# A Pollution Trading System with Cost Asymmetry
# An Application to Nonpoint Source Trading in the Boone River Watershed

**Adriana M. Valcu**

Center for Agricultural and Rural Development and

Department of Economics

Iowa State University

Email: amvalcu@iastate.edu

**Catherine L. Kling**

Center for Agricultural and Rural Development and

Department of Economics

Iowa State University

Email: ckling@iastate.edu

Abstract

The goal of watershed scale analysis is to assign to each field unit the best set of agricultural practices in order to achieve a maximum outcome from both environmental and economic perspectives. Watershed physically based models linked to multiobjective optimization models can overcome the high dimensionality of watershed pollution problem. Market based instruments such as permit trading settings which consider abatement measures' cost heterogeneity have been regarded as being superior to command and control programs. Empirical analysis reveals that when local environmental authority and farmers have different cost information, a permit trading program has the potential to offer cost savings.

Key words: cost asymmetric information, command and control program, evolutionary algorithms, nonpoint source pollution, water quality trading

*1.1.General overview*

Water quality impairments have been created as a result of both modern agriculture and urban activities. Over time, the measures taken under the Clean Water Act have succeeded in reducing many point source emissions, but currently, non point emissions and agricultural emissions are the most significant contributors to water quality problem in the United States (EPA,2003). The latest National Summary of State information indicates that more than 50% of the 26% of nationwide rivers whose water quality have been assessed are inadequate to support wildlife, fishing and recreational activities. The same survey states that more than half of wetland nationwide areas have been impaired by agricultural activities.

Market based instruments such as permit trading programs have been regarded as successful instruments for a broad range of environmental problems such as air pollution control, habitat protection and resource compensation. Based on the historical achievements of the Acid Rain Program that used tradable permits for sulfur dioxide emissions, market based instruments have been proposed to address water quality pollution. Point-nonpoint source trading systems, by requiring a mandatory participation of the point sources and a voluntary participation of the non point sources have the potential for achieving the proposed caps on point source emissions at lower cost, but there have not been a large number of trades or documented successes of these programs. Following the EPA beliefs that "market based approaches to water quality trading provide greater flexibility and have the potential to achieve water quality and environmental benefits greater than would otherwise be achieved under more traditional regulator approaches" (EPA 2003), designing and enforcing a trading system that encourage emission trading among non point sources might be a solution for the current state of water quality pollution.

*1.2. Literature review*

In the following section.We outline a brief review of water quality trading literature, focusing on the literature that directly relates to nonpoint –nonpoint trading.

The basic idea behind a permit trading system is not complicated. In order to reduce the amount of pollution, the regulator, an environmental agency, determines a total standard to be implemented and the number of permits to be given to the polluters. Permits can be freely traded.

A polluter's total emissions cannot exceed the amount allowed by the number of permits held at a given moment. The permit price is the result of market equilibrium forces. Following Coase's (1960) argument that if the property rights are well defined and transferable, the market forces give the best use of the resources, Crocker (1966) and Dales (1968) provided the first theoretical models of tradable permits for air pollution, and water pollution, respectively. The experience with the sulfur dioxide trading program brought the idea of using tradable permits as a solution to the water quality impairments (Colby, 2000).

Most research to date has been focused on modeling trading systems that include either only point sources or both point and nonpoint sources (Montgomery 1972, Krupnick et al, 1983, Shortle and Abler, 1997;Hung and Shaw 2005). Much attention has been given to the size of "diffusion" or "delivery coefficients". Delivery or diffusion coefficients are used to define the impact of one unit of emissions to the total ambient pollution, where ambient pollution refers to the pollution concentration measured in stream as opposed to emissions at the source of the pollution, such that edge -of--field. The total ambient pollution,$W(r,d)$ or the damage function is defined as a function of individual emissions, $r$ and delivery coefficients,$d$. The trading ratio, the central element of a point point or point non point emissions trading, is defined by the delivery coefficients. Earlier theoretical approaches assumed that diffusion coefficients are fully determined and that the pollution damage function is a convex combination of individual emissions weighted by the delivery coefficients (Montgomery, 1972). Hung and Shaw (2005) use trading ratios defined by the delivery coefficients to design a zonal permit trading system able to achieve water quality goals in a least cost manner. At the same time, Montgomery recognized that assuming a linear combination can impose significant limitations on the viability of permit trading market. In the context of water quality trading, the majority of existent market transactions use delivery coefficients as proxies for trading ratios (USEPA, 2004) and most pollution reductions are based on the delivery coefficients, thus the efficiency of any policies depends on their accuracy.

In the watershed, agricultural activity is the main source of water pollution, with many potential pollution sources, and an equal number of delivery coefficients to be estimated. Theoretically, one would need to estimate a number of delivery coefficients equal to the number of polluting sources in the watershed. Of course, empirically this would be cumbersome and

almost impossible to enforce, hence it would be feasible to divide the watershed in a number of smaller subwatersheds and estimate a diffusion coefficient for each of them. Estimating delivery coefficients may be a daunting task, but is essential for achieving sound policy. Furthermore the delivery coefficients are site specific, but lessons can be learned about their characteristics and the techniques employed in their estimations.

Previous studies assumed that delivery coefficients can be estimating using information related by source characteristics such as slope, soil characteristics, distance to the water body, and agricultural practices (Carpentier, Bosch and Batie, 1989) or the practices used on the sites that are located down slope of a particular slope. Khanna *et al*. (2003) assumes that the contribution of each site emissions is determined by two factors. The first factor is a trapping coefficient that depends not only on the site characteristics and agricultural practices used but also on the characteristics and land use practices of the sites located upslope. The second coefficient is a sediment transport coefficient that determines the onsite emissions that adds up to the emissions measured at the offsite receptor point. The authors state that the relationship is too complex to be exogenous, and that an endogenous treatment is required. Consequently, the diffusion coefficients of one source are influenced by its own characteristics but also by the upslope and down slope sources' characteristics and land use practices.

There are not many studies in the context of trading water quality that approach agricultural non point sources only. This is partially due to the fact that nonpoint source emissions are considered difficult to measure and monitor, making it difficult to link the agricultural production function to the ambient pollution measured at the receptors (Morgan et al., 2000).

Morgan, Conggins and Eidman (2000) describe a marketable permit trading scheme able to manage nitrate pollution of groundwater supplies for rural communities with intensive agricultural activity. The level of nitrate leaching is measured at the level of drinking water well. The authors use soil and groundwater transportation models to predict nitrate leaching rates from a particular crop area. According to their model each farm is made accountable for its emissions to a given water well, hence nonpoint source emissions are transformed into point source emissions. Their model takes into account that the farm's potential to contribute to total ambient

pollution depends on its location. The permit trading system is defined as an ambient permit system, defined in Montgomery sense, where farms are allowed to emit up to a certain level[1].

Three integrated models: production, soil, and groundwater represent the foundation of the permit trading model. The permit trading model is designed for trading nitrate emissions. The production model defines the profits as a function of yield, where yields are defined as a function of the fertilizer, agricultural practices and rotations. The abatement cost is defined as the difference in profits before any regulation is imposed and the profits after regulations are adopted. The farm minimizes its abatement costs, where the cost is defined as the sum of the loss profits and the expenditure on permits. By selling permits the compliance cost is more likely to decrease.

In implementing the trading system the authors underline the importance of the time framework and of the baseline. Estimating the transfer coefficients, the marginal abatement cost, and initial permit allocation are also considered to have an important role in the trading scheme. Marginal abatement costs are defined as the change in the nitrate levels at the well due to a shift in the agricultural practice. The allocation of permits is made at the beginning of the planning period. The equilibrium price is determined through repeated auction, the amount of abatement and the trading decision is made by comparing the equilibrium price with the marginal abatement cost. The abatement cost is higher to the farms whose emissions have the greatest impact on the water quality measured at a specific well.

Prabodanie *et al.* (2010) propose an offset tradable permit system as a solution to non point source water pollution, focusing on nitrate loadings on an aquifer. They use the same approach followed by Morgan et al. (2000), but in addition run several simulations regarding the trading outcome. The trading is overseen by a central authority that via an auctioning procedure determines the clearing price for the permit trading market. Their findings confirm that farmers are better off by being allowed to trade than when a command and control program is in place. For example per farm average profits increased by almost 10 % in when trade is allowed.

---

[1] In an ambient permit system, the permits are denominated in emissions measured at the receptor point, rather than emissions measured at the edge-of-field.

*1.3. Ancillary literature review*

In addition to building on previous literature in nonpoint emission trading, we will use a number of models and tools. In this section, we will provide a short description of these tools.

Difficulties in establishing a direct link between the agriculture activity and ambient pollution level measured at receptors, where each source is made liable for its discharges, have been one of the main impediments in the development of a trading system that approaches agricultural nonpoint sources. Better understanding of the interactions between agriculture activity and water quality has been achieved with development of hydrological model.

*Soil and Water Assessment Tool*

The Soil and Water Assessment Tool (SWAT) is a complex water quality watershed based hydrological model developed by the US Department of Agriculture to simulate the impact of point and nonpoint source emissions (Arnold *et al* (1998); Arnold and Fohrer (2005), and Gasmann *et al*. (2008)). The model is designed to run watershed simulations based on a wide range of inputs such as: climate data (precipitation, temperature, etc.), soils characteristics information (slope, soil quality, topography, erosion, etc.), plant growth and crop rotations, nutrient management, nutrient transport and transformation, and land use and management practices. Using the above data as input, SWAT outputs consist of in stream concentration estimates for nitrogen, phosphorous and sediment loadings. The output provides overall measures of the concentrations, as well as detailed information about the components of each type of discharges. For example, for nitrogen loadings, we can retrieve detailed information about components of nitrogen loadings. The obtained information can be used to predict watershed loadings on wide time range, from daily to annually based estimates.

