Using Carbon Offsets to Fund Agricultural Conservation Practices in a Working-Lands Setting

Carson J. Reeling[†] **and Benjamin M. Gramig**[‡]

Purdue University
Department of Agricultural Economics
403 West State Street
Lafayette, IN 47907

[†] **creeling@purdue.edu**
(760) 920-7179

[‡] **bgramig@purdue.edu**
(765) 494-4324

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Abstract

The nitrogen cascade concept indicates that agriculture serves as a significant link between emissions of the potent greenhouse gas (GHG) nitrous oxide and losses of nitrate-N to surface waters. Conservation practices have the potential to exploit this link, as their implementation is found to reduce fluxes of GHGs and nonpoint source (NPS) water pollution. Several studies have recognized this link and have documented the potential to improve environmental quality through the use of programs which retire land, the cost of which can be offset by the sale of carbon credits. However, the ability to use land for both agricultural production and environmental conservation is important. As such, this study provides a novel analytical framework that is used to examine the potential for implementing agricultural conservation practices to reduce NPS water pollutants and fluxes of GHGs in a working-lands setting. The extent to which carbon pricing can affect practice implementation costs and the optimal distribution of these practices throughout the watershed is also explored. Results from this study indicate that carbon offsets can sharply reduce conservation practice implementation costs and therefore have the potential to reduce greater amounts of NPS pollution for a given cost of implementation. This conclusion has significant implications for policymaking, particularly with regard to using market mechanisms to improve water quality in watersheds where markets have historically been unsuccessful. However, this study found that the optimal allocation of practices was heavily reliant on fertilizer management, which is difficult to enforce in practice.

Keywords: *greenhouse gases, nonpoint source pollution, agricultural conservation practices, DAYCENT, SWAT, genetic algorithm*

1. Introduction

Nitrogen (N) abounds in the environment and is especially prevalent in agricultural ecosystems. Most N that enters the agroecosystem comes from or is applied to the soil. Biological N fixation contributes to the roughly 1,600 kg N in the top twenty centimeters of the soil profile of each acre of prairie soil in the Corn Belt, although only a small fraction of this is in a form that is available to crops (Cassman, et al 2002). N placed on the land as fertilizer adds to this sum. Fertilizer N is highly reactive in the agroenvironment and can enter the ecosystem surrounding the field via numerous loss pathways, including surface waters and the atmosphere (Galloway, et al 2003).

By far the greatest loss pathways are air and water; Galloway, et al (2003) estimate that, of the 170 Tg N per year that enter the agroecosystem worldwide, 121 Tg N per year are lost to air and water. The remainder is lost to human and animal consumption of crops. N lost to the air usually takes the form of oxides of nitrogen (NO_x, N_2O), ammonia (NH_3), and N_2, a nonreactive species. Many of these forms of N are associated with negative environmental and economic effects. NO_x and NH_3 cause myriad health damages including mortality and major and minor respiratory problems which, especially in populous regions, have huge economic implications (Birch, et al. 2011). N_2O is an extremely potent greenhouse gas (GHG) which has nearly three hundred times the global warming potential of carbon dioxide (Gross, et al. 2008). N lost to water can enter both surface and groundwater in the form of nitrate (NO_3^-). Consequences of N losses to surface waters are particularly wide-reaching; examples of these include the Gulf of Mexico Hypoxic Zone, a region of oxygen-starved water that forms annually off the coast of Alabama, Louisiana, Mississippi, and Texas (Rabalais, et al. 2001; NOAA 2010).

Row-crop agriculture is a major contributor to reactive N fluxes, particularly in Indiana. Goolsby, et al. (2001) estimate that the Wabash River Basin – which covers the majority of Indiana – delivers about 1,580 kgN km^{-2} annually to the Gulf of Mexico. Other researchers have demonstrated that various land management practices such as cover cropping, no-till, and fertilizer management can influence fluxes of N_2O to the atmosphere and can also impact rates of carbon sequestration (Li, et al. 1995; Wagner-Riddle and Thurtell 1998; Six, et al. 2004; McSwiney and Robertson 2005; Kim and Dale 2008). Recognizing that agriculture acts as a source of both GHG fluxes and water quality impairment, several researchers have attempted to improve environmental endpoints such as water quality and wildlife habitat by proposing innovative policy measures that support the implementation of conservation practices like land retirement and afforestation (Dwyer, et al. 2009; Mehan III, et al. 2009). Because idle land can sequester carbon dioxide, these practices can be funded through carbon offsets.

While land retirement programs such as the Conservation Reserve Program are effective in helping to abate water pollution and GHG fluxes, increasing demand for food and grain for biofuels indicates that the ability to pursue goals of agricultural production and environmental conservation jointly will be important for the future of agriculture. As such, the goal of this study is to assess the potential to improve environmental quality through the use of working-land conservation programs funded by carbon offsets. A novel ensemble modeling framework for the analysis of environmental effects of agricultural land management practices is proposed. The biophysical modeling framework is combined with an optimization model to derive the optimal set of conservation practices for minimizing both cost of practice implementation and pollutant yield in an intensely-farmed 8-digit Midwestern watershed, the Wildcat Creek Watershed (WCW). Using this framework, it was found that agricultural land management practices have a significant effect on fluxes of GHGs and agricultural nonpoint source NPS pollution in the WCW and that funding practice implementation with carbon offsets has the potential to drastically reduce the cost of achieving a given level of NPS pollution.

The following section describes the biophysical and optimization models that comprise the ensemble framework. The third section applies the framework to the WCW and presents results from the analysis. The final section provides conclusions and a discussion of the policy implications of the research.

2. Methodology

The ensemble modeling approach employed in this paper combines the outputs from GHG and hydrologic simulation models for use as inputs to an optimization model. The optimization model can be used to determine the effect of various carbon offset prices on pollution abatement and practice implementation cost.

Modeling the GHG emissions reductions from various conservation practices requires the use of a model that can simulate the soil N and carbon dynamics that result from various land management practices at the field scale. A model that has been widely used for this application is Colorado State University Natural Resource Ecology Laboratory's CENTURY model (Metherell, et al 1993). CENTURY has been shown to be accurate in simulating changes to soil organic matter in Midwestern soils under various land management practices and crop rotations common to the region (Del Grosso, et al. 2001). DAYCENT v4.5, a submodel of CENTURY that runs on a daily rather than monthly timestep (NREL 2011), can robustly estimate the fluxes of the trace gases nitrous oxide (N_2O) and methane (CH_4) from land to the atmosphere (Del Grosso, et al 2005). DAYCENT has also been found to be more accurate in predicting N_2O

fluxes than simple UN International Panel on Climate Change emissions coefficients (Delgado, et al. 2010). For these reasons, DAYCENT v4.5 was selected for use in estimating the fluxes of GHGs that result from farm-level land management practices. The practices modeled here include no-till farming (NT), reduced fertilizer application (FM), the implementation of a cover crop (CC), and all possible combinations of these practices. These practices were included in this study because each has been found to have some effect on both NPS pollution and GHG emissions (Angle, et al. 1984; Mannering, et al. 1985; Wagner-Riddle and Thurtell 1998; Six, et al. 2004; McSwiney and Robertson 2005; Kim and Dale 2008). "No-till" farming indicates continuous no-till for both corn and soybeans. "Fertilizer reduction" in this study means that total N applied to the crop, including starter N and the N contained in diammonium phosphate (18-46-0), is reduced from 185 lbs ac^{-1} to 160 lbs ac^{-1}. "Cover crop" indicates the presence of an annual ryegrass cover crop that is planted immediately after grain harvest and burned down with herbicide before planting the following spring.

