Reversing the Property Rights: Practice-Based Approaches for Controlling Agricultural Nonpoint-Source Water Pollution When Emissions Aggregate Nonlinearly

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ABSTRACT

Nonpoint-source pollution remains a troubling source of water quality problems despite decades of economics research on the matter. Among the chief difficulties for addressing the issue are the property rights assignments implicit in the current policy environment that favor agricultural nonpoint-source pollution, the unobservability of field-level emissions, and complex fate and transport relationships linking them to ambient water quality. Theoretical and practical considerations lead to the focus on observable abatement actions (conservation practices). Biophysical models are increasingly more capable of linking abatement actions to policy-relevant water quality outcomes. If costs of abatement actions are known, finding the least-cost mix of abatement actions is possible, while incorporating the nonlinearity of the pollution process. When costs are not known or information is incomplete, regulators can rely on flexible incentive-based programs, but the design of such programs is complicated by the complexities of emission aggregation. In this work, we focus on the regulator capable of focusing on nonpoint-source emitters. We address the design and performance of three practice-based approaches, ranging from the command-and-control approach mandating practices, to the more flexible performance standard approach where farmers are free to select the optimal mix of on-farm conservation practices, to a fully flexible approach where credits for conservation practices are freely tradable. We do so by utilizing the representation of the nonlinear emission aggregation (fate and transport) process (the Soil and Water Assessment Tool model), and consider cases ranging from the regulator having perfect information on the costs of conservation practices to no information at all. We show how workable programs utilizing the biophysical models and simulation-optimization approaches can be designed, and assess their performance relative to the efficient case. We find that flexible programs perform well both in terms of cost and water quality goals attainment. In particular, a trading program designed around an approximation of the nonlinear pollution process performs well, relative to first-best under no information on the cost of conservation practices.

INTRODUCTION

Environmental and agricultural economists have been studying the design of efficient programs to address nonpoint-source (NPS) water pollution from agriculture for decades. Issues studied extensively include taxes, subsidies, and standards capable of achieving the first-best outcomes (Griffin and Bromley, 1982; Shortle et al., 1998), or as one would realistically expect from a workable policy, second-best outcomes (Shortle and Dunn, 1986; Shortle and Horan, 2001). Much of this work has focused on the design of these programs within the context of the existing regulatory structure and its associated focus on the voluntary adoption of abatement actions from agriculture (Ribaudo, 2001). Within that property rights approach, researchers investigated the cost-effective design of subsidies to induce adoption (Shortle and Dunn, 1986; Braden et al., 1989; Wu and Babcock, 1996; Carpentier, Bosch, and Batie, 1998; Khanna et al., 2003) and optimal trading ratios between point and nonpoint sources (Shortle, 1990; Letson, 1992; Malik et al., 1993; Horan, 2001; Horan and Shortle, 2005; Hung and Shaw, 2005; Hennessy and Feng, 2007; Lankoski, Lichetenberg, and Ollikainen, 2008; Rabotyagov and Feng, 2010). Additionally, instruments focusing on ambient pollution and efficient contract design have been investigated (Segerson, 1988; Horan et al., 1998; 2002; Cabe and Herriges, 1992), but did not receive much attention in the policy community.

Despite subsidy programs and the development of nascent water quality trading programs targeting nonpoint-source agricultural water pollution, poor water quality pervades much of the United States, and a large amount of the remaining water quality problems are attributable to nonpoint agricultural sources.

Recent US Environmental Protection Agency (EPA) national water quality inventories shows that agriculture is the leading source of river and stream impairments and the third-largest source of lake, pond, and reservoir impairments. According to the latest National Summary of Assessed Waters Report (2010), the water quality of 53% of nationwide rivers and streams assessed in the survey has been found as improper for the designed use (Figure 1). The increasing trend (50% in 2008, and 44% in 2006) shows that there has been little success in reducing the impact of nonpoint-source pollution (US EPA, 2011).