The SWAT model is used to estimate the changes in nutrient loadings as a response to alternative conservation practices under different crop choices and rotation alternatives. In order to run simulations, the watershed, a well-defined geographical entity is divided into several sub watersheds or sub basins. In SWAT, each subwatershed is delineated further into small hydrological response units (HRU). An HRU is a conceptual entity, with no precise spatial location within the subwatershed. It is identified as a percentage area in the subwatershed with homogenous soil, land use and management practices. The primary water and loading simulations are made at the HRU level. The estimated loadings can be interpreted as edge-of-

field run off emissions. The nutrient loadings measured at the final outlet located at the base of the subwatershed are obtained by adding the loadings corresponding to each HRU that previously have been routed through a network of channels and reservoirs.

The development of hydrological models like SWAT, calibrated with watershed specific data, makes possible the simulation of impact on water quality of different watershed scenarios. A watershed is divided in hundreds of fields, and each field may have multiple agricultural practices that are suitable for its type of soils. For example, for a set of nine agricultural practices and 2900 fields, the total number of possible watershed scenarios is $9^{2902}$ possible scenarios. Using SWAT, a water quality level can be estimated for each watershed configuration. With appropriate economic data the cost of agricultural activity associated with a particular scenario can be assessed. The question arises: which of those scenarios is most desirable from a cost and/or pollution reduction perspective? Unfortunately, the high dimensionality of the problem makes finding a solution through traditional optimization tools practically impossible.

*Evolutionary algorithms*

One way to deal with the combinatorial nature of the watershed simulation-optimization model is the implementation of an evolutionary algorithm. Evolutionary or genetic algorithms (EA) are designed to mimic biological evolution, considered by Mitchel (1996) to be "in effect, .a method of searching for solutions among an enormous set of possibilities". Genetic algorithms are heuristic global search algorithms that are able to find the nearly optimal solution by using principle like "natural selection" and "survival of the fittest". The first studies that use EAs for finding the "nearly optimal" solution for conservation practices best placement were published only in the early 2000s, even though the theoretical background for evolutionary computation started at the beginning of the 1950s.

The main terminology used in defining EAs is similar to that used in biology, and consists in terms such as: population, genome, individual, allele set, offspring, recombination, mutation, etc. Next, we are going to give a brief description of this terminology in the context of watershed optimization context. The terminology definitions closely follow the one used by Rabotyagov (2007).

A population is defined by the individuals that share the same defining elements or characteristics. The genome or the chromosome represents the set of elements that defines an

individual. A gene or allele can have several properties. The collection of all properties defines the allele set that is the same for entire population (i.e. all individuals have the same number of genes). Each individual of the population is defined by a unique combination of genes and the properties from the allele set. The evolutionary process assumes a continuous and dynamic process where the fittest individuals become parents and are able to pass their genes to off springs by the mean of crossover. The resulted off springs may suffer mutation with a given probability. The newly created individuals define the new generation or population. The evolutionary process can span over an unlimited number of generations.

In our case, an individual represents the watershed. A gene is represented by a field, thus the total number of fields defines the genome. The fields' properties are defined in terms of the agricultural practices available in the watershed. The set of all agricultural or conservation practices defines the allele set. Hence, an individual is defined by a particular combination of fields and the conservation practices. It represents a possible solution to the pollution cost minimization problem, where as a population represents the set of all potential solutions to the same problem. The goal of the evolution process is to find the watershed configuration that ccount only N reductions and disregard P reductions. Second,r given a budget achieves the lowest level of ambient pollution.

Genetic or evolutionary algorithms can successfully handle optimizations problems that have (i) a large space whose characteristics are not well known or have complex properties such as non convexities and discontinuities, (ii) are complex, and (ii) a solution near global is acceptable. There are many reasons that make watershed pollution management suitable area for the use of an EA. First, there are measurement errors in the conservation practices' abatement efficiency, second a watershed is defined by hundreds of fields, with each field having more than one conservation practice available, and most of the cases and realization of ambient pollution target on average is considered sufficient.

When water quality optimization is considered with respect to a single pollutant, the optimization problem can be defined as single objective optimization problem. In most of the cases, water quality impairment is not limited to a single pollutant; hence the optimal solution requires solving a multi objective optimization problem. In some cases, genetic algorithms can accommodate this by combining competing multi objectives into a single known objective function and the solution yields a single optimal solution. In the cases when a single objective

function cannot be determined, the solution to a multi objective optimization will consist of a set of solutions, or a Pareto frontier optimal set. This set is a "near-optimal" set that reveals the tradeoffs between the different objectives. The near optimal characteristics come with the "temporal" aspect of the algorithm. More precisely, since there is no clear stopping criteria the solutions can always improve if more generations are allowed to survive. The solutions are optimal given the generations number that survived.

Earlier applications of EAs to watershed management focus on a single objective function, either pollution reduction effectiveness or cost (Srivastava et al; 2002), or on sequential optimization of effectiveness and cost (Gitau et al; 2004;Veith et al; 2003), where optimization is made in stages. Bekele and Nicklown (2005) use a multi objective function, but the set of agricultural practices is limited to crop management practices. Maringanti, Chauby and Popp (2009) provide a recent application of an EA for a watershed scale optimization problem, with two conflicting objectives simultaneously: a cost increase and pollution reduction. The set of conservation practices consists of 54 different combinations. Three different nonpoint pollutants are considered: phosphorus, nitrogen and sediment but only one pollutant is considered at time, hence three different optimization models were estimated. For each model, a Pareto frontier depicts the tradeoff between the two objectives. The allocations of conservation practice in the watershed according to the optimization results are shown to be superior to random allocation, resulting in 33 % reductions in sediment loading, 32 % nitrogen loadings and 13% phosphorus loadings.

I use an EA application developed by Rabotyagov (2007). He considers the cost effectiveness of joint pollution reduction. Specifically, two pollutants, nitrogen and phosphorus, are considered simultaneously. As a consequence, the Pareto frontier is three dimensional, depicting the tradeoff between two different pollutant reductions and cost. The fact that one conservation practice often has the potential to reduce more than one pollutant provides a solid reason for this joint approach. Next,we  provide a brief description of the particular multi objective evolutionary algorithm (MOEA) implemented by Rabotyagov (2007) that was used to obtain the numerical results.

The MOEA is a modification of the Strength Pareto Evolutionary Algorithm2 (SPEA2), proposed by Zitzler and Thiele (1999). The search process starts by creating a random population of possible solutions. The random population plays the same role as starting values do in

ordinary optimization routines. Individuals undergo a process of mutation, crossover and ultimately selection. An objective function is evaluated for each individual.

The selection is made based on a fitness score. The fitness score of each individual $i$ in the population takes into account the number of individuals that are dominated and the number of individuals that dominates individual $i$. The degree of "crowding" around individual $i$ is a measure of diversity in the population. A lower fitness score implies the individual is closer to the Pareto frontier and a zero value implies that the individual is on the frontier. Next,we give a brief description of the algorithm's principles.

Two types of populations are required at a given time $t$: the original population, $P_t$, and a temporary, or storing population, $P_{temp_t}$. At the time t=0, $P_t$ is generated by randomly assigning individuals with different values from the allele set. These individuals play the same role as choosing starting values in any other optimization problem. The temporary population is empty at time zero. It will be populated with individuals created by crossover and mutations. A fitness value is calculated for each individual from $P_t$ and, $P_{temp_t}$ sets. In order to determine the fitness value, each individual is compared with all other individuals. For example, take two individuals A and B, then individual A is said to dominate in Pareto sense, individual B, if all its genes have better values. In this case, individual B is said to be dominated. Strength value is a metric measure that defines the number of individuals that an individual $i$ dominates. An individual $i$ can dominate some individuals but can be dominated by other individuals. Another metric measure, the raw fitness is obtained by summing the strength values of individuals $j$ that dominate. The raw measure is also a metric of the likelihood of individual $i$ to generate off spring that pass his characteristics to next generations. If its raw measure is high, this means that it is dominated by many individuals and less likely to survive, hence it is desirable that the raw measure to be as closest to zero as possible. A non dominated individual is an individual with zero raw value.

The searching process can create individuals that do not spread uniformly over the search space. Some of them tend to cluster into certain areas, leaving some others areas sparse. The metric measures defined above do not provide any information about the degree of clustering. Another two metrics measures are defined to incorporate information about clustering around certain areas of the search space. One of the measures differentiates among individuals that are too close one to another; the second measure preserves the diversity in the search space by

rewarding the individuals that are further away on the frontier. The resulted individuals will be more uniformly spread over the search space

*2. Model*

In this this section ,we study the efficiency of a tradable performance standard for water quality in a watershed area where agriculture activity is the main source of water quality impairment. We assume that the environmental authority decides to monitor and enforce a cap on the total level of ambient pollution. The ambient pollution level is monitored at single receptor located at the watershed exit. The authority identifies a set of conservation or abatement practices that have been demonstrated to reduce the amount of agricultural discharges from fields (i.e. conservation tillage, cover crops, reducing the fertilizer application rate and land retirement). Adopting a conservation practice imposes costs on the farmers in the watershed. Next,we assume that using available cost information together with an evolutionary algorithm and a complex biophysical model, the authority is able to identify the optimal placement of conservation practices across the watershed. The optimal solution is designed to achieve the environmental cap in the least cost way.