Table 1. Conservation practices modeled

BMP	**No-till** [a]	**Fertilizer reduction** [b]	**Cover crop** [c]
Baseline [d]	-	-	-
No-till (NT)	X	-	-
Cover crop (CC)	-	-	X
Fertilizer management (FM)	-	X	-
NT+CC	X	-	X
NT+FM	X	X	-
CC+FM	-	X	X
NT+CC+FM	X	X	X

[a] *Denotes continuous no-till*
[b] *160 lbs ac^{-1} total N fertilizer applied, compared with 250 lbs ac^{-1}*
[c] *Denotes presence of annual winter ryegrass cover crop*
[d] *This is the baseline practice relative to which all other BMPs will be compared*

Information on 41 dominant soil types from throughout WCW was collected using data from the USDA Web Soil Survey (USDA 2009). DAYCENT was used to simulate the changes in GHG fluxes that result from the implementation of the seven conservation practices shown above for each of the 41 soils. Using GIS, the area-weighted changes (based on soil type) in average GHG flux from each of the conservation practices were calculated.

Analysis of the effects of agricultural land management on a region's hydrology requires a watershed-scale model capable of simulating the complex relationships between landscape characteristics and nutrient fluxes. The Soil and Water Assessment Tool (SWAT) is widely used and well-suited to researching the effects of land management strategies on a region's hydrology (Arnold, et al 1998). SWAT is particularly appropriate for simulating nutrient fluxes from tile-drained agricultural watersheds (Singh, et al 2005; Du, et al 2006). This study employs a SWAT model of the WCW developed by Cibin Raj and Indrajeet Chaubey of Purdue University's Agricultural and Biological Engineering Department. The implementation of each of the seven conservation practices was modeled using SWAT. The resulting average per-hectare changes in NPS pollution (total nitrogen [TN], total phosphorus [TP], and total suspended sediment [TSS]) were then calculated for each practice.

Although SWAT is capable of modeling the effects of land management strategies in an agricultural watershed, using the model alone to determine the spatial allocation of practices that would optimize the placement of BMPs in a watershed would be a tedious iterative exercise. Several researchers have recently used watershed models such as SWAT in conjunction with a search optimization technique known as a genetic algorithm (Srivastava, et al. 2002; Jha, et al. 2009; Maringanti, et al. 2009a; Rabotyagov 2010). Genetic algorithms employ the concept of the biological processes of evolution in order to optimize some objective function and generally consist of three operations: selection; crossover; and mutation (Mitchell 1998). The algorithm is initialized when a population of potential solutions to the optimization problem – referred to as "chromosomes" – is randomly generated. These chromosomes, representing different spatial allocations of conservation practices in the watershed, are entered into the objective function and the individual objective values are compared. The chromosomes that are determined to best optimize the value of the objective function are chosen for crossover. During crossover, the chromosomes are combined to form "child" chromosomes which contain features of the original "parent" chromosomes. These child chromosomes undergo a process of mutation with a set probability. This is used to maintain genetic diversity from the parent solutions (Maringanti, et al 2009a). The process is repeated for a set number of generations (iterations), which is generally determined to be the point at which the difference in the value of the objective function is almost imperceptible for the given set of chromosomes. This population of "ultra-fit" chromosomes is then assumed to be the optimal solution to the objective function. Evolutionary fitness in the context of economics can be thought of as a strategy that yields the best outcome, which might be cost-effectiveness of abatement or maximum net benefits. The structure of the objective function determines how the set of ultra-fit chromosomes are selected.

An advantage to genetic algorithms is their ability to search massive quantities of potential solutions in order to find the optimal one. Such a technique is useful for optimizing conservation practice allocation within an agricultural watershed, as several practices can potentially be employed in each field, and over the course of an entire eight-digit watershed, the potential number of allocations is daunting; for example, a watershed with 400 farm fields and 7 potential conservation practices for each field can have 7^{400} potential practice allocations. Further, genetic algorithmss are helpful in optimizing models that are composed of highly nonlinear and discontinuous functions. Linear and nonlinear programming methods optimize an objective function over a gradient of decision variable values. For highly complex and nonlinear models, this often results in the determination of local – rather than global – optima. Genetic algorithms select values for comparison over the entire universe of potential solutions, making them better able to solve complex models for global optima.

A variant of the genetic algorithm that is particularly well-suited for use in BMP implementation in a watershed is a multiobjective genetic algorithm (MOGA). Traditional genetic algorithms use a single objective function to determine the relative fitness of a child chromosome. However, because the decision about whether to implement a conservation practice is based on both its cost and the effectiveness of pollution control, a single objective function will not suffice. As such, a MOGA can be used to find a set of optimal solutions known as the "Pareto frontier," which takes into account the tradeoffs between competing objective functions (Fonseca and Fleming 1993). It should be noted here that the Pareto frontier that results from this model is distinct from an economic Pareto frontier in that the monetized benefits from reducing water pollution and GHG emissions are not accounted for. Rather, the model optimizes based solely on the total pollutant load emitted and practice implementation cost. In order to maintain the distinction between economics and computer science, from this point on the Pareto frontier will be referred to as a "tradeoff frontier," following the precedent set by Rabotyagov, et al. (2010).

Maringanti and Chaubey (2009b) develop a MOGA that uses output from a SWAT model of the WCW to optimize the spatial allocation of various conservation practices at the least cost. As mentioned above, MOGAs typically generate a tradeoff frontier that demonstrates the tradeoffs between the two objective functions. For the MOGA developed by Maringanti and Chaubey, the dual objective functions over which practice placement is optimized are given by

$$\min_{\gamma}\{[f(X)] \wedge [g(X)]\}\,\forall f \in [P, N, S], \quad (1)$$

where f(X), the total reduction of the pollutant phosphorus (P), nitrogen (N), and/or sediment (S) is expressed as the weighted average over the watershed,

$$f(X) = \textstyle\sum_{x\in X}[P(x) \times A(x)][1 - R(x)]/\textstyle\sum_{x\in X}[A(x)]. \quad (2)$$

The net cost of practice allocation is expressed as

$$g(X) = \textstyle\sum_{x\in X}[A(x) \times C(x)]/\textstyle\sum_{x\in X}[A(x)]. \quad (3)$$

where x represents a field in the watershed, P is the pollutant load from x, R is the pollutant reduction efficiency of a given practice γ, A is the land area of a given field x in hectares, and C is the per-hectare cost of implementing a given practice.

The goal of the present study is to examine water quality improvements and reduced GHG emissions from the implementation of a carbon offset program in which farmers can sell offsets based on reductions in GHGs that result from the installation of various working-land conservation practices. In order to accomplish this, the scenario under which such an offset program does not exist – and, therefore, the implementation of practices is optimized solely for water quality – must be compared against a scenario under which such a program does exist and the implementation of practices is optimized by jointly considering water quality and GHG reductions. The latter scenario requires that the cost function from (3) above be redefined to account for the carbon offset revenue that would accrue to farmers who adopt a given practice. This is accomplished by redefining C(X) as the cost of implementation less the benefit earned by selling GHG offsets:

$$C(X) = C_i - \bar{p}R_i \quad (4)$$

where C_i is the per-hectare cost of implementing practice i, $\bar{p}$ is the market price per metric ton for a carbon offset, and R_i is the per-acre reduction in GHG, in metric tons, that results from implementing practice i.

It is important to keep in mind that the optimal solution arrived at by the genetic algorithm is simply that which would most effectively reduce both cost of practice implementation and pollutant yield. This is consistent with cost minimization in neoclassical economics, and does not attempt to account for the likelihood of decentralized practice adoption on the part of agricultural producers.

The biophysical models described above must be utilized together in such a way that they provide a framework for analyzing the effects of agricultural conservation practices on water and air quality. Figure 1 illustrates how the ensemble modeling approach is integrated with the optimization procedure just described. DAYCENT is used to model the changes in GHGs that result from the implementation of various conservation practices in the WCW. Using estimates of practice implementation costs (Table 2), the cost component of the genetic algorithm inputs were calculated using equation 4. These costs include the change in machinery, labor, and chemical usage that result from the implementation of the practice as well as the opportunity costs associated with any resulting yield changes (Vetsch and Randall 2004; Cain 2006; Clark 2007; Dobbins, et al. 2010; Iowa State University 2010; USDA 2010a; Seedland, Incorporated 2010; University of Illinois 2010). For detailed accounting of the cost estimates, see Reeling (2011). The SWAT model of Wildcat Creek was used to model the effects on NPS pollution from implementing the conservation practices. These results were then combined with the implementation cost estimates and served as inputs to the MOGA, which was used to determine the optimal set of conservation practices for jointly minimizing pollutant yield and implementation cost. The resulting tradeoff frontiers could then be used to determine the potential abatement in NPS pollution and GHG fluxes as well as the cost of abatement of a program which uses carbon offsets to fund the implementation of conservation practices.