These statistics suggest that existing efforts that grant the implicit right to pollute to nonpoint sources may not be adequate to achieve stated water quality improvement goals.

In addition to voluntary approaches and price instruments, economists have also long pointed out that instruments that regulate nonpoint sources using quantity instruments could be used to address nonpoint-source pollution issues. This can be achieved by either focusing on observable inputs and technologies or estimated emissions (Griffin and Bromley, 1982; Shortle and Dunn, 1986), or by using cap-and-trade approaches (Shortle, 1990; Malik et al., 1993). Despite the analyses demonstrating the theoretical viability of the strategies that directly regulate inputs or agricultural practices to achieve efficient pollution reduction, there have been relatively few examples of implementation of such strategies. One reason for the scarcity of quantity controls is due to the federal policy foundation for water pollution control in the United States — the Clean Water Act (CWA) and its amendments (Shabman and Stephenson, 2007). The Act, at the federal level at least, effectively assigns property rights to pollute in the nation's waterways to agricultural nonpoint sources. Specifically, nonpoint sources are excluded from NPDES permit requirements, which is the main mechanism in the Act through which reductions in emissions to water are regulated and achieved.

It is important to note however that states are free to implement their own agricultural pollution control reduction policies, which can involve direct regulation. While not common, existing programs indicate the potential for this approach. The state of Florida provided an interesting example with the Everglades Forever Act in 1996, when agricultural nonpoint sources in the South Florida Agricultural Management District were directly required to implement conservation practices for lowering the phosphorus levels in the Everglades area. Over the 17-year history of the program, measureable reductions in ambient pollution from these sources have been more than 55% on average (SFWMD New Release, July 2012).

Recently, Kling (2011) reviewed the policy context and argued that the state of economic theory, the environmental science knowledge on the fate and transport of emissions and the effectiveness of abatement practices, and the policy environment all allow for immediate policy focus on NPS pollution. Relying on established ideas on water quality trading, Kling (2011) argued for a new NPS trading system that capitalizes on biophysical models and new computation tools. In this paper, we expand on the ideas of Kling (2011) and study the efficient design of agricultural water pollution control when the regulator is allowed to impose regulations or standards (either tradable or otherwise) on agricultural nonpoint sources. We do not suggest that such a change is on the horizon soon for many states, and recognize the important political economy issues associated with such a change; but, the Florida case and other statewide programs warrant serious analysis of these options, particularly given the significant water quality problems remaining in agricultural watersheds. The focus of this study is on nonpoint sources, although the inclusion of point sources is clearly an important issue to consider. The reasons for this include (*a*) the extent of nonpoint sources' contribution to water quality problems, (*b*) the regulatory environment described above, and (*c*) additional regulatory and risk issues raised in including point sources. For example, Ribaudo et al. (2008) found that if point sources' emissions were fully eliminated in two-thirds of the 700 nitrogen-impaired watersheds across the United States, the maximum achievable nitrogen reduction would fall below 10%. Further, involving point sources invokes the complex CWA regulatory requirements associated with point sources—which may limit the efficacy and flexibility of trading programs (Shabman and Stephenson, 2007)— and issues of definition and treatment of different degrees of risk involved in control of point vs. nonpoint emissions (Shortle and Horan (2008) provide an excellent treatment).

Specifically, we are looking for a simple (for the regulated entities) and effective (in terms of reaching water quality goals) nonpoint-source regulation under the three sets of difficulties facing regulators. The difficulties regulators face are: (*a*) imperfect information on the abatement costs of individual farms, (*b*) difficulty (rather, impossibility) in observing pollution at the farm level, and (*c*) inherent nonlinearities in the water quality production function (i.e., the fate, transport, and interactions between individual farmer's emissions that ultimately affect the water body of concern). We believe that these characteristics typify most, if not all, agricultural watersheds.