Two alternatives program are considered for enforcing the ambient pollution cap: command and control and a tradable performance standard program. Assuming away the issues related to legality of enforcement, we first show that the two approaches will have the same outcome if the environmental authority has perfect information on the cost of adopting conservation practices (i.e. abatement costs). In reality, abatement costs are heterogeneous across farmers and locations and it is unlikely that the authority has the cost information for each farm in the watershed.

Next,we examine the efficiency of a command and control versus a tradable performance standard; first under perfect cost information, then under asymmetric cost. In the case of a command and control program, the farmer is constrained to adopt a specific conservation practice, regardless of whether an alternative practice could achieve the same emission reductions at a lower cost. In this chapter we show that, a more efficient solution would be a tradable performance based program, where farmers are allowed to choose the abatement or conservation practice that works best for them as long as the total discharges satisfy a pollution

standard. The tradable pollution standard can be either an emission based standard (i.e. measured at the field edge) either an ambient based standard (i.e. measured at the outlet of watershed).

Consider a simple model of pollution where a watershed is impaired by agricultural runoff consisting of nitrogen and phosphorus. My model follows uses similar notations as the model presented by Shortle and Abler (1997).

There are F farms in the watershed. The farms are heterogeneous from the point of view of soil characteristics, ambient pollution contributions and abatement costs. The ambient standard is monitored at the outlet, located at the base of the watershed. Run off pollution is an externality associated with conservation activity. Let $r_i$, the *ith* farm's contribution measured at the edge of the field, be defined as:

$$r_i = r_i(x_i, \alpha_i) \ \forall \ i = 1, \dots, F \tag{2.1}$$

Where $x_i$ is a Jx1 vector of J's conservation practices available to farm *i*, and $\alpha_i$ represents the farm's idiosyncratic characteristics such that soil type, corn suitability rate, slope. Hence, the edge-of-farm emissions are influenced by two factors: the choice of the conservation practice, and the farms characteristics.

Farms are considered to be decision making agents that maximize profits; they are price takers both in output and input markets. The baseline edge-of-field emissions are the result of this maximization behavior absent any regulations on the pollution levels.

A water quality production function, $W(r)$, measures the total ambient pollution monitored at the main outlet . The function is defined in terms of each farm's individual edge-of-field emissions, described by the vector $r$ . Location and the agricultural activities of the surrounding farms are other factors that enter in the ambient pollution function. In reality, the water quality function is unlikely to be known given the complexity of the agricultural and hydrological process that take place in a watershed and is assumed to be a highly non linear and non differentiable function of individual edge of-field emissions.

Most economics studies assume that the damage function is a linear combination of each source weighed by its delivery coefficients (also known as diffusion or dispersion coefficients).The terminology was introduced by the empirical economics literature that studies trading system as instruments to implement water quality policies (Montgomery, 1972). In this study, we assume that the water quality production function is known and can be expressed as an

exact combination of delivery coefficients and edge of field emissions. This is equivalent to assuming that there edge-of-fields discharges can be determined free of measurement errors.

$$W(r) = \sum_i^F d_i r_i(x_i) \tag{2.2}$$

where $d_i$ is the delivery coefficient for source $i$, measure the amount of edge of field nutrient loading that reaches the main outlet[2].

One of the objectives is to study the change in farmers' behavior under an imposed cap, $\overline{W}$, on the total ambient pollution relative to a command and control solution. Abatement costs are defined as the difference between baseline profits and the profits associated with less polluting production activity[3]. The cost can be defined as a function of the conservation practice and an idiosyncratic parameter $\theta$, that accounts for the fact that adoption costs vary by location due to differences in physical characteristics of the farm (i.e., soils, slope, etc.), location and farms' management abilities.

$$C_i(x_i; \theta_i) \forall i = 1, \dots, F \tag{2.3}$$

I assume that individual farmer knows the cost of adopting a conservation practice. The environmental authority cannot access cost information at farm level, but rather can infer information about the distribution of the costs. The first best solution is defined as the least cost solution when at a cap is imposed on the total level of ambient pollution and the regulator has complete information about the conservation costs. In what follows, the first best solution is contrasted with the solution obtained in the case where the regulator knows only the distribution of the costs across the farmers.

*Command and control program*

The environmental agency decides to enforce a cap on total ambient emissions, $\overline{W}$. It seeks to minimize the expected abatement cost of all farms across the watershed such that the total expected ambient emissions are less than the ex-ante established cap.

$$min_{x_{ij}} \sum^F C_i(x_{ij}, \theta_i) \qquad s.t \quad \sum_i^F d_i r_i(x_i) \leq \overline{W} \tag{2.4}$$

The Lagrangian is given by :

$$L = min_{x_{ij}} \sum_i^F C_i(x_{ij}, \theta_i) - \lambda \left( \sum_i^F d_i r_i(x_i, \alpha_i) - \overline{W} \right) \tag{2.5}$$

---

[2] To simplify, I drop $\alpha_i$ from $r_i(x_i, \alpha_i)$ with no consequence on the results' derivation.
[3] Alternatively, assuming risk neutrality, the abatement costs represent the farm's willingness to accept to implement a conservation practice

The optimal solution, $x_{ij}^*$, must satisfy:

$$\{x_{ij}\} \quad \frac{\partial L}{\partial x_{ij}} = \frac{\partial C}{\partial x_{ij}^*} - \lambda \frac{\partial \sum_i^F d_i r_i(x_i, \alpha_i)}{\partial r_i} \frac{\partial r_i}{\partial x_{ij}^*} < 0, \qquad \frac{\partial L}{\partial x_{ij}} x_{ij}^* = 0 \qquad (2.6)$$

$$\{\lambda\} \quad \frac{\partial L}{\partial \lambda} = W(r) - \overline{W} < 0 \qquad\qquad\qquad \frac{\partial L}{\partial \lambda} \lambda^* = 0 \qquad (2.7)$$

If $x_{ij}^* > 0$ , i.e. the conservation practice is chosen, then the first order condition is equal to zero. The second equation is for $\lambda$, the shadow price of the environmental constraint. Assuming that an interior solution exists, the following result will emerge:

$$\frac{\partial C}{\partial x_{ij}^*} = \lambda^* d_i \frac{\partial r_i^*}{\partial x_{ij}^*} \ \forall \ i = 1, \dots, F \qquad (2.8.)$$

Where $r_i^*$ gives the optimal amount of discharges associated if conservation practice $j$ is chosen.

Equation (2.8) states that the marginal abatement cost is equal to the product of the shadow price of the pollution constraint multiplied by the marginal reduction in edge-of-field emissions due to conservation practice $j$

Under perfect information, the environmental authority would assign for each farm an optimal plan consisting of the placement of optimal conservation practice, $x_{ij}^*$, and thus implicitly an optimal amount of edge of field pollution $r_i^*$, $\forall \ i = 1, \dots, F$ farms and $\forall \ k = 1, \dots, J$ available conservation practices. The optimal choices can be used to implement either a command and control program or an ambient standard program. In this case, since the ambient pollution function is assumed to be a linear function, in the case of command and control programs, farms might be asked to limit their ambient emissions to $d_i r_i^*$ by implementing the $x_{ij}^*$, as abatement practice, or in the case of an ambient standard program, farms are able to choose the conservation practice as long as their edge of field discharges do not result in a violation of their performance standard $d_i r_i^*$ .

Total abatement cost, denoted by $TC^*$ is obtained by summing the cost of adopting the conservation practices for all farms across watershed.

$$TC^* = \sum_i^F C_i \ (r_i^*(x_i^*), \theta_i) \qquad (2.9)$$

*Tradable ambient standard program*

Assuming that the true form of water quality function is a linear function of edge of field discharges weighted by known and well defined delivery coefficients, the social optimal solution can be implemented under a command and control system where specific conservation practices are prescribed for each location. Alternatively,we can consider a tradable performance standard setting, where each farm has the freedom to choose its own conservation practices, but its emissions are constrained by an individual pollution standard. In both cases, the water quality target is achieved at the least cost solution.

Now, assume that the authority decides to implement an ambient standard for each farm. Given that the set of conservation practices is the same, farm minimizes the abatement cost $(C_i)$ such that the ambient emissions are less or equal to the cap imposed by the environmental agency.

$$\min_{x_j \in X} C_i(x_{ij}, \theta_i) \tag{2.10}$$

$$s.t \quad d_i r_i(x_{ij}, \theta_i) < d_i r_i^* \tag{2.11}$$

The optimality conditions, $x_{ij}^{PS}, r_i^{PS}$ are given by, in the case of an interior solution,

$$\frac{\partial C_i}{\partial x_{ij}^{PS}} = \lambda_i^{PS} d_i \frac{\partial r_i^{PS}}{\partial x_{ij}^{PS}} \tag{2.12}$$

Where, $\lambda_i^{PS}$ is the individual shadow price of ambient pollution, quantifying the incremental increase (decrease) in cost if the ambient standard is more (less) stringent

Assuming perfect information, optimal solution and performance standard solution are equivalent, $r_i^* = r_i^{PS}$. This implies:

$$\lambda^* d_i \frac{\partial r_i^*}{\partial x_{ij}^*} = \lambda_i^{PS} d_i \frac{\partial r_i^{PS}}{\partial x_{ij}^{PS}} \quad \forall i = 1, \dots, F \tag{2.13}$$

Hence, $\lambda^* = \lambda_i^{PS}$ that optimal individual shadow prices must be the same across watershed.

Total cost of a tradable performance standard program is defined as:

$$TC^{PS} = \sum_i C_i \left( r_i^{PS}(x_i^{PS}), \theta_i \right) \tag{2.14}$$

If there is perfect information and if the water quality production function is a linear function of the edge- of-field discharges and well defined delivery coefficients, then total cost of the two programs will be same, and the ambient target will be realized in the least cost way.