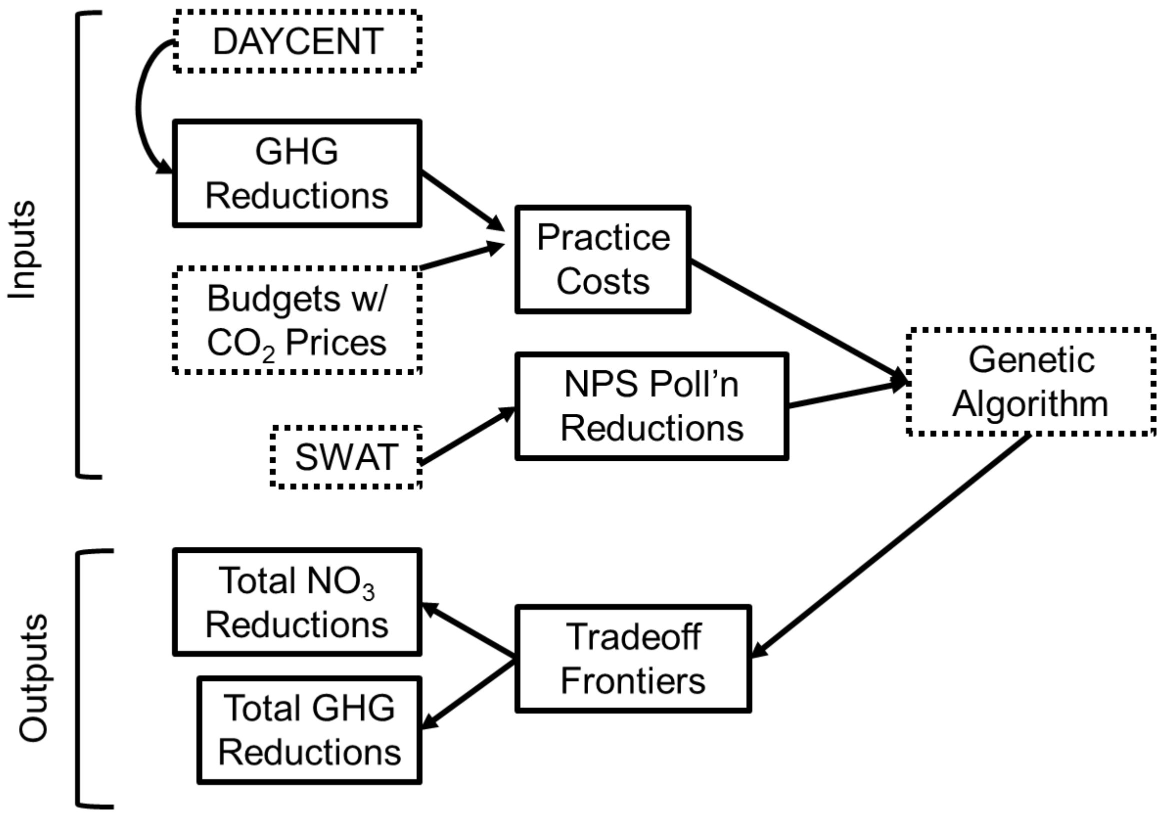

Figure 1. Flow Diagram of Framework Components

Table 2. Estimated Cost of Conservation Practice Implementation

Practice	**Cost ac^{-1}**
No-till (NT)	$46.45
Cover crop (CC)	$60.41
Fertilizer management (FM) [1]	$8.32
NT+CC	$82.02
NT+FM	$54.77
CC+FM	$61.68
NT+CC+FM	$83.29

[1] *Cost figure applies to corn acreage only*

3. Results

The framework developed above was applied to the WCW, an eight-digit hydrologic unit code basin located in central Indiana that covers 2,103 km^2 (~812 mi^2) in portions of seven counties, including Carroll, Clinton, Grant, Howard, Madison, Tippecanoe, and Tipton (Figure 2). The land use in the watershed is dominated by agriculture, with nearly 90% of the acreage devoted to crops or pasture. Of the cropland, 72% is planted with corn and soybeans. In 2008, Wildcat Creek was listed as an impaired stream under Section 303(d) of the Clean Water Act, due largely to PCBs in fish tissues and *E. coli* (IDEM 2010). However, as recently as 2006, the Indiana Department of Environmental Management warned of impairment of biotic communities and low dissolved oxygen levels, both attributed to elevated levels of nitrate-N and phosphorus in the South Fork of the river (IDEM 2008). Further, many stretches of the Wabash River downstream of the confluence of Wildcat Creek with the Wabash are listed as impaired due to high nutrient concentrations.

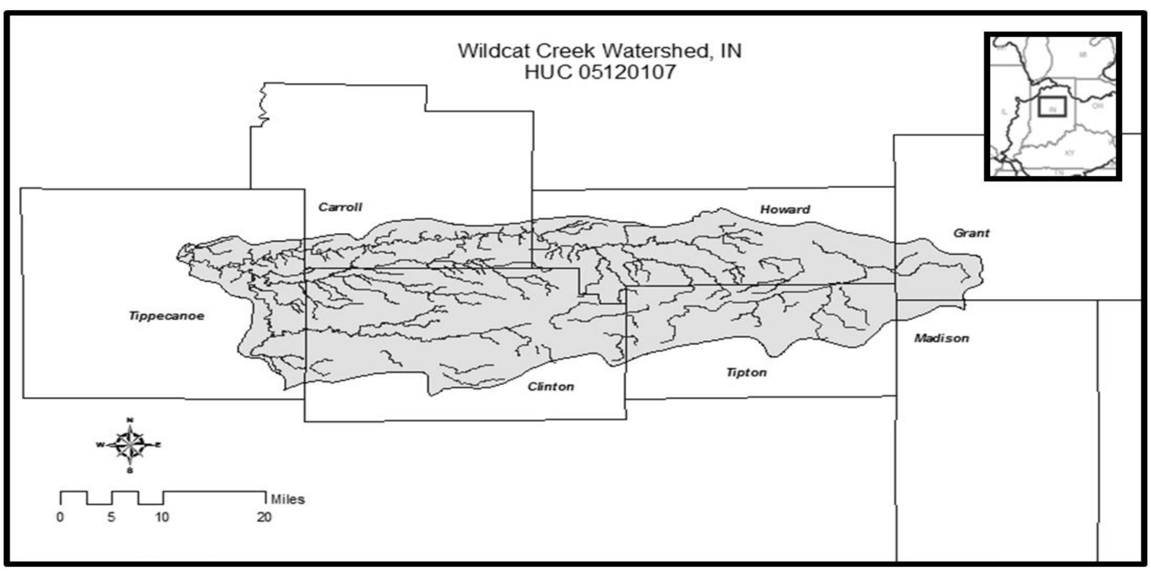

Figure 2. Wildcat Creek Watershed. Source: USDA 2010c, USGS 2010b

DAYCENT and SWAT were used to estimate the changes in GHG fluxes (measured in global warming potential [GWP] or metric tons of carbon equivalent per hectare[1]) and NPS pollution, respectively, from the implementation of the seven conservation practices. The results of the modeling are presented in Table 3 and Figure 3.