Producers have a variety of conservation practices from which to choose, many of which require both direct costs and implicit costs (lost yield, additional risk, etc.) that are likely to vary by farm characteristics, climate, and other idiosyncratic features of farms. Thus, individual producers are quite likely to have better information about their true cost of adopting conservation practices than regulators. From the regulator's perspective, this means that it can be difficult to identify the least-cost allocation of emission reductions efficiently across sources to achieve a given water quality improvement goal.

The second difficulty relates to the challenges of observing and monitoring the pollution impacts of farming activities in agricultural watersheds. A well-known feature of nonpoint-source pollution is that each polluter's emissions are stochastic and unobservable (Shortle and Horan, 2001). Although it is not technically impossible to strictly monitor the amounts of fertilizers and other chemical applications, it is likely significantly easier to focus on observable abatement actions such as adoption of pollution-reducing practices. This challenge was one of the reasons Kling (2011), following the nonpoint-source literature tradition dating back to at least Griffin and Bromley (1982), proposed a system based around observable actions.[1]

Finally, the ultimate fate and transport of these emissions once they leave the edge of a field and find their way into the water bodies of concern is an area with interesting theoretical and practical implications. While theoretical papers often postulate that the fate and transport process is linear and separable between emissions from various fields, hydrologists note that this process is actually likely to be highly nonlinear and nonseparable. We refer to the process as a "water quality production function" and describe it below.[2] The state of practice in environmental sciences is to rely on various biophysical simulation models that can (albeit imperfectly) capture the key nonlinearities and interactions between individual emissions as they contribute to watershed-level indicators of water quality.

With these challenges in mind, we propose and evaluate a range of simple and practical policy approaches for regulating emissions from nonpoint agricultural sources within a watershed which are focused on abatement actions at the farm scale, and which utilize the full state-of-the-art environmental process models. The three approaches we consider allow differing degrees of flexibility for individual emitters. First, we examine a command-and-control (CAC) approach whereby the regulator requires abatement actions (conservation practices) to specific fields in a watershed. Second, we consider a type of "performance standard" (PS) where each

[1] Some abatement activities are easier to monitor than others. Structural conservation practices are, for instance, easier to observe and monitor than input use. The monitoring and certification of input use is possible, as evidenced by various organic certification schemes. In this paper, we include a range of abatement activities, including input use modification, and leave the exploration of consequences of degrees of observability of different abatement activities to future work.

[2] In the literature, Shortle and Horan (2001) refer to it as the "fate and transport function." We note that the biophysical models are often capable of producing outputs beyond the water quality indicators discussed in this paper. One argument for the approach we propose (to integrate the process model into an economic pollution control policy) is that in the proposed approach changing the environmental indicator (for example, considering phosphorus or sediment, or pesticides, as opposed to nitrogen) may often be accomplished by simply selecting the relevant model output. Approaches which seek to replace the model with a mathematical function that is differentiable may require a lot of work tailored to the particular pollutant. Further, in practice, once an economic policy controlling, say, nitrates, is proposed, stakeholders often wish to know the impacts on other environmental indicators, which a tailor-made mathematical relationship used to formulate economically efficient policy is not capable of addressing; but, the consistent use of the same biophysical model can easily assess the impacts of any policy outcome with respect to other modeled environmental variables.

farmer has the flexibility to choose relevant abatement actions, subject to certain farm-level performance requirements. Finally, we evaluate the performance of a trading program proposed by Kling (2011), where the producers can trade credits associated with abatement actions with other emitters in the watershed (conditional on meeting their farm-level performance target). For each of these approaches, we discuss the information and optimization requirements for regulators, and if they can improve the performance of a policy approach by using some cost information in conjunction with water quality models. We demonstrate the application of our approach to a real agricultural watershed of substantial size, utilizing field-scale spatial information.