*Achieving the first best under cost asymmetry*

In reality, given the idiosyncratic nature of conservation cost, environmental authority does not have the same level of cost information as farms do, instead it can only infer some estimates of the distribution of the true costs referred as: $\bar{\theta}$ . In this case, the best the authority can do is to consider the second best problem:

$$min_{x_{ij}} \sum_i C_i(x_{ij}, \bar{\theta}) \qquad s.t \quad \sum_i^F d_i r_i(x_i) \leq \overline{W} \qquad (2.15)$$

where $\bar{\theta}$ represents a vector of the mean costs of the J conservation practices.

The solution to this problem will generally differ from that obtained in (2.1) and the assignment of abatement practices, $\hat{x}_i$, will not necessarily coincide with the least cost solution, $x_i^*$. Likewise, the edge-of-field emissions, $\hat{r}_i(\bar{\theta})$, will be different from the first-best, $r_i^*$. Total costs are given by:

$$\widehat{TC} = \sum_i^F C_i(\hat{x}_i, \bar{\theta}) \qquad (2.16)$$

Under a command and control implementation system, the solution imposed by authority, $\hat{r}_i(\bar{\theta})$, may not reflect the least cost allocation of conservation practices since some farms may have much lower or higher costs than the mean, which, if known by the authority, could be used to more cost-effectively assign practices to fields. Nonetheless, the overall abatement target, $\overline{W}$, will be met

In this case, the authority can increase social welfare relative to a command-and-control assignment of conservation actions, $\hat{x}_i$, by allowing firms to meet a performance standard, $d_i \, \hat{r}_i \, (\bar{\theta})$. Since firms know their true costs, they may be able to meet the performance standard allocated to them less expensively by using a different conservation practice (or combination of practices). If faced with a performance standard, firms will face the following optimization problem,

$$min_{x_{ij}} C_i(x_{ij}, \theta_i) \; s.t \; d_i r_i(x_i, \theta_i) \leq d_i \, \hat{r}_i \, (\bar{\theta}) \qquad (2.17)$$

The farmers minimize the abatement costs given the true costs, subject to a performance standard based on average estimates of true costs. The solution is given by $x_i^{PS}, r_i^{PS}(x_i^{PS})$ and the corresponding costs:

$$TC^{PS} = \sum_i^F C_i(x_i^{PS}, \theta_i) \qquad (2.18)$$

The magnitude of cost savings under asymmetric cost information is given by the difference between total costs under $\bar{\theta}$ and total cost under $\theta = (\theta_1, \dots, \theta_F); \theta$ defines the vector

of field level stock. Since optimal placement of conservation practices can be different under the two cost sets and the costs set are different, a direct comparison of the two total costs is not feasible. In order to make the costs comparison, the solution of the environmental agency needs to be reevaluated at the set of costs used in individual optimization The size of the cost savings, $\Delta C$, if any, is be given by:

$$\Delta C \ = \ \sum_i^F C_i \ (\hat{x}_i, \theta_i) - \sum_i^F C_i (x_i^{PS}, \theta_i) \tag{2.19}$$

Where $\sum_i^F C_i \ (\hat{x}_i, \theta_i)$ represents the total cost of a command and control program whose solution given by equation (2.16) is re-evaluated at the true set of costs, $\theta$.

Another comparison that can be made is the difference between the total cost of a command and control program under a cost set defined $\overline{\theta}$ and total costs when the same outcome evaluated at the set of true costs, $\theta$. The difference can be interpreted as how much would a command and control program designed with $\overline{\theta}$ cost if the true costs are given by $\theta$; it represents the extent to which the regulator underestimates or overestimates the overall costs of the program.

$$\Delta CC \ = \ \sum_i^F C_i \left( \hat{x}_i, \overline{\theta} \right) - \sum_i^F C_i \ (\hat{x}_i, \theta_i) \tag{2.20}$$

*3. Data and methodology description*

Next,we provide a description of data and methodology used to generate the empirical evidence for cost the savings given by equation (2.19) and (2.20).

*Study area*

The study area is represented by a watershed located in the north central part of Iowa, the Boone Watershed River (BWR). The watershed covers more than 237,000 acres in six counties. The watershed area is crop intensive, with corn and soybean representing almost 90% of the agricultural activity. The surface area had been intensively tile drained, as a consequence the wetlands area had been reduced significantly. Moreover, the Boone watershed agricultural area has been found responsible for some of the highest nitrogen loadings among Iowa's watersheds (Libra *et. al* 2004).

Land use in the watershed is dominated by agriculture: with 89.7% of the area representing crop land, 5.6% of the area representing retired land, 2.6% forestry area and the rest of the area accounting for urban areas and water surfaces. Most of the land is flat area,

characterized by soils with low slopes, i.e. 73% of the areas have the length of the slope less than 0.01 inches. Slope characteristics are relevant to our analysis in two ways. First, the size of the slope affects the choice of the conservation practices. Second, it affects the total discharges associated with a particular area. Corn suitability rating is another characteristic that defines the potential yield[4]. CSR is an index that ranges between 0 and 100, where high values are associated with high quality soils. A soil with a high CSR value is less likely to have high rates of fertilization, and at the same time is less likely to be considered for land retirement as a solution for reducing the nitrate loadings. In the BWR more than 50% of the soils have been rated with CSR values ranging 50 to 79 and for 40% of the soils have CSR values higher than 80.

The required data for modeling system (i.e. SWAT mode) was collected at Common Land Unit level (CLU)[5]. More than 16,300 CLUs have been identified in the BWR. As HRU is the unit required by SWAT model, the CLUs were regrouped in roughly 2,900 HRU. Data about crop rotation, land use, fertilizer management, tillage and conservation practices were provided by a field level survey conducted by Kiepe (2005).

### *Conservation practices*

The set of conservation practices selected as abatement practices for achieving the nutrient loading standards includes: reducing the rate of fertilizer application, conservation tillage (i.e., no till), cover crops, and land retirement. The above set is augmented with all feasible combinations of these practices but land retirement (i.e. combination of no till and cover crops is considered as an independent conservation practice). The baseline is also considered as choice alternative. This allows considering the cases when a farm does not take any abatement action In the context of the evolutionary algorithm optimization's process, the conservation practices represent the allele set.

Table 1: Conservation practices

---

[4] CSR is a procedure that rates different kind of soils for its potential row crop productivity. It was developed for Iowa soils. Detailed information can be found at: (link)

[5] "A Common Land Unit (CLU) is the smallest unit of land that has a permanent, contiguous boundary, a common land cover and land management, a common owner and a common producer in agricultural land associated with USDA farm programs. CLU boundaries are delineated from relatively permanent features such as fence lines, roads, and/or waterways."( http://www.fsa.usda.gov)

| | Conservation Practice | Conservation practice description |
|---|---|---|
| 1 | Baseline | The baseline existent agriculture practices |
| 2 | No till (NT) | No till, no more than 30 % of crop residue remaining. |
| 3 | Reduced Fertilizer (RF) | Reducing fertilizer application rate by 20 %. |
| 4 | Cover Crops (CCr) | Establishment of cover crops between crop rotations. |
| 5 | Land retirement (CRP) | Retirement of land from production |
| 6 | NT RF | No till, no more than 30 % of crop residue remaining |
| 7 | NT CCr | No till and 20 % reduction in nitrogen application rate |
| 8 | RF CCr | No till and establishment of cover crops. |
| 9 | NT RF CCr | No till,20 % reduction in nitrogen application rate  and cover |

*Conservation practices cost*

Costs for each conservation practice were drawn from several sources. All costs are expressed as dollar per acre. The cost for adoption of no till was drawn from Kling et. al (2005). The cost of adopting no till is $9.62 per acre if the baseline has assigned conventional tillage and $4.81 if the baseline is assigned mulch tillage[6].Cover crops cost estimates were provided by local farmers[7]. The average cost for cover crops is $25[8].

An implied yield curve for corn-soybean rotation , where yield is estimated as function of fertilizer applied was used to derive the cost for reducing the fertilizer application rate. The procedure is the similar with the one used by Rabogtyagov (2007), Sawyer *et al*.(2006) Libra, Wolter, and Langel (2004). Data from Iowa field experiments, available through ISU Extension was used to estimate an implicit nitrogen based yield curve. The cost of nitrogen fertilizer reduction varies across fields based on the fertilizer application rate reported for the baseline scenario. The implied yield curve is a four degree function of fertilizer rate[9]. The cost of

---

[6] Much tillage is an interim type of tillage

[7]  The cover crops cost estimate was provided by Tom Kaspar scientist at USDA-ARS National Laboratory for Agriculture and the Environment

[8] Estimated Costs of Crop Production in Iowa – 2008 (FM-1712) and Estimating Farm Machinery Costs (PM-710), actual seed costs, and bulk generic glyphosate in 2008.  No fertilizer applied for cover crop growth

[9]  The coefficients of  nitrogen response yield curve $Y = -3.32904824784026E\text{-}09*N^4 + 8.88402E\text{-}06*N^3 - 0.004459448*N^2 + 0.822128904200617*N - 0.374570292118776$

reducing fertilization is given by multiplying a 20 % percent reduction in the baseline fertilizer rate by the price of corn. The price of corn used is $3.08 per bushel.[10]

Cash rental rates available online (Edward and Smith, 2009) in conjunction with the corn suitability ratings (CSR) available were used to compute the cost of retiring land out of production. The cost of land retirement for each field is obtained by multiplying the cash rental rate per unit of CSR by area and corresponding CSR. The cash rental rates are used as proxies for the opportunity cost of land retirement (Secchi and Babcock, 2007).A zero cost is considered for no change from the baseline practices. The cost of the conservation practices obtained as a combination of the primary ones (i.e. no till and reduced fertilizer) are obtained by summing per acre cost of each conservation practice considered in the combination.