Table 3. Average Annual Reductions Across All Fields in NPS Pollution from Conservation Practices (Three Years Following Implementation)

Practice	**TP**	**TN**	**TSS**
Baseline	1.8 kgP ha^{-1}	57.76 kgN ha^{-1}	2.4 mtTSS ha^{-1}
NT	-23.77%*	-0.42%*	8.67%
CC	52.33%	30.05%	47.37%
FM	0.40%	26.20%	0.19%
NT+CC	14.73%	24.39%	56.90%
NT+FM	-21.99%*	27.73%	9.03%
CC+FM	52.65%	52.84%	48.03%
NT+CC+FM	13.51%	47.68%	57.49%

**Negative numbers indicate an increase in NPS pollution*

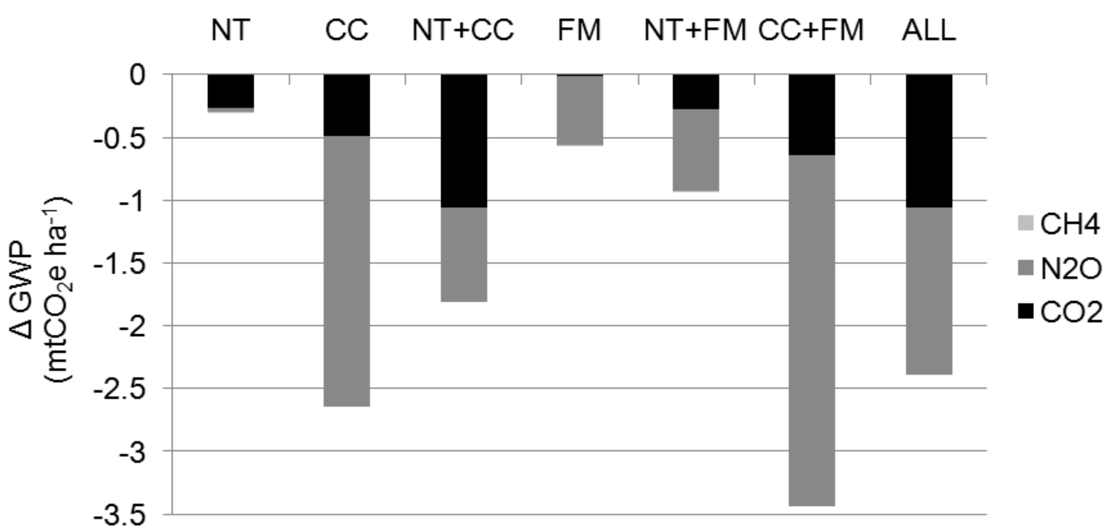

Figure 3. Annual Average Change in GWP Weighted over All Soil Types (Three Years Following Implementation)[2]

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[1] 1 mtN_2O = 296 $mtCO_2e$; 1 $mtCH_4$ = 23 $mtCO_2e$ (US EPA 2010).
[2] A three-year implementation period was used for this analysis. This period mimics the three-year contracting period used for these practices in current federal cost-sharing programs such as EQIP (Spinelli 2010).

The GHG modeling results and practice cost estimates from Table 2 were plugged in to equation (4) to estimate the implementation costs for each practice net of carbon offset income. The costs were then combined with the NPS pollution estimates from Table 3 and entered into the MOGA. The MOGA then optimized the placement of conservation practices in the watershed by jointly minimizing cost and the yields of all three NPS water pollutants over all seven conservation practices. The results from the optimization can be seen in Figure 4. The first three plots – Figure 4a-c – demonstrate the effects of carbon pricing on the water pollutants nitrogen, phosphorus, and sediment, respectively. The curves are the tradeoff frontiers. Each point on the tradeoff frontier represents an individual chromosome, or a solution to the objective functions that corresponds to a particular allocation of conservation practices within the watershed. Because the objective functions are competing with one another (minimizing cost competes with minimizing pollutant yields), the gently-curved shape of the plots demonstrates a tradeoff between the two goals. Given the baseline yields of each pollutant (represented by the vertical bar at the far right of each plot's x-axis), it is evident that the implementation of conservation practices at any level has the potential to result in improvements to environmental quality. In each case, the curve rises exponentially as pollutant yield decreases, indicating that the cost of abatement increases drastically as abatement increases. Under the baseline assumptions in which no carbon price exists, total yield of nitrogen has the greatest potential for abatement as this pollutant is present in the highest quantity in the watershed. From baseline pollutant yield levels of 57.8 kgN ha^{-1}, 1.8 kgP ha^{-1}, and 2.4 mtTSS ha^{-1}, optimizing the placement of conservation practices within the Wildcat Creek Watershed has the potential to reduce TN, TP, and TSS yields by approximately 13%, 6%, and 8%, respectively, at the lowest implementation cost of ~\$20 ha^{-1}. These costs quickly rise at greater levels of abatement;

reductions in TN, TP, and TSS of approximately 48%, 50%, and 51%, respectively would cost nearly \$160 ha^{-1}.

Figure 4d presents the tradeoff frontiers for global warming potential measured in $mtCO_2e$. Unlike the gently-curved frontiers derived for the water quality variables, the GWP frontiers are linear. This is due to a limitation in the methodology used to calculate GWP from cropland; the per-hectare value of GWP – a weighted average of all soil types present in the watershed – is assumed to be constant for each field, whereas the per-hectare value of water quality pollutants is distinct among fields. Because of this, incremental per-hectare changes in GWP occur proportionally with changes in implementation cost, resulting in the linear shape of the tradeoff frontier. Regardless of this limitation, the behavior of the frontiers is largely the same.

Figure 4 also demonstrates the changes in the tradeoff frontiers that result from the use of carbon offset prices to reduce conservation practice implementation costs. As expected, increasing the carbon offset price results in greater reductions in nonpoint source pollution and GHG fluxes at a given cost of implementation. For example, reducing TN yields by ~30 kgN ha^{-1} would cost roughly \$150 ha^{-1} if no carbon offset price existed. However, when increasing the carbon offset price to \$7 and \$30 $mtCO_2e^{-1}$, it becomes possible to reduce that same 30 kgN ha^{-1} for only \$130 ha^{-1} and \$50 ha^{-1}, respectively. Given these results, a general trend is observed in which greater carbon offset prices cause the tradeoff frontiers to rotate counterclockwise towards the origin, resulting in an implementation cost reduction that is greater than the carbon price. This is due to the fact that increasing carbon offset prices have a relatively greater effect on practices that most effectively mitigate GHG fluxes. Because these practices are generally the most expensive and also are the most effective at reducing NPS water pollution, increasing the carbon offset price allows for greater pollution abatement at highly reduced costs.

As can be seen in Figure 5 and Figure 6, relatively few of the available practices are chosen by the optimization process. Each differently-shaded region in the chart describes the percentage of the land area in Wildcat Creek Watershed that is in the corresponding practice. Figure 5 demonstrates that the optimal practices chosen by the genetic algorithm with no carbon price include CC, FM, CC+FM, and no conservation practice at all (baseline/no practice). As one moves up and to the left along the tradeoff frontier, the proportion of watershed land area devoted to FM stays roughly constant at ~40% until TN yield reaches 39.9 kgN ha^{-1}. Over this interval, land area that is not under any conservation practice diminishes while the proportion of land area under CC+FM increases. This trend continues until CC+FM swamps FM and the baseline (no practice), resulting in the greatest amount of TN abatement.

Figure 6 shows the distribution of land area under each practice given a carbon offset price of \$30 $mtCO_2e^{-1}$. The picture is largely the same, although fertilizer management initially takes up a significantly larger share of the watershed land area (~75%) due to the greatly reduced cost of implementation. The extra land for fertilizer management is taken from land that was under no conservation practice in the zero carbon price assumption, while the proportion of land dedicated to CC+FM is roughly the same.