We evaluate the ease of implementation and efficiency of these regulatory approaches under four scenarios. First, we assume that the regulator has perfect cost information, perfect information regarding farm-level emissions, and that the water quality production function is in fact linear and separable. In this benchmark case, it is straightforward to see that either the CAC, the on-farm performance standard, or credit trading can achieve the "first-best" cost-efficient case (least-cost solution, with watershed-level water quality objective, specified as a mean ambient loading, met).[3] In the second case, we relax the assumption that the regulator has perfect information on costs, but retain the other two assumptions. It is also straightforward to show that the permit trading program can achieve the least-cost solution, but in general, the CAC and performance standard approaches cannot. These two cases are simple examples of well-known efficiency properties of permit trading approaches.

Of more interest are the third and fourth cases. In the third case, we assume that for purposes of ease of implementation, the trading program is implemented using a linear approximation to the true nonlinear, nonseparable production function, while maintaining the assumption that the field-level emissions reductions are known. In the fourth, this assumption is relaxed and observable abatement actions become the focus of the program—we assume the use of a linear approximation to the production function, and the use of a point system, to approximate emission reductions associated with abatement actions at the field scale.

We show that allowing for the more realistic water-quality production process does not preclude the regulator from using any of the three approaches. We do see, however, that two

[3] For example, the policy goal for reducing the Northern Gulf of Mexico Hypoxic zone (a direct consequence of nutrient enrichment from agriculture), is specified as a 5-year average (EPA-SAB, 2007).

findings emerge: (*a*) some approximations may be required, which introduces the possibility of non-attainment of the water quality goal (even on average), and (*b*) under some conditions (having unbiased cost information and a good (unbiased) model of the water quality process) the regulator can do better by engaging in optimization exercises prior to implementing the policy.

In comparing the cases, we consider both the ease of implementation of a least-cost solution by the regulator and the potential for efficiency enhancements from implementing a market-based solution. We consider that the regulator may face a tradeoff between the cost-efficiency and the effectiveness of a program (where the specified water quality target may not be met, which can occur in both Cases 3 and 4).[4] Using simulation-optimization tools, we provide an empirical assessment of the magnitudes of inefficiencies in terms of cost and potential ineffectiveness in terms of nutrient reductions. Finally, we suggest simple corrections to the design of market-based programs that are capable of overcoming the issue of ineffectiveness.

We begin the paper with a simple model that captures the key attributes of the nonpoint-source water quality problem as related to agricultural emissions from farm fields. We then identify the first-best solution. We describe each of the second-best designs described above and evaluate their efficiency properties relative to the first-best (cost-efficient allocation of conservation practices).

Conceptual Model

Consider a simple model of pollution where water quality in a watershed is impaired by runoff from agricultural fields (for example, nitrogen or phosphorus).[5] There are N farms in the watershed. The farms are heterogeneous with respect to physical characteristics such as soil, slope, rainfall, etc. The ambient water quality level is monitored in-stream, at the outlet of the

[4] We are framing the discussion in terms of meeting a target specified as some statistic of the distribution of pollutant loadings which results from a specific set of on-farm abatement actions. Due to the inherently stochastic nature of weather, precipitation, and other driving factors, abatement targets can only be achieved in probabilistic terms (e.g., mean, or as a quantile). For simplicity, we focus on the mean water quality indicators, but the conceptual discussion applies to targets formulated as other functions of the water quality distribution. In our discussion, we focus on expected water quality with respect to natural variability, and alternative policy approaches are evaluated under the same implicit environmental conditions. Further, the expectations are taken with respect to natural uncertainty, and not the regulator's uncertainty over abatement costs. The latter case leads to results which lead the optimal trading ratios and permit market designs to depend on the parameters of cost uncertainty (Shortle and Horan, 2008; Rabotyagov and Feng, 2010; Yates and Rigby 2012: http://www.webmeets.com/AERE/2012/prog/viewpaper.asp?pid=99).