Two sets of data are required to derive my cost savings analysis. A set of costs, $\theta$ representing the individual farm/field costs, and a set of costs $\bar{\theta}$, representing the set of costs used by environmental agency. The data collected from the sources describe above do not provide detailed cost estimates as farm level. Thus, this data will be considered as the cost set employed by environmental agency. The set of true costs that are known just by farmers was simulated as a mean preserve spread of the real data cost estimates.

The present analysis considers that only the cost of cover crops varies across farmers. Since the Boone watershed spans over six counties, six different cost estimates are considered, one for each county. The six estimates were randomly drawn as a mean preserving spread around the real field cost estimate, $25/acre[11].

*Methods*

SWAT_EA analysis was used to determine the optimal placement of conservation practices such that a water quality goal is achieved. The evolutionary algorithm starts with an initial set of population. In this study, the populations' individuals are referred as watershed configurations[12]. The first created individuals are also known as original seeds. Once the

---

[10] Price per bushel and represents the average corn price for Iowa for 2004-2009. Source of corn price is: http://www.extension.iastate.edu/agdm/crops/pdf/a2-11.pdf

[11] The six cost estimates for cover crops are: $32.$3,19.$26,$12.53,$38.83,$29.95,$23.37,per acre

[12] To eliminate further confusions, an individual is referred as a watershed configuration, where each watershed is unique in the sense that provides a unique placement combination of

optimization process is initialized, the original population undergoes processes of crossover, mutation and selection. The optimization process can be run over an undetermined number of generations, although the marginal gains are getting smaller as the number of generations increases. The final solution consists of a Pareto frontier, an entire set of watershed configuration able to achieve different levels of ambient pollution in a least cost manner. The stopping criterion is most of the time at the researcher hand. In our case, we analyze the shape of the Pareto frontiers by running evolutionary algorithms by increasing the number of generations in steps. The stopping criterion was heuristically chosen when the marginal improvements in the shape of the Pareto frontier were small enough.

*Evolutionary Algorithm: Pareto frontier sensitivity*

Results specific to EA implementation together with a brief description of the initial population are presented next. An EA sensitivity analysis to the number of generations allowed to survive is conducted by comparing the shape of the Pareto frontier. Evolutionary algorithm is initialized with an initial population, the starting point of the optimization algorithms. The size of initial generation should be large enough to give good coverage of the search space, where the search space is defined by all possible combination of nitrogen (N), phosphorus (P)and costs levels. The initial population has 40 individuals corresponding to 40 different watershed configurations. The first nine individuals are created by uniformly assigning the same conservation practice for each field in the entire watershed, i.e. assigning only to each field only no till, or only cover crops, etc. The rest of 31 individuals are created by randomly assigning different combinations of conservation practice

---

abatement practices. This unique combination will result in a unique levels of nitrogen and phosphorus discharges and a unique total cost of achieving ambient level.

Table 2: Summary of uniform seed individuals

| Uniform seed | Cost ($/acre) | Nitrate (kg) | N reductions (%) | Phosphorus (kg) | P reductions (%) |
|---|---|---|---|---|---|
| Baseline | 0 | 4,837,160 | 0 | 187,888 | 0 |
| No till (NT) | 4.9 | 3,472,694 | 28.21 | 104,832 | 44.21 |
| Cover crop (CCr) | 24.92 | 3,673,834 | 24.05 | 128,004 | 31.87 |
| NT CCr | 29.82 | 2,507,894 | 48.15 | 108,318 | 42.35 |
| Reduced Fertilizer | 4.16 | 4,550,998 | 5.92 | 187,474 | 0.22 |
| NT, RF | 9.05 | 3,179,288 | 34.27 | 104,114 | 44.59 |
| RF, CCr | 29.08 | 3,423,958 | 29.22 | 127,286 | 32.25 |
| NT, CCr, RF | 33.98 | 2,253,732 | 53.41 | 106,244 | 43.45 |
| CRP | 206.31 | 883,706 | 81.73 | 14,583 | 92.24 |

Table 2 presents the first nine individuals used in EA initialization. The first column gives a description of the conservation practices. The second column cost for each watershed configuration expressed in dollar/acre. The third and the fifth column give the levels of N and P expressed in kilograms. The percentage reductions in N and P levels relative to the baseline are presented in the fourth and the sixth column. For example, if no till is uniformly assigned across the entire watershed, the N discharges will be reduced by 28.21% (i.e. from 4.83 to 3.47 mil kg), P discharges will be reduced by 44.21% (i.e. from 0.188 kg to 0.105 mil kg), at a cost of $4.9 per acre.

The ambient level associated with each individual (watershed configuration) is evaluated by watershed water quality model, SWAT. The total cost is obtained by evaluating each individual at the set of conservation practices costs. Thus, each individual, watershed configuration, has associated a cost and a particular level of nitrogen and phosphorus.

Using the above information (cost, N and P data), EA compares each individual with all other individuals. Following all possible comparisons, an individual is Pareto dominant if it has either both levels of nitrogen and phosphorus lower at the same level of cost, or, alternatively, at the same level of reductions it has a lower cost. After all individuals have been compared, each a strength value is assigned to each individual. The strength value of a particular individual counts how many individuals dominate it (how many individuals have lower costs, or given the same costs have a higher level of reduction). A measure of fitness is computed, providing the selection or survival criterion. A lower value for the fitness score gives a higher the probability of an individual to be selected for next generation. The Pareto frontier is constructed by individuals with a fitness score equal to zero, i.e.; they are not dominated by any other individuals. A density measure is useful later on, to avoid the clustering effect and allow the Pareto frontier to span over a larger area of the search space.

The Pareto dominant individuals are selected to be the next generations' parents. New offspring emerge as a result of the crossover and mutation processes. Once a new population is created, the process described above is repeated. This algorithm can be run over any number of generations. Once the algorithm is stopped, the solution, a frontier, consists of a set of non dominated individuals. In the context of watershed scale analysis, the individuals represent different watershed configurations. In particular, one individual represents optimal placement of a set of conservation practices that achieves a particular level of nitrogen and phosphorus in the least costly way.

To check the algorithm sensitivity given that the number of generations allowed to survive is increased, the algorithm was run in steps. In particular, a Pareto frontier was saved after every 63 generations and another one after another 60 generations. Figure1 depicts the evolution of Pareto frontiers in terms of nitrogen (N) percentage reductions on the X- axis and associated costs expressed in as thousand dollars on the Y-axis. The frontiers should move downright, meaning that as more generations are allowed, better solutions are found. Also, the

individuals that are on the first frontier and survive the first 63 generations but do not survive the next 60 generations, being dominated, should lie on the inner side of the frontier created after the first 63 generations.

Figure1 depicts the changes in EA's frontier when the number of generations is increased from 63 to 123. The blue stars represent the Pareto dominant individuals that survive at the end of 63 generations. The red squares represent the individuals that survive the first 63 generations, but are dominated after another 60 generation. Note their position is on the inner part of the frontier. Finally, the green triangles represent the new dominant individuals, individuals that where created between generation 63 to 123. Notice that their locations on the frontier is farther on the downright part of reduction – cost space, meaning that EA found either individuals that achieve the same level of reduction less costly, either individuals that achieve higher levels of reduction at the same cost.

*4 Cost asymmetry: Cost saving empirical assessment*

The regulator uses the SWAT-EA analysis to find the optimal placement of abatement practices given his assumption about costs, $\bar{\theta}$. The result, a Pareto frontier, consists of hundreds of individuals, or watershed configurations, able to achieve different combinations of nitrogen (N) and phosphorus (P) reductions in the least cost way. Once the frontier is generated, the authority is able to choose the ambient pollution target. Furthermore, for each field he can assign the optimal conservation placement and optimal amount of discharges measured either at the edge-of –field, either at the watershed exit.

The true costs, $\theta$, associated with this set of practices may differ from the costs that the authority uses. If a tradable performance standard program is implemented, each farm will minimize its abatement effort by choosing from the same set of conservation practices such that the edge-of-field emissions are less than the standard imposed by the environmental authority. The individual standards are designed such that the ambient cap is binding at the main watershed outlet.