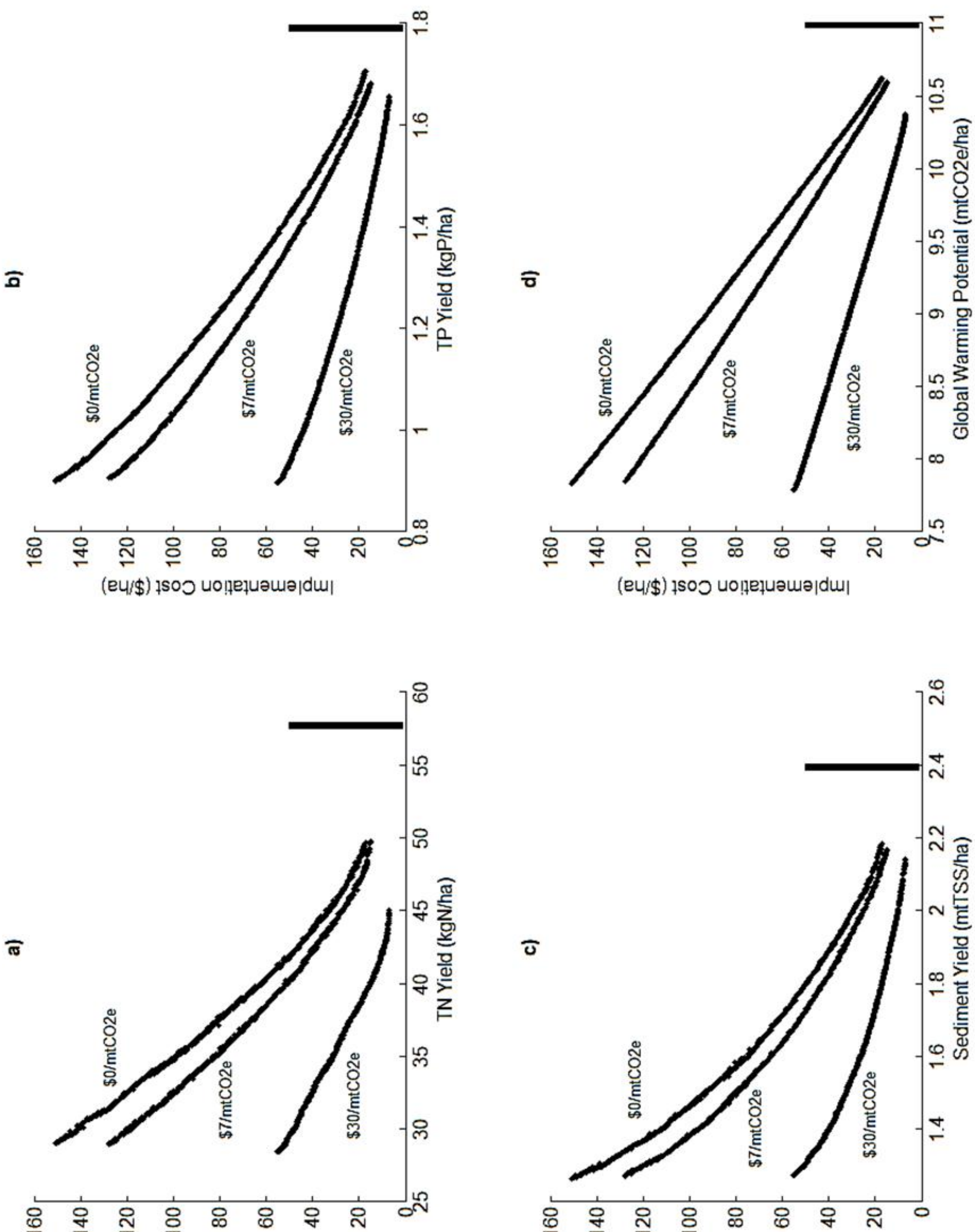

Figure 4. Results of MOBOT Optimization for All NPS Pollutants under Various Carbon Offset Prices

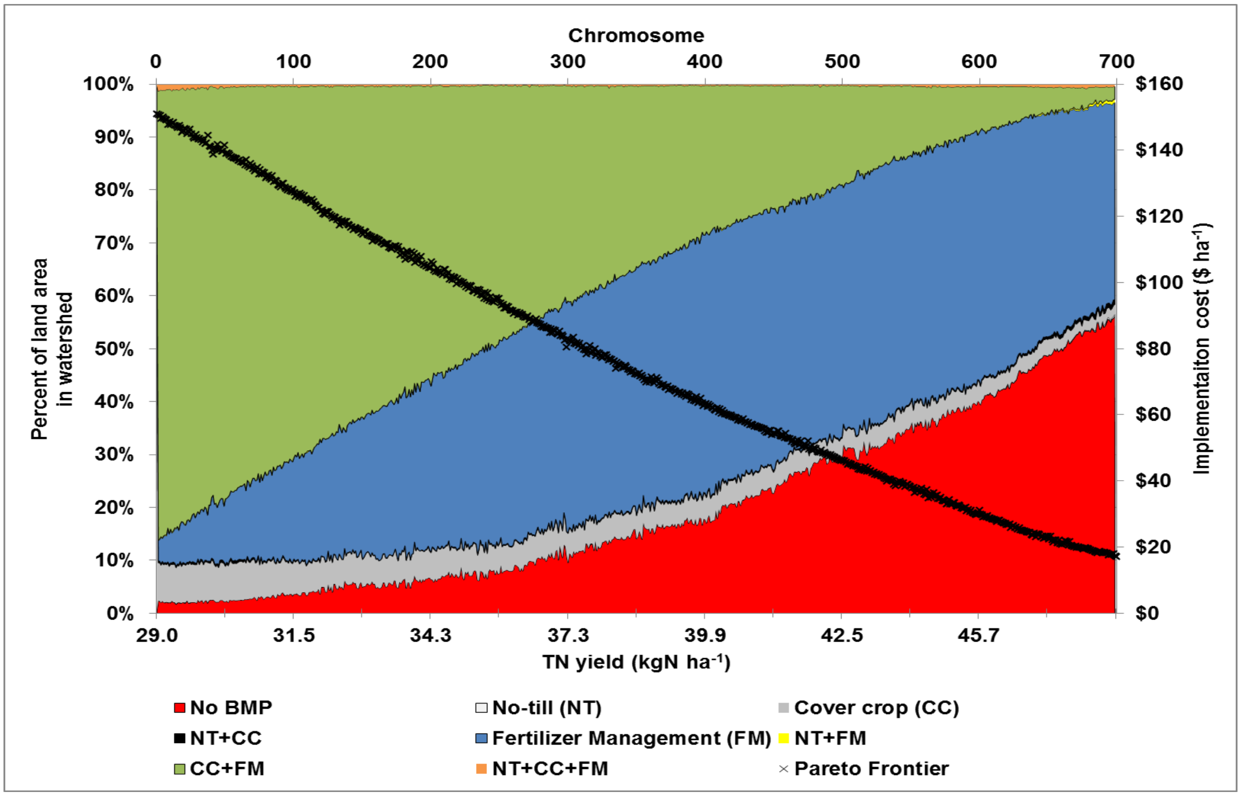

Figure 5. Distribution of Optimal Practices in Watershed along the Tradeoff Frontier, No Carbon Price, Optimized for All NPS Pollutants