[5] We adopt notation similar to Shortle and Abler (1997).

watershed. Let r_i be the i^{th} farm's reduction in pollution measured at the edge of the field (that is, farm-level pollution abatement):

$$r_i = r_i(x_i, \gamma_i, \xi) \;\forall\, i = 1, \ldots, N, \tag{1}$$

where x_i is a $J \times 1$ vector of J mutually exclusive conservation practices farm i,[6] γ_i represents the farm's physical characteristics, and ξ represents the random factor related to the weather and/or other stochastic influences.

Abatement costs are defined as the difference between baseline profits and the profits associated with adopting a conservation practice on a given field.[7] We assume that the costs of adoption vary across locations due to both difference in physical characteristics (soils, slope, etc.) and management abilities.

Farms are decision-making agents that maximize profits by choosing conservation practices based on the regulations, if any, they face. Farms are price takers in both output and input markets. The baseline edge-of-field emissions are the result of this maximization behavior absent any regulations regarding the pollution or conservation practices.

The total ambient pollution is given by an expected water quality production function, $W(r)$, which is a function of each farm's individual edge-of-field emission reductions, where r is the vector of r_i.[8] In addition to depending on the edge-of-field emissions, the ambient pollution level, in general, will also depend on the location of those fields within the watershed. The water quality production function reflects the complexity of the hydrological processes that affect the fate and transport of nutrients from the land to the water. In practice, the true form of this function is not likely to be known, though there is a range of watershed-based water quality models that approximate these hydrological and biophysical processes, such as the Soil and Water Assessment Tool (SWAT), and the Water Erosion Prediction Project (WEPP). This

[6] For notational simplicity, we define the simultaneous use of two conservation practices as a separate, unique practice.
[7] Equivalently under risk neutrality, abatement costs can be defined as the farms' willingness to accept to adopt a conservation practice.
[8] Focusing on expected water quality is efficient under social risk-neutrality, but social preferences may require "safety-first"-type pollution constraints (Shortle and Horan, (2008) provide a review). We do not take up such constraints in this work, although we sketch out how the policy could be modified to incorporate such preferences on the part of society. Instead, in this work, we focus on nonlinearity in the deterministic component of the water quality process. Nonlinearities may emerge as a result of covariances between field-level loadings and delivery coefficients (succinctly demonstrated in Eqs. (1) and (2) of Shortle and Horan (2008)) even in a linear specification of the water quality production process. Our linear (which we argue is not accurate) specification of W(r) can be interpreted as corresponding to Eq. (3) (ibid.).

function is likely to be highly nonlinear, non-differentiable, and nonseparable in the sense that the effects of an abatement action at one location in the watershed on the ambient water quality will be affected by the abatement actions (conservation practices) elsewhere in the watershed.[9]

The ambient water quality at the watershed outlet can be expressed as

$$W(r) = W^0 - A(r), \tag{2}$$

where W^0 is the level of water quality in the absence of regulation, and $A(r)$ is the ambient pollution reduction associated with r emission reductions—or more simply the abatement function. Equation (2) simply notes that the ambient water quality level associated with any given set of emission reductions can be expressed as the difference between the no-control (baseline) ambient water quality level and the in-stream abatement associated with the edge-of-field emission reductions.

In the following subsections, we identify the least-cost solution to a cost minimization when a first-best solution can be identified, and contrast it to the solution that is feasible when the regulator knows only the distribution of costs across the farms. Next, we add further realism to the problem by considering two additional complications. First, we consider the possibility that in addition to imperfect cost information the regulator is relying on a linear approximation to the water quality production function. This case could also be interpreted as a situation in which the authority knows the true, nonlinear watershed production function, but prefers to use a linearized version for watershed implementation.

Finally, we consider the possibility that the relationship between the adoption of a conservation practice and the edge-of-field abatement resulting from that practice may be imperfectly measured, and thus the environmental authority uses approximations for the effectiveness of these practices in reducing edge-of-field emissions. We suggest the use of a points-based system as a simple approach for implementing a performance standard or trading program in this situation.

