farm | | | | | |
| P balance, kg/ha | 9.6 | +1.8 | 0 | –9.6 | –9.8 |
| Economic aspects of the farm, $/year/cow | | | | | |
| Milk and animal income | 3,318 | 0 | 0 | 0 | 0 |
| Total production cost | 2,880 | +68 | –43 | –237 | –253 |
| Cost of production | 2,152 | –43 | –43 | +98 | +64 |
| Cost of purchased feed | 728 | +111 | 0 | –335 | –318 |
| Farm net return | 438 | –68 | +43 | +237 | +253 |

[1]change in value = alternative scenario value – baseline scenario value
[2]data from Ghebremichael et al. (2007); No-corn scenario changed all corn land to grass; PFM (Precision Feed Management) reduced dietary phosphorus and increased forage productivity and utilization
[3]data from Ghebremichael et al. (2009); No-till scenario removed the conventional tillage from the corn land

The predicted reduction in farm profit was due to an increase in purchased animal feed as more feed energy was required to offset reductions in on-farm corn silage production. Also, as more P was brought onto the farm in the increased feed purchases, the predicted P surplus increased slightly.

However, switching from conventional to no-till corn (Ghebremichael et al. 2009) slightly increased the farm's net return compared to the baseline level by lowering production costs, including fuel, tillage equipment, and labor (Table 1). Because Task 2 also predicted that the no-till practice would reduce TP losses from the watershed, the no-till BMP positively addresses both the water quality and farm economic goals. Conversely, some management solutions planned at a watershed level, such as conversion of corn land to grass production, may have negative farm-level consequences. Such negative consequences are likely to hinder successful BMP adoption by farmers unless compensatory changes can be made elsewhere on the farm.

For example, as demonstrated by Ghebremichael et al. (2007), strategies of increasing forage productivity and utilization in animal diet and reducing dietary P can be added to the strategy of converting corn land use to grass production in order to lessen the negative economic effects and address the farm's impending P imbalance. With these strategies combined, Ghebremichael et al. (2007) predicted increased farm net return as the farm utilized more on-farm produced forage and reduced purchased dietary P supplements (Table 1). As the farm used more on-farm produced feeds and less purchased feeds, the P imported through feed also decreased, resulting in a reduced farm P surplus, which is a potential root cause for soil P buildup and subsequent loss in runoff.

### Task 4: Reevaluate Farm-Level BMP at the Watershed Scale

Finally, combined effects of farm system and (or) farm-level land use changes on watershed-level water quality should be assessed using watershed-scale tools. Data from farm-level modeling can also be used to supplement inputs to watershed models. For example, as demonstrated by Ghebremichael et al. (2008) through SWAT modeling, farm-level changes that increased forage productivity and decreased dietary P levels were predicted to be environmentally beneficial by reducing P loss at the outlet of the R-farm watershed (PFM in Figure 3).

In the same study, when these strategies were complemented with the strategy of converting corn land use to grass production, SWAT reaffirmed a positive environmental effect by predicting reduced P losses at the watershed outlet (Figure 3). To use SWAT in evaluating farm system changes that are not directly included in the SWAT processes, information resulting from IFSM simulations were used. For example, IFSM was used to determine the change in P content of manure as a result of altering dietary P in cow feed. Then, changes in dietary P in SWAT were modeled by representing the consequential effects in the concentrations of different P forms in the applied manure.

Task 4 of the modeling framework helps assess the expected environmental effects at a watershed level resulting from the implementation of farm-level land use changes and other BMPs. It also helps evaluate collective effects of the farmers' management decisions and BMP implementations on the water quality of downstream rivers and water bodies.

## Conclusions

In this paper, a modeling framework integrating appropriate hydrologic and farm scale tools is described and demonstrated for a small watershed in the northeastern United States. The framework provides a guideline for developing and implementing targeted agricultural management strategies that are both environmentally and economically sustainable to the farmers and to the watershed. The modeling framework applies a tiered approach in identifying CSAs at a watershed scale and planning targeted measures at both watershed and farm scales.

Examples are provided for transferring CSA-related findings obtained from complex watershed models into forms that can be applied at a field level and then into farm-level plans. The integration of watershed- and farm-scale models allows an all-inclusive assessment of CSAs and associated measures for both watershed-level strategic planning and farm-level tactical management within an agricultural watershed. The integration of watershed and farm models also allows the transfer of important information across scales.

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