Two different sets of EA optimization are performed in order to show the cost difference due asymmetric information. The first EA optimization uses a set of costs determined by using

real field data, where a conservation practice has the same the per acre estimate for each farm or field. The EA optimizations allowed 180 generations to survive. The Pareto frontier consists of more than 1,014 individuals. The first EA optimization is corresponding to environmental agency cost minimization problem with the conservation costs expressed in mean levels (i.e. cost

Figure 1 : EA Pareto frontier sensitivity
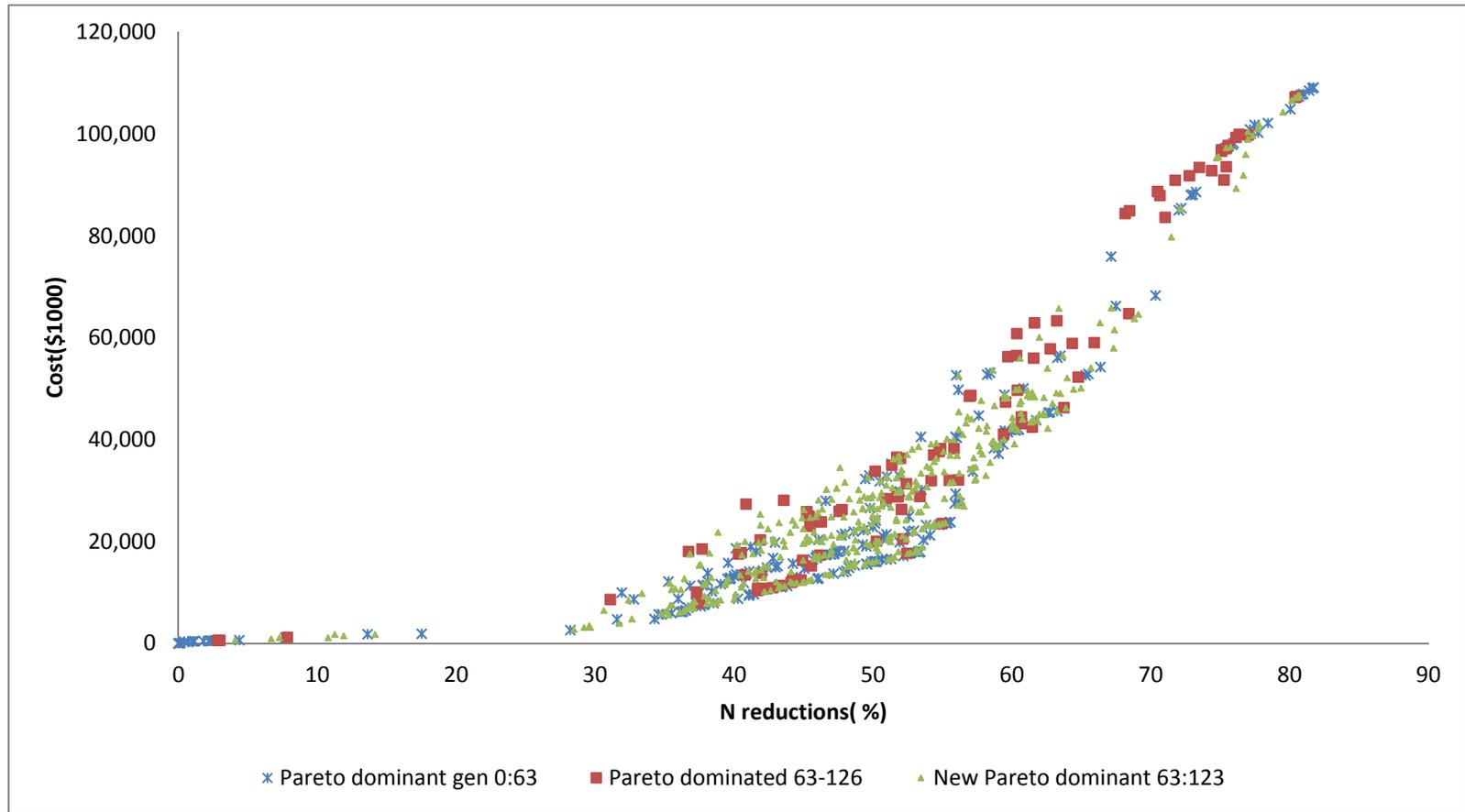
minimization defined by equation (2.15). The total cost is equivalent to equation (2.16). It represents the least cost of achieving a particular combination of N and P discharges.

$$CAC_{cost} = \sum_i^F C_i(\hat{x}_i, \bar{\theta}) \tag{2.21}$$

The set of individuals on this frontier will be referred as $CAC_{sol}$:

$$CAC_{sol} = \{ CAC_{cost_k} | N_k^{CAC} = \bar{N}_k^{CAC} \wedge P_k^{CAC} = \bar{P}_k^{CAC} ; \bar{\theta} \ \forall k = 1, \dots, 1014\} \tag{2.22}$$

Equation (2.22) defines $CAC_{sol}$ as the set of all solutions generated by EA optimization; where each element of the set gives the least cost solution for achieving a unique combination of $\bar{N}^{CAC}$ and $\bar{P}^{CAC}$ discharges.

The second EA optimization corresponds to the individual cost minimization problem or the outcome of a tradable performance standard program defined by equation (2.17). It uses the same set of conservation practices as first EA optimization, but incorporates the asymmetric information aspect of the problem, by allowing the cover crops to vary across watershed. Total cost is equivalent to equation (2.18):

$$PS_{cost} = \sum_i^F C_i(x_i^{PS}, \theta_i) \tag{2.23}$$

The second Pareto frontier consists of 914 individuals; the solutions set will be referred as $PS_{sol}$, and can be defined in a similar way to $CAC_{sol}$

$$PS_{sol} = \{PS_{cost_l} | N_k^{PS} = \bar{N}_k^{PS} \wedge P_k^{PS} = \bar{P}_k^{PS}; \theta; \ \forall l = 1, \dots, 914\} \tag{2.24}$$

Equation (2.24) defines $PS_{sol}$ as the set of all solutions generated by EA optimization; where each element of the set gives the least cost solution for achieving a unique combination of $\bar{N}^{PS}$ and $\bar{P}^{PS}$ discharges.

The $CAC_{sol}$ and $PS_{sol}$ are different frontiers generated with two different cost sets. Given the different nature of the two sets, $CAC_{sol}$ solutions must be transformed in terms of $PS_{sol}$: $CAC_{sol}$.Pareto frontier is re-evaluated with the set of conservation costs used to obtain $PS_{sol}$ frontier. The new frontier is referred as $CACPS_{sol}$.

$$CACPS_{sol} = \{CAC_{cost_k} \in CAC_{sol} | CACPS_{cost_k} = \sum_i^F C_i(\hat{x}_i, \theta_i) \ \forall k = 1, \dots, 1014\} \tag{2.25}$$

If there any cost savings, then for the same level of ambient target, the cost associated with an individual from $CACPS_{sol}$ frontier should be higher than an individual on $PS_{sol}$ frontier. The cost comparison is made as it follows. First, each individual in $CAC_{sol}$ was reevaluated at the true set of costs, $\theta$, obtaining $CACPS_{sol}$. This could be easily done, since the SWAT_EA output provides the placement of conservation practices and area data is available is available for each field. After this transformation, individuals from $CACPS_{sol}$ and $PS_{sol}$ can be compared. The cost comparison is made by selecting individuals from the two sets that achieve the same, or almost the same ambient levels in N (nitrogen) and P (phosphorus). The set of individuals subject to cost comparison, $\Delta COST$, is given by:

$$\Delta COST = PS_{sol} \cap CACPS_{sol};\ \text{where}$$

$$PS_{sol} \cap CACPS_{sol} = \{CAC_{cost} \in CAC_{sol} \wedge PS_{cost} \in PS_{sol} | \bar{N}_k^{PS} \cong \bar{N}_k^{CAC} \wedge$$
$$\bar{P}_k^{PS} \cong \bar{P}_k^{CAC}\} \quad (2.26)$$

## $CAC_{sol}$ versus $CACPS_{sol}$

Before presenting the outcome of the above comparison, it would be interesting to take a look at the difference between $CAC_{sol}$ and $CACPS_{sol}$. This is to determine how much a command and control cost if the true costs are given by $\theta$. A priori, we have no beliefs about the size and the direction of the differences. The $CAC_{sol}$ is the EA solutions where a single cost for cover crops is used; $CACPS_{sol}$ solution reevaluates the former solution by using a set cost of six estimates for cover crops. $CAC_{sol}$ and $CACPS_{sol}$ compare the same individuals but evaluated at different set of costs.

Table 3 summarizes the comparison results. First column shows the percentage reduction levels in terms of nitrogen. The second column gives the distribution of the $CAC_{sol}$ individuals that are less expensive than corresponding $CACPS_{sol}$ individuals. The third column presents by how much, on average, the costs are underestimated. The fourth and the fifth columns are the mirror cases for the second and the third columns and represent the cases of the individuals that are more expensive. There are 319 individuals whose costs were underestimated. Among these 254 have N percentage reductions between 40 % and 60 %. The cost of each individual was, on average, underestimated by 1.35 %. On the other side, there are 695 individuals whose costs

would be overestimated. Among these, 546 individuals have both N and P percentage reductions between 40 % and 60 %, and the costs being overestimated by 1.1%.

Table 3: $CAC_{sol}$ vs $CACPS_{sol}$

| N reductions (%) | $CAC_{cost} < CACPS_{cost}$ | % Cost underestimation | $CAC_{cost} > CACPS_{cost}$ | % Cost overestimation |
|---|---|---|---|---|
| less than 40 | 52 | 1.65 | 65 | 1.13 |
| between 40-60 | 254 | 1.35 | 546 | 1.1 |
| more than 60 | 12 | 0.2 | 84 | 0.96 |
| Total Individuals | 319 | | 695 | |

This comparison exercise is useful to show that, in the case of a command and control program, for some levels of pollution reductions, the regulator's beliefs about the overall cost program are be overestimated, but for the most of the cases, the overall cost are underestimated. Even if the deviations are small, around one percent, it should keep in mind, that only cover crops cost was varied.

## .$CACPS_{sol}$ versus $PS_{sol}$

The following costs comparisons are based on $CAC_{sol}$ and $PS_{sol}$ solution sets. $CAC_{sol}$ is the result of EA optimization that used a single cost estimate for each conservation practices. The purpose of $CACPS_{sol}$ is to make the ''authority" optimization solution comparable with farm level optimization solution. If in the case $CAC_{sol}$  $CACPS_{sol}$ the individuals subject to comparison were on the same (i.e. located on the same frontier), in this case the compared individual lie on two different Pareto frontiers. In order to make the comparison as accurate as possible, the selected individuals have similar levels of N and P reductions ( i.e. within an interval of 0.01 percent ).