Cases 1–3: Linear Water Quality Production Function (that is, $(\boldsymbol{r}) = \sum_i^N \boldsymbol{d_i r_i (x_i)}$)

[9] See for examples Braden et al. (1989), Lintner and Weersink (1999), Khanna et al. (2003), from agricultural economics perspective of inherent endogeneity (which we call non-separability) of ambient effectiveness of field-level abatement actions. Briefly, both downstream and upstream abatement actions may have effects on abatement efforts at a field, and atmospheric deposition may affect locations not in surface or subsurface (as in the case of tile drainage), flowpaths.

Case 1: Perfect information on costs

Suppose we seek to achieve a particular level of total ambient emissions reduction, $\bar{A}$. We seek to minimize the abatement cost of all farms across the watershed such that the total ambient emissions are reduced by at least this *ex ante* established abatement goal. Thus, the cost minimization problem is

$$\min_{x_{ij}} \sum_i C_i\left(x_{ij}\right) \; s.t. \mathrm{A(r)} \;\geq\; \overline{A}, \tag{3}$$

For each farm i, we wish to choose a conservation practice, x_{ij}, such that the total ambient emissions in the watershed are reduced by at least $\overline{A}$.

Under perfect information, the solution can be achieved by the environmental agency assigning each farm the optimal conservation practice, x_{ij}^*, thus achieving the efficient edge-of-field discharges, r_i^*, $\forall\, i = 1, \ldots, N$ farms and $\forall\, j = 1, \ldots, J$. The total abatement cost will be given by:

$$TC^* = \sum_i C_i(x_i^*). \tag{4}$$

An "*" is used to indicate that this is the least-cost solution. Under perfect information, the environmental agency could assign the efficient conservation practice to each location. Alternatively, the environmental agency could require that each farm meet an individualized performance standard. This requirement could take the form of an edge-of-field standard to each farm ($= r_i^*$) or an ambient standard ($= d_i r_i^*$).

In the case of an ambient standard, an individual farm would face the following cost minimization problem: [10]

$$\min_{x_{ij}} C_i\left(x_{ij}\right) \text{ s.t } d_i r_i\left(x_{ij}, \gamma_i\right) \geq d_i r_i^*. \tag{5}$$

Clearly, under perfect information, the firm will choose the socially efficient solution, so that $TC^{ps} = TC^*$, where

$$TC^{ps} = \sum_i C_i({x^{PS}}_i) \tag{6}$$

is the total cost of the performance-based system , and "PS" denotes the cost minimization solution under performance standard program .

[10] The farm's solution to Eq. (5) will be invariant to whether the constraint is written as an ambient standard or whether it is written in terms of an edge-of-field constraint which would simply eliminate d_i from both sides of the equation.

Another alternative is to allow trading amongst farms such that a total ambient emissions cap is met. As Montgomery (1972) demonstrated, an "ambient based permit system" where each firm is faced with an ambient cap such that the total ambient emissions reduction target is met can achieve the least-cost allocation.

In short, under perfect information on costs and farm-level emissions, and a linear and separable water quality production function, any number of regulatory approaches can be employed to achieve the least-cost solution. We now turn to more realistic settings.

Case 2: Imperfect Information on Costs (Linear Water Quality Production Function)

In reality, it is likely that while farms will know the true cost of their abatement actions, the environmental authority will not. Thus, the environmental authority will be unable to identify the most efficient conservation practice for each field and corresponding edge-of-field emissions. However the environmental agency is likely to have some limited information on the distribution of costs. We assume that the agency knows the vector of average costs, $\overline{\theta}$, but not the cost at each individual location. In this case, the environmental authority can solve the cost minimization problem:

$$\min_{x_{ij}} \sum_i C_i\left(x_{ij}, \bar{\theta}\right) \; s.t. \, \mathrm{A(r)} \geq \; \overline{A}, \tag{7}$$

where $\overline{\theta}$ represents a vector of the mean costs of the J conservation practices, and the total cap is set at the $\sum_i^N d_i \hat{r_\iota} \, (\bar{\theta})(x_i, \gamma_i) = \bar{A}$. The solution to this problem will generally differ from that obtained in solving (3), and the assignment of abatement practices, $\widehat{x_\iota}$, will not necessarily coincide with the least-cost solution, x_i^*. Likewise, the edge-of-field emissions reductions, $\widehat{r_\iota}(\overline{\theta})$, will be different from the first-best, r_i^*.