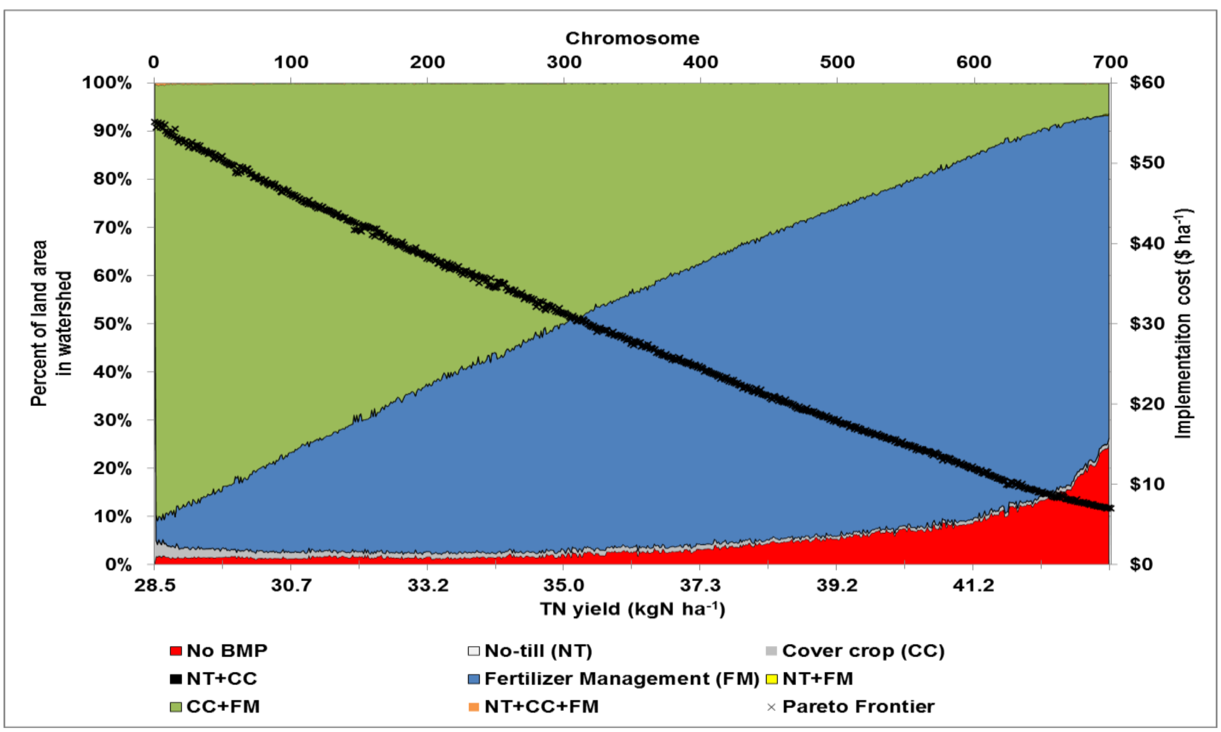

Figure 6. Distribution of Optimal Practices in Watershed along the Tradeoff Frontier, $30 mtCO2e Carbon Price, Optimized for All NPS Pollutants

A second run examines what occurs when MOBOT is used to optimize conservation practice placement for greenhouse gases only. Comparing Figure 4d and Figure 7d, it appears that focusing exclusively on GHG emissions has a negligible impact on the tradeoff frontier of GWP; the tradeoff between cost of implementation and GWP is, in both cases, nearly identical. Figure 7a also demonstrates that optimizing exclusively for GWP changes the frontier for TN. While the relationship between cost of implementation and TN abatement remains roughly the same, the curve is not a smooth, convex shape as in Figure 4; the individual chromosomes become somewhat scattered near the middle of the tradeoff frontier. The explanation for this behavior likely lies in the distribution of practices chosen during optimization; comparing Figure 8 and Figure 5, it is evident that, when optimizing only for GWP, very little land is placed under CC until very high levels of abatement are achieved. However, when optimizing over all pollutants jointly, CC comprises a small but significant portion of the land use in the middle section of the tradeoff frontier (~8%). This lack of cover cropping likely causes the somewhat scattered appearance of the frontier in Figure 7. Focusing exclusively on GWP also has the effect of making the tradeoff frontiers for TP and TSS concave to the origin. This is likely due to the fact that this optimization relies heavily on fertilizer management alone and in combination with cover cropping. Because this high reliance on fertilizer management affects N to a greater degree than TP or TSS, greater use of this practice will result in higher costs and lower abatement of TP and TSS relative to GWP and TN.

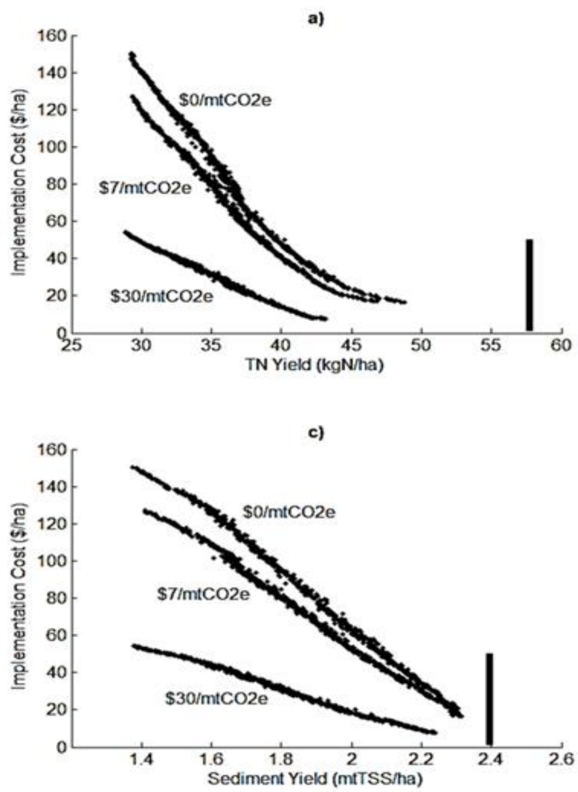

Figure 7. Results of MOBOT Optimization for GWP Only

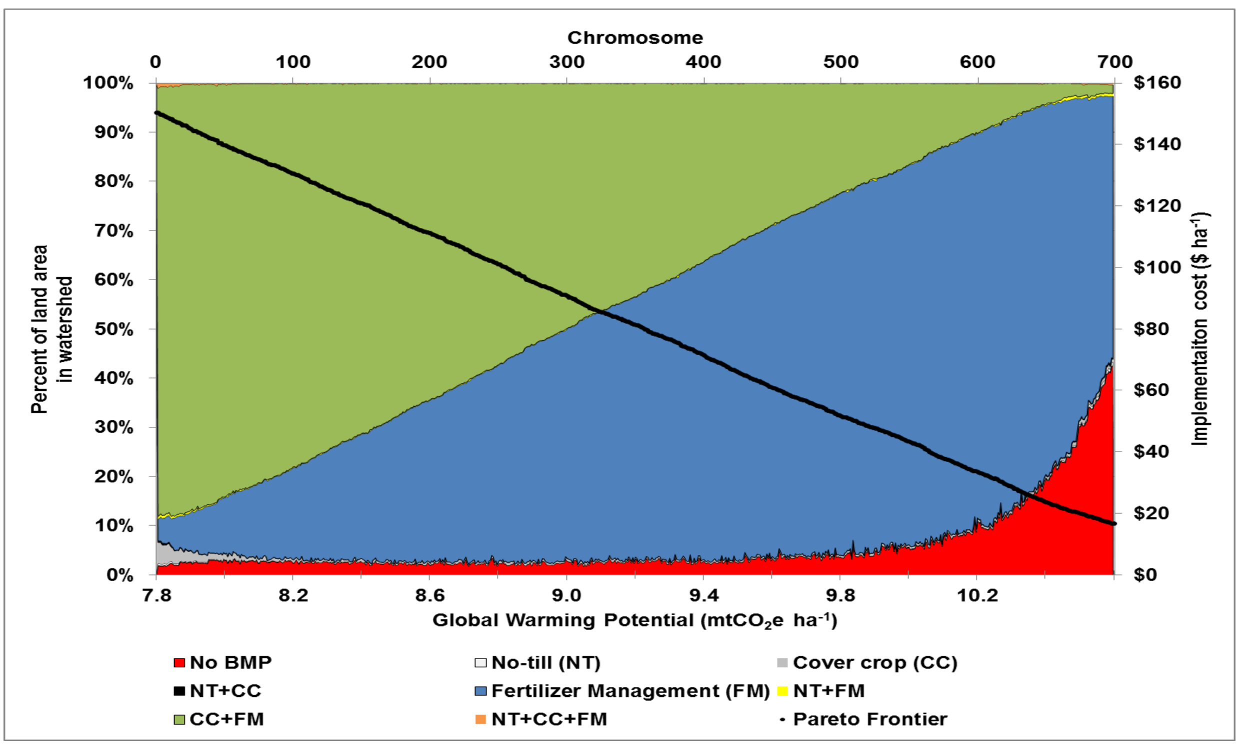

Figure 8. Distribution of Optimal Practices in Watershed along the Tradeoff Frontier
($0 mtCO$_2$e Carbon Price, Optimized for GWP Only)

4.1. Marginal Abatement Costs and Alternative Metrics

The information used to run the genetic algorithm can also be used to generate marginal abatement cost (MAC) curves for pollutant abatement in the WCW. Using the baseline nitrogen yields for each field within WCW and the average annual reductions from conservation practice implementation from Table 3, the cost per unit of abatement was calculated for each practice. Because it is assumed that each individual conservation practice reduces TN yields for each field by the same percentage, the conservation practice with the lowest abatement cost per kilogram of nitrogen was applied to each field in order to calculate the reduction in N and the cost per kilogram of N abatement. These data were then plotted, as can be seen in Figure 9.