Before comparing the chosen individuals, it is useful to have an overall picture of how all individuals that define $PS_{sol}$ set stands relative to individuals on $CACPS_{sol}$ set. Figure 2 depicts

the percentage reductions in N, on the horizontal axis, versus cost, expressed in $1000, on vertical axis. The blue triangles represent the $CACPS_{sol}$ set, and the green stars represent $PS_{sol}$ set. If there are any cost gains, the $PS_{sol}$ curve should bend more outward (achieve higher level of reduction at the same costs, or achieve the same level of reductions at lower costs). The results, at this stage, are ambiguous, with some areas where $PS_{sol}$ is lower than $CACPS_{sol}$ curve, with some other areas that do not support the cost savings. This might be due to several factors. First, graph takes into account only N reductions and disregard P reductions. Second, due to the approximation natures of EA algorithm, there are only a few exact matches with respect both N and P reductions. For example, some individuals on $PS_{sol}$ set are characterized 40.35% reductions in N and 51.25% reductions in P, but a corresponding individual on $CACPS_{sol}$ curve at the same level of N reductions has different levels of P reduction.

Next, we describe the individuals chosen for comparison. The individuals were chosen according to equation (2.26). Seven pairs of individuals were selected from each set sets by requiring the same N reductions while as the absolute difference in P reductions within 0.001. The selected pairs are presented in Table 4. The first and the fourth columns indicate the individual's position in its set. The numbers itself do not bear a great importance but provide information about timing, i.e. whether they were "born" later or sooner in the EA's evolution. A higher position number means that the individual was created after a higher number of generations. The second and the third columns present N and P percent reductions associated with the individuals that were selected from $CACPS_{sol}$ set. The fifth and the sixth column offer similar information regarding the individuals form $PS_{sol}$ set. The seventh column introduces the absolute size of the cost savings; finally the last column represents the cost savings as percentage.

Table. 4. $CACPS_{sol}$ Individuals versus $PS_{sol}$ Individuals

| # $CACPS_{sol}$ | $CACPS_{sol}$ | | # $PS_{sol}$ | $PS_{sol}$ | | $PS_{sol}$ | $CACPS_{sol}$ |
|---|---|---|---|---|---|---|---|
| | N % | P % | | N % | P % | Cost | % |
| 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 4 | 28.21 | 44.21 | 4 | 28.21 | 44.21 | 0 | 0 |
| 6 | 34.27 | 44.59 | 6 | 34.27 | 44.59 | 0 | 0 |
| 9 | 81.73 | 92.24 | 9 | 81.73 | 92.24 | 0 | 0 |
| 303 | 42.64 | 44.63 | 1450 | 42.64 | 44.64 | 81,375.3 | 0.77 |
| 940 | 28.22 | 44.19 | 1657 | 28.22 | 44.19 | - | -0.13 |
| 1892 | 51.26 | 56.03 | 2042 | 51.26 | 56.03 | 173,074. | 0.59 |

The first four pairs are identical and have zero cost savings; i.e. the individuals achieve the same target with the same cost. The position numbers indicate that these individuals coincide with the initial individuals where a single practice is used. The first pair represents the baseline scenario, the second pair represents no till only scenario, the third pair represents the scenarios where reduced fertilizer is used in conjunction with no till, and finally , the last pair represents the scenario were all land is retired out of production. The results are as expected since, there is no change in costs for these conservation practices. The pairs (#303 ,#1450) and  (#1892, #2042) have $CACPS_{cost}$ higher than $PS_{cost}$(i.e. the idea of cost savings is supported). One pair of individuals (#940,#1657) has negative savings.

Table 5 describes the distribution of conservation practices as percentage of total area in the watershed. Table 6 describes the field frequency for each conservation practice (how many fields use a particular conservation practice) .The most used practices are combinations of reduced fertilizer and no till (CS6), or  reduced fertilizer, no till and cover crops(CS8).
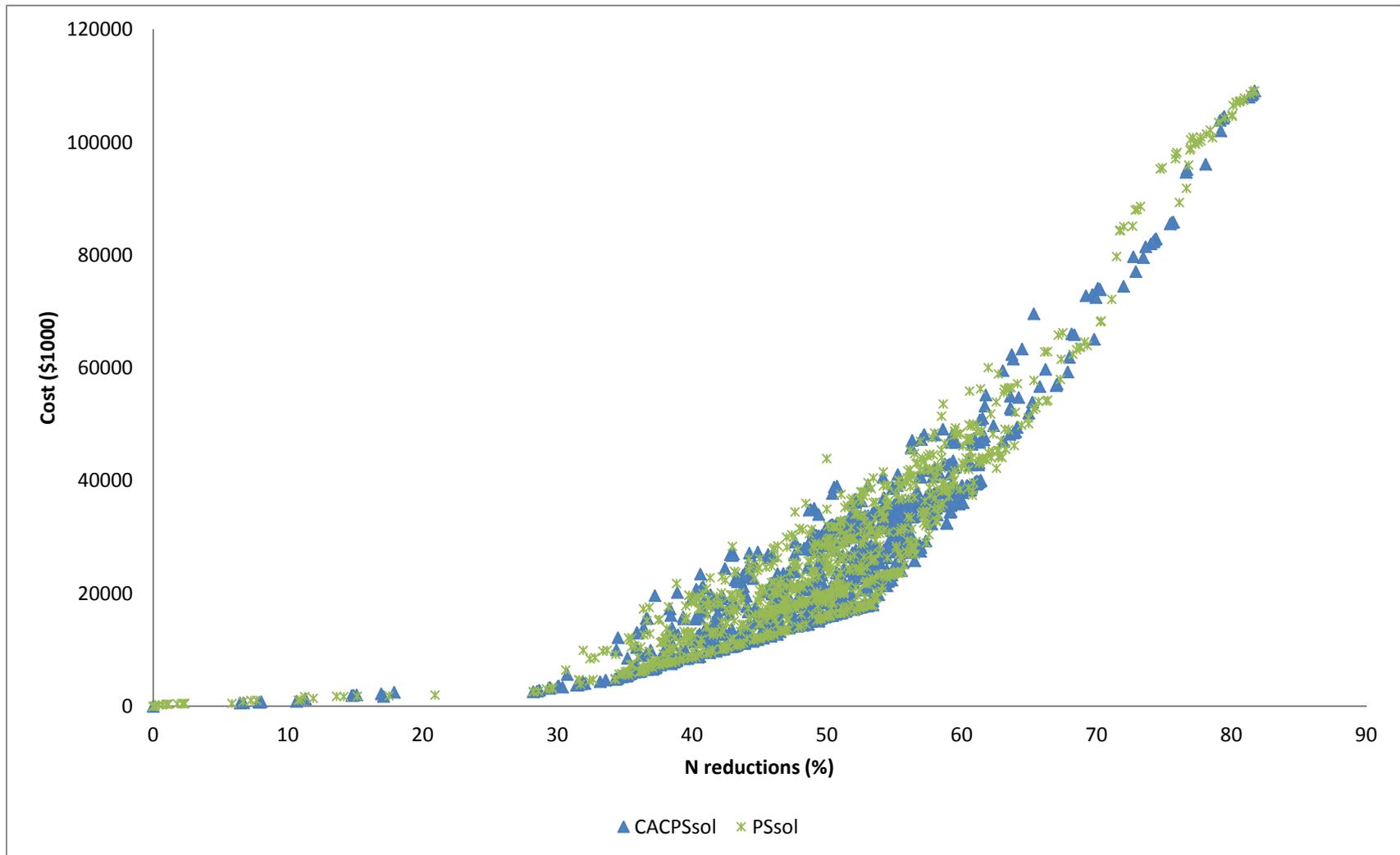
Figure 2 $PS_{sol} - CACPS_{sol}$

Table 5 Distribution of conservation practice by area : % in total watershed area[13]

| $CACPS_{sol}$ | CS1 | CS2 | CS3 | CS4 | CS5 | CS6 | CS7 | CS8 | CS9 |
|---|---|---|---|---|---|---|---|---|---|
| 940 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 303 | 0 | 0 | 0 | 11 | 0 | 58 | 0 | 30 | 0 |
| 1892 | 1 | 0 | 0 | 16 | 0 | 40 | 0 | 24 | 19 |
| $PS_{sol}$ | CS1 | CS2 | CS3 | CS4 | CS5 | CS6 | CS7 | CS8 | CS9 |
| 1657 | 0 | 100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1450 | 0 | 0 | 0 | 0 | 0 | 60 | 0 | 39 | 0 |
| 2042 | 0 | 0 | 0 | 7 | 0 | 43 | 0 | 31 | 19 |

Table 6 Distribution of conservation practice: field frequency

| $CACPS_{sol}$ | CS1 | CS2 | CS3 | CS4 | CS5 | CS6 | CS7 | CS8 | CS9 |
|---|---|---|---|---|---|---|---|---|---|
| 940 | 3 | 2874 | 2 | 22 | 0 | 0 | 0 | 1 | 0 |
| 303 | 5 | 1 | 3 | 443 | 4 | 1606 | 5 | 830 | 5 |
| 1892 | 7 | 8 | 5 | 504 | 6 | 1139 | 7 | 695 | 531 |
| $PS_{sol}$ | CS1 | CS2 | CS3 | CS4 | CS5 | CS6 | CS7 | CS8 | CS9 |
| 1657 | 3 | 2874 | 2 | 0 | 0 | 0 | 0 | 23 | 0 |
| 1450 | 6 | 9 | 9 | 6 | 5 | 1687 | 8 | 1172 | 0 |
| 2042 | 7 | 8 | 8 | 175 | 2 | 1256 | 8 | 833 | 609 |

---

[13] CS1: baseline; CS2: no till; CS3: cover crops; CS4 no till and cover crops; CS5; Reduced fertilizer; CS6 reduced fertilizer and no till, CS7 reduced fertilizer and cover crops; CS8: reduced fertilizer, cover crops and no till, CS9 land retirement;

The individuals of the first pair (#940, #1657) have almost the same placement for conservation practice The only difference is given by the #22 $PS_{sol}$ individual that switches from no till and cover crop ( CS4) to cover crops, no till and reduced fertilizer (CS8), the 22 The negative value could be explained as an approximation error.

The next two pairs have cost savings. The pair ( #303, #1450) has the highest relative cost savings. Individual #303 has 11 % of its area in no till and cover crop (CS4), 58% percent in reduced fertilizer and no till (CS6) , and the rest in no till, reduced fertilizer and cover crops (CS8). Under$PS_{sol}$, the #1450 individual's configuration does not include no till and cover crops (CS4), instead  area covered by  reduced fertilizer and no till (CS6) increased by 1 % and  area covered by reduced fertilizer, no till and CRP (CS8) increased by 10 %.

The last pair (#1892, #2042) has the highest absolute cost savings. Individual #1892 places 40% of its area in no till and cover crops (CS8), 24 % in reduced fertilizer, no till and cover crops (CS9), and finally 19% in CRP (CS9). Individual #2042 under $PS_{sol}$ has a similar watershed configuration places 7% of its area in no till and cover crops (CS4), 43 % in reduced fertilizer and no till (CS6), 31% in  reduced fertilizer, no till and cover crops (CS8), the difference  is in CRP (CS9).

*5 .Conclusions*

In the setup considered here, the regulator seeks to enforce a cap on total ambient pollution. Two alternatives are investigated: a command and control program and a tradable performance based standard program. In the first one, the authority, using an incomplete cost information set, decides what conservation practices to be implemented by each farm. In the second case, the authority recognizes that it does not have complete cost information and implements a performance standard program, allowing farmers to choose the conservation practice according to their cost information.

Two different SWAT_EA optimizations are performed to generate the results needed to confirm or infirm the cost savings. First optimization uses a unique set of conservation costs, $\bar{\theta}$. The Pareto frontier represents the solutions of a command and control program. Second optimization is equivalent to individual optimization problem under a tradable performance

34

standard program. The costs set used in the second optimization reflects the cost heterogeneity across the watershed by imposing variation for the cost of cover crops, $\theta$.

      Overall, the size of the costs savings under a tradable performance standard program is small, but it should be kept in mind only one conservation cost had been diversified across watershed. Further analysis must be conducted where the cost of each conservation practice is varied across the watershed's fields.

References:

Arnold, J.G., Srinivasan,R., Mutiahh, R.S., and Williams, J.R.,, 1998, "Large area hydrologic modeling and assessment part I: Model development", Journal of American Water Resources Association 34 (1) :73:89

Arnold, J.G., and Fohrer, N. 2005. Current capabilities and research opportunities in applied watershed modeling. Hydrological Processes 19: 563-572.

Bekele, E.G and Wicklow,J.W, 2005." Multiobjective management of ecosystem services by integrative watershed modeling and assessment part I: Model development" Water Resources Research, 41, W10406, doi:10.1029/2005WR00590

Carpentier,C.L.,Bosch,D.J. ans Batie,S.1998 "Using spatial information to reduce costs of controlling agricultural nonpoint source pollution". American Journal of Agricultural Economics, 61:401-413

Coase, R.H. 1960 The problem of social cost. *J Law Econ* 3(1):1–44

Colby, B.G (1990)  Transactions costs and efficiency in western water allocation, *Am. J. Agric. Econ.* **72** ,pp. 1184–1192

Crocker, T. 1966. "The structuring of atmospheric pollution control systems, volume 1 of the economics of air pollution". Journal of Economic Theory, 5(3): pp. 395-418.

Corn N rate calculator. Iowa State University Agronomy Extension. Available at http://extension.agron.iastate.edu/soilfertility/nrate.aspx. Accessed April 2010. File C2-10

Dales ,J.H. 1968 Land, water and ownership. Can J Econ 1(4):791–804

Edwards, W, and D. Smith.2009 Cash rental rates for Iowa 2009 survey. Iowa State University Extension Ag. Decision Maker

Feng and C. Kling 2005 The consequences of cobenefits for the efficient design of carbon sequestration programs, *Canadian Journal of Agricultural Economics* **53** (2005), pp.

Hongli Feng, Manoj Jha, and Phil Gassman  2009 The Allocation of Nutrient Load Reduction across a Watershed: Assessing Delivery Coefficients as an Implementation Tool *Appl. Econ. Perspect*. Pol. 31: 183-204. 461–476.

Gassman, P.W., M. Reyes, C.H. Green, and J.G. Arnold. 2007. "The Soil and Water Assessment Tool: Historical development, applications, and future directions". *Trans. ASABE*. 50(4):1211-1250.

Gassman, P.W. 2008. A Simulation Assessment of the Boone River Watershed: Baseline Calibration/Validation Results and Issues, and Future Research Needs. Ph.D. Dissertation, Iowa State University, Ames, Iowa.

Gitau, M.W., T. L. Veith, andW. J. Gburek (2004), "Farm-level optimization of BMP placement for cost-effective pollution reduction" , Trans. ASAE, 47(6), 1923–1931.

Hung, M. *and* D. Shaw*, 2004.* A Trading-Ratio System for Trading Water Pollution Discharge Permits*. Journal of Environmental Economics and Management* 49*:83–102.*

Khanna, M.,W.H. Yang, and R. Farnsworth.2003.  "Cost-effective Targeting of Land Retirement to Improve Water Quality with Endogenous Sediment Deposition Coefficient",  American Journal of Agricultural Economics, 85(3), pp. 538-53.

Krupnick A, Oates W,VergEVD .1983. "On marketable air pollution permits: the case for a system of pollution offset." J Environ Econ Manage 10:233–247

Kling ,C.L., S. Secchi, M. Jha, L. Kling , H. Hennessy, and P.W. Gassman 2005. "Non point source needs assessment  for Iowa : The cost of improving Iowa's water quality. Final Report to the Iowa Department of Natural Resources. Center for Agricultural and Rural Development, Iowa State University, Ames, Iowa

Kurkalova, L.A., C. Burkart, and S. Secchi. 2004. "Cropland Cash Rental Rates in the Upper Mississippi River Basin." CARD Technical Report 04-TR 47. Center for Agricultural and Rural Development, Iowa State University.

Mitchell,M., 1996 An introduction to genetic algorithms. Cambridge, Massachusetts; MIT press

Libra, R.D, Wolter, Langel, C.F., 2004. Nitrogen and phosphorus budget for Iowa and Iowa watersheds. Iowa Geological Survey, Technical Information Series 47.

Maringanti,C., Chaubey, I., Popp, J. 2009 "Development of a multiobjective optimization tool for the selection and placement of best management practices for nonpoint source pollution control" Water Resources Research

Montgomery, W.D .1972 "Markets in licenses and efficient pollution control programs". J. Econ. Theory (3):395–418

Morgan, C.L., Coggins, J.S., Eidman, V.R. 2000 "Tradable permits for controlling nitrates in groundwater at the farm level: a conceptual model" . J Agric Appl Econ 32(2):249–258

Prabodanie, R.A.R, Raffensperger, J.F,nd Milke, M.V .2010 "A Pollution Offset System for Trading Non-Point Source Water Pollution Permits", Environmental and Resource Economics 45(4)499-515

Rabotyagov, S. 2007"Four Essays on Environmental Policy under Uncertainty with Applications to Water   Quality and Carbon Sequestration." Ph.D. thesis, Department  of Economics, Iowa State University

Sawyer, J., E. Nafziger, G. Randall, L. Bundy, G. Rehm, B. Joern. 2006. Concepts and rational for regional nitrogen rate guidelines for corn. Iowa State University, Ames, Iowa. Available at: http://extension.agron.iastate.edu/soilfertility/nrate.aspx.

Secchi, S., B.A. Babcock "Impact of High Crop Prices on Environmental Quality: A Case of Iowa and the Conservation Reserve Program" 2007,Working Paper 07-WP 447. Center for Agricultural and Rural Development Iowa State University,Ames, Iowa

Secchi, S., P. Gassman, M. Jha, H.H. Feng, T. Campbell, and C. Kling. 2007 "The Cost of cleaner water: Assessing agricultural pollution reduction at the watershed scale.  Journal of Soil and Water Conservations 62 (1):10:21

Shortle, J. S., D. G. Abler. 1997 "Nonpoint pollution", in H. Folmer and T. Tietenberg, eds., The International Yearbook of Environmental and Resource Economics. Cheltenham,UK Eduard Elgar.

Srivastava, P, Hamlett, J.M., Robillard, P.D, Day, R.L, 2002, "Watershed optimization of best management practices using AnnAGNPS and a genetic algorithms", Water and resources Research, 38(3): 1-14;

US EPA 2003. Water Quality Trading Policy, Office of Water, January 13. (http://www.epa.gov/owow/watershed/trading/tradingpolicy.html).

US EPA, 2004. Water Quality Trading Assessment Handbook: Can Water Quality Trading Advance Your Watershed's Goals? (http://www.epa.gov/owow/watershed/trading/handbook/ )

Vache, K.B, Eilers,J.M. and Santelman,M.V .2002. "Water quality of alternative agricultural scenarios in the U.S corn belt". Journal of the American Water Resources Association, 38(2):773-787

Veith, T.L, Wolfe,M.L and Heatwole, C.D. 2003, "Development of optimization procedure for cost effective BMP placement". Journal of American Water Resources Association, 39(6):1331:1343

Zitzler, E., and L. Thiele (1999), "Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach", IEEE Trans. Evol. Comput., 3(4), 257– 271;