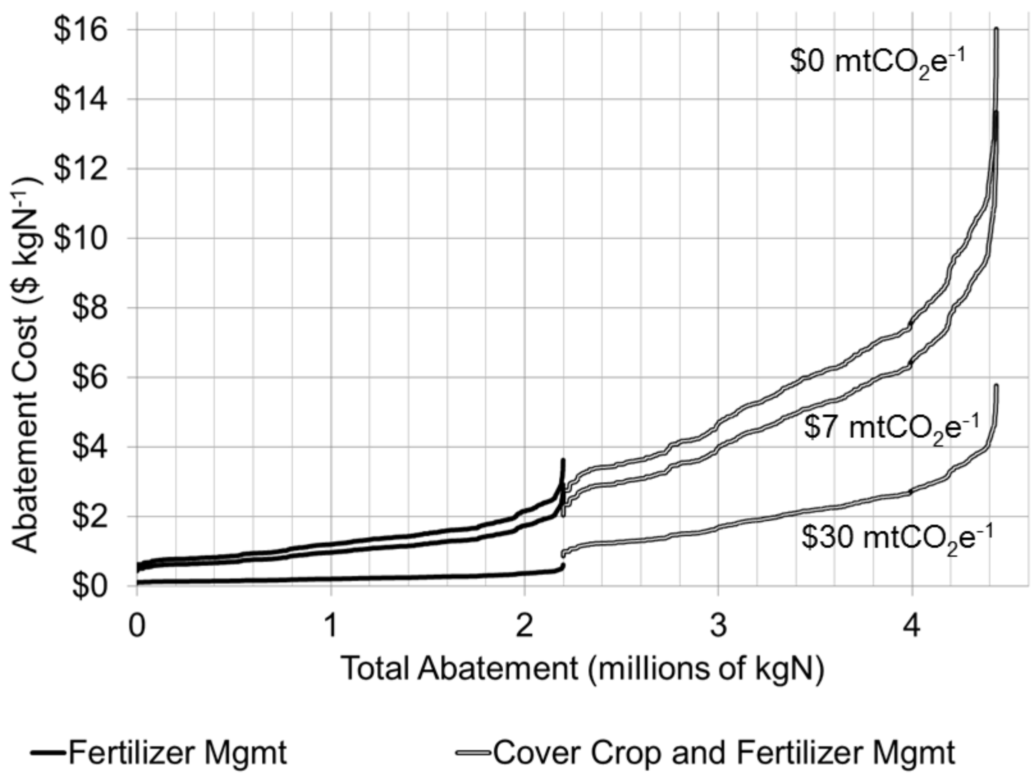

Figure 9. Nitrogen Marginal Abatement Cost Curves by Conservation Practice for Carbon Prices of $0, $7, and $30 $mtCO2_e^{-1}$

The solid black line represents the marginal abatement cost from implementing FM. The curve slopes upward as additional fields are brought under FM. Due to hydrological considerations such as slope, soil type, etc., some fields have greater TN yields than others. Because the per-hectare cost of and percentage reduction in TN from FM is assumed to be the same for each field, implementing the practice on the field with the greatest TN yield will result in the lowest per-unit abatement cost. As additional fields are brought under FM, the per-unit cost of abatement increases because each successive field has a lower baseline TN yield. Figure 9 shows that, from a total baseline TN yield of ~9 million kgN, approximately 2.2 million kgN can be reduced. When no carbon price is assumed, the costs associated with these reductions ranges from ~\$0.50 kgN^{-1} for the first kgN of reduction to nearly \$4 for the 2.2 millionth kgN.

Because only one practice (or combination of practices) can be used in each field at any given time, additional abatement at higher per-unit costs from implementing a different conservation practice must come at the expense of removing the previously-implemented practice. The hollow line in Figure 9 demonstrates abatement and costs from removing FM and instead implementing CC+FM. By removing FM and replacing it with CC+FM field-by-field, it is possible to generate a total abatement of ~4.4 million kgN. However, this comes at a much greater cost; the MAC of the 4.4 millionth unit is \$16 when no carbon price is assumed, quadruple that of the 2.2 millionth unit abated through fertilizer management alone. In essence, then, what is shown in Figure 9 is not a single or “true” MAC curve; rather it is a combination of two separate curves for two different practices.

Figure 9 also demonstrates the effect of carbon pricing. When the carbon price is assumed to be \$7 $mtCO_2e^{-1}$, the marginal cost of the 4.4 millionth unit decreases nearly 16%.

The effect is even greater when a carbon offset price of \$30 $mtCO_2e^{-1}$ is assumed: the marginal cost of the 4.4 millionth unit decreases to ~\$6 kgN^{-1}, a reduction in cost of over 60%.

These marginal abatement cost curves can be used as any other MAC curve and have the potential to be useful in policy analysis. The costs of alternative methodologies for reducing fluxes of reactive nitrogen can be compared with the costs generated by this tool to decide the most cost-effective nitrogen abatement strategy.

The value of using multiple metrics to analyze abatement strategies has previously been demonstrated for regions such as the Chesapeake Bay Watershed in the Eastern United States (Birch, et al. 2011). As such, it may be useful to compare various alternative metrics to the marginal abatement cost presented above. Figure 10 shows the cost per metric ton of concommitant carbon equivalents that are reduced in the least-cost TN abatement scenario represented by the marginal abatement curves in Figure 9. Due to the assumption that the per-hectare emissions of GHGs are a weighted average based on watershed soil composition, each field is assumed to emit the same per-hectare quantity of carbon equivalents for a given practice. This assumption results in the abatement cost per metric ton of carbon equivalent being the same across all fields. When this figure is plotted, FM is found to reduce CO_2e at a much higher cost per metric ton than CC+FM; when no carbon pricing is assumed, the abatement cost per metric ton associated with FM is roughly six times as high as the cost associated with CC+FM. Comparing this metric with that from the MAC curves in Figure 9 and the per-hectare implementation costs shown in Figure 11, it is clear that the relationships are opposite. The addition of cover crops to fertilizer management doesn't appear to contribute much to abatement of nitrate runoff to surface waters, but does significantly contribute to GHG abatement from cropland over the three-year time horizon depicted. As such, using abatement cost per $mtCO_2e$

as a metric would result in a significantly different implementation outcome than would the use of abatement cost per kgN or implementation cost per hectare.

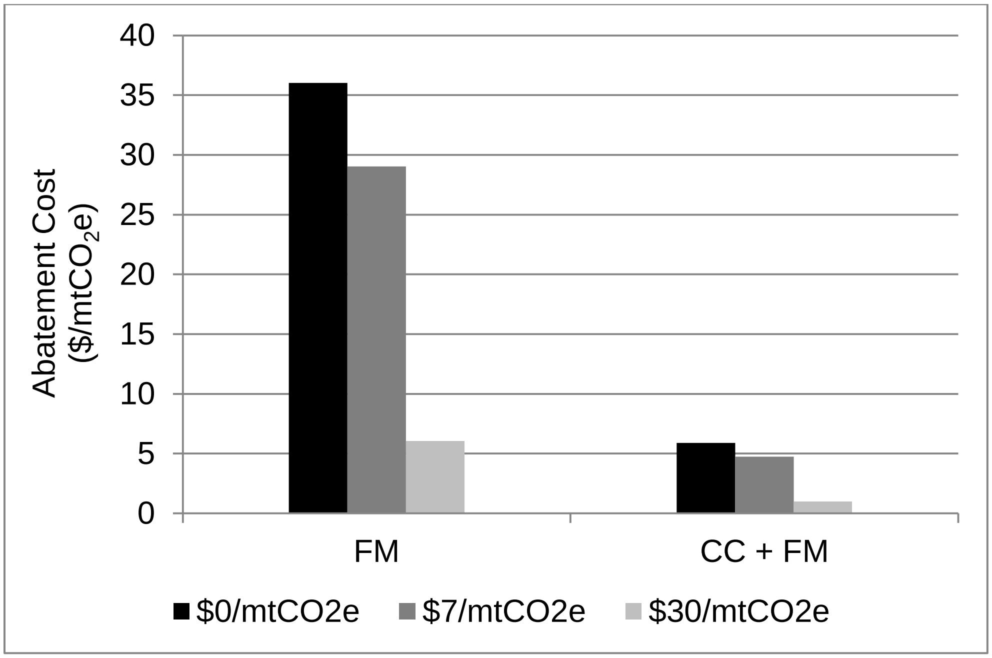

Figure 10. Cost per mtCO_2e Associated with Least-Cost TN Abatement (CO_2e Modeled Over a Three-Year Implementation Period)

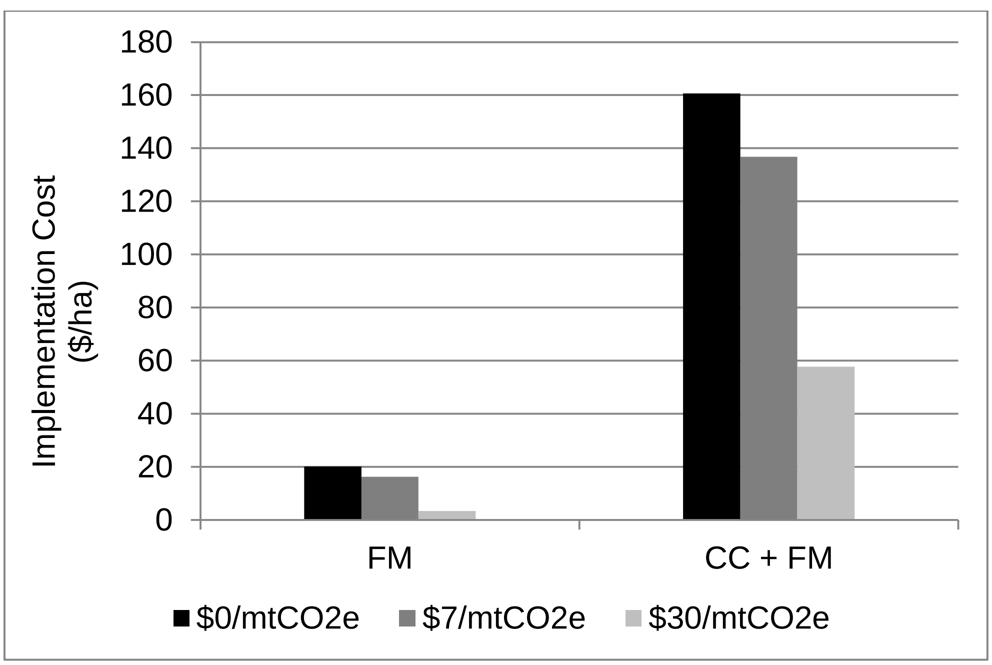

Figure 11. Per-Hectare Implementation Cost of Practices Associated with Least-Cost TN Abatement

5. Discussion and Policy Implications

The above analysis reaffirms the findings of other researchers in that agriculture serves as a major link between fluxes of GHGs to the atmosphere and losses of NPS pollutants to surface waters. It is also clear from the results presented in the previous section that significant potential exists for exploiting this link by using carbon offsets to fund agricultural conservation practices, for doing so would result in significant reductions in practice implementation costs at the farm level as well as significant improvements to environmental quality.

That said, a finding that has significant policy implications is that the optimal allocation of practices for the optimization runs performed in this study relies heavily on fertilizer management; Figure 5 and Figure 6 demonstrate that as much as 90-95% of watershed land can be devoted to fertilizer management or a combination of fertilizer management and other practices, depending on the level of abatement desired. Further, analysis of the marginal abatement cost curves for nitrogen NPS pollution demonstrates that fertilizer management is the most cost-effective practice. However, while the implementation of no-till or cover crops is relatively easy to enforce, it is effectively impossible to monitor farmers' fertilizer application rates. This calls into question the feasibility of using fertilizer management as a major component of NPS of GHG pollution abatement. The exclusion of fertilizer management from the portfolio of available practices can be compensated for by increasing the amount of land under cover crops, but the cost of doing so would certainly be much greater than if fertilizer management was used. Similar difficulties arise when considering the implementation of a nitrogen tax, which has been proposed by other authors (Huang and LeBlanc 1994; Bontems and Thomas 2006).

An interesting result from the GWP-only optimization is that, while the tradeoff frontier for TN (Figure 7a) has a somewhat scattered shape, the frontier is, in general, very similar to the TN frontier derived from optimizing over all NPS water pollutants (Figure 4a). Further, the sets of optimal practices given by the MOGA are very similar for both the GWP-only optimization and the joint optimization for all NPS pollutants. This finding implies that there is at least some potential for using carbon offset markets in Wildcat Creek and other agricultural watersheds to achieve NPS pollution reduction where traditional water quality trading markets have failed in the past (Ribaudo and Nickerson 2009). By targeting the concomitant GHG fluxes that accompany losses of nitrogen, phosphorus, and sediment to surface waters, agricultural producers and industrial GHG emitters may be able to exchange carbon credits in emissions markets which have been successfully implemented throughout the world. This would lead to improvements in NPS pollution – particularly for TN – as the most effective practices for reducing GHG fluxes are also the most effective practices for reducing NPS nutrient pollution.

In an effort to prevent the inappropriate use of its contents or the unwarranted extension of its conclusions, it is important to note the limitations to application of this research. Primarily, it should be noted that reasonable effort was made to ensure the quality of the DAYCENT greenhouse gas modeling results. However, verification of the results was limited to a comparison of the estimated magnitude of the fluxes to reported values from the peer-reviewed literature. While some literature can be found on the reductions of GWP from no-till and fertilizer management, the effects on fluxes of GHGs from the implementation of cover cropping are generally not well-understood. Cover cropping was found in this research to be an important component in any effort at cross-media environmental improvement. Given the lack of extensive field observations to validate the modeling results, one must be cautious in relying too heavily on the results arrived at here. Indeed, for all practices, the range of observed effects on GWP in the literature is extremely wide; as such, the exact estimates of the changes in GHG fluxes from the implementation of no-till, cover crops, and fertilizer management should not be viewed as authoritative measurements even within the Wildcat Creek Watershed. Further, their applicability to other watersheds in Indiana or elsewhere should be evaluated very carefully. Despite the limitations inherent in extending the magnitudes of the changes in GHG fluxes from implementing the various conservation practices, the results from this study are useful for evaluating the direction of the environmental effects and the relative magnitude of different practice effectiveness.

Compared with the DAYCENT work, the results of the hydrological modeling of Wildcat Creek can be viewed with more confidence. The SWAT model used in this research has been validated against observed data from the field and has been compared successfully against other validated models. The primary limitation to the SWAT results resides in the estimation of the average effect on NPS pollution resulting from the implementation of the various practices. This was performed by taking the per-hectare difference in pollutant yields among each field between the baseline case and the scenario in which a practice was implemented. A simple average was then calculated and was applied equally to all fields using the genetic algorithm. Such a process is likely to introduce some amount of error into the optimization process. The magnitude of this error is unknown, but it is hypothesized that using a watershed-wide average rather than a more spatially-explicit estimate is likely to bias the estimates of implementation cost upwards.

Despite the limitations of this study, this research will be useful for informing policy discussions of how to effectively evaluate cropland management activities that affect multiple environmental media (air, land, and water). More than accurately modeling the effects of conservation practices on GHG fluxes and NPS pollutant yields, the goal of this study was to examine the link that agriculture serves between global warming and water pollutants. In achieving this, a novel framework was established which allows for a quantifiable estimate of this link. This is the single largest contribution of this research, and it is hoped that further extensions of this work will focus not on a direct application of its results but on the refinement of the methods employed here. This will hopefully include increased data collection, empirical validation and model sophistication, as well as a more seamless integration of the various ecological models used. This will result in a greater understanding of the cross-media effects of agricultural land management and has the potential to serve as an important input to future environmental policymaking.

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