Thus, if the environmental authority were to impose the solution, $\widehat{r_\iota}(\overline{\theta})$, this may not reflect the least-cost allocation of conservation practices since some firms 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, $\bar{A}$, will be met by design.

In this case, the authority can potentially increase social welfare relative to a command-and-control assignment of conservation actions, $\widehat{x_\iota}$, by allowing firms to meet a performance standard, $d_i \, \widehat{r_\iota} \, (\bar{\theta})$. 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,

$$\min_{x_{ij}} C_i\left(x_{ij}, \theta_i\right) \text{ s.t } r_i(x_i, \gamma_i) \geq \hat{r_i}\,(\bar{\theta}) \tag{8}$$

where they use their true vector of conservation practice costs, θ_i, to solve the problem.

Additional cost savings are potentially achievable if the environmental authority makes the performance standard tradable. For example, the following system could be instituted. Suppose farmers in a watershed are brought under an "abatement credit trading system," where every farmer is obligated to earn a set number of credits (points), with additional opportunities to earn credits from undertaking abatement at their fields or purchasing credits from other farms. If producers undertook conservation actions that generated more points than their minimum requirement, they could sell those credits. Let $\overline{l_i}^0$ be i^{th} farm's abatement credit requirement, which can be satisfied in two ways—obtaining credit for on-farm conservation practices or purchasing (or selling) credits l_i from (to) other farms. A farmer solves:

$$\min_{x_j, l_i \in X} C_i^P(x_{i,}) + pl_i \quad \text{s.}t. \;\; d_i\, r_i\left(x_j, \theta_i\right) + l_i \geq \overline{l_i}^0 \tag{9}$$

and the credit price is determined in a market equilibrium where $\sum_i l_i = 0$. This model implicitly assumes that the edge-of-field nutrient losses, $\hat{r_i}$, are known, which defines a one-to-one relation between the edge-of-field discharges and the number of credits.

Indeed, when the performance standard is fully tradable, the least-cost solution would be achievable, as this would be equivalent to implementing Montgomery's ambient-based permit system. Since by construction the $\sum_i \overline{l_i^0} = \bar{A}$, unfettered trading amongst firms who each know their own true costs will achieve the least-cost solution and the ambient environmental goal is satisfied.

Case 3: No information on costs (Linear Water Quality Production Function)

This case is perhaps the most vivid demonstration of the appeal of market-based systems. In particular, although a regulator is capable of devising a CAC system which ensures that the water quality goal is met (by picking any farm-level allocation of abatements r_p s.t. $A\left(r_p\right) = \bar{A}$), the cost-efficiency of such a program is likely to be quite low (hence the term "third-best" in Table 1, which summarizes the cases). However, a trading system is capable of achieving first-best, where both the environmental goal is reached by construction and the total abatement costs are minimized.

When the water quality production function is described by a linear, separable function with exogenous (fixed) delivery coefficients, market-based solutions clearly outperform command-and-control strategies, regardless of any information that the regulator possesses. This is, of course, the theoretical basis for the appeal of permit trading systems.

Cases 4–6: Nonlinear and Nonseparable Water Quality Production Function.

Cases (1)–(3) rely on a linear, separable water quality production function. The actual pollution processes are not likely to be well described by such functions. Yet the longevity of the linear and separable model of the water quality production process can probably be attributed more to analytical convenience and the well-known attractive features of incentive-based systems (recapitulated in Cases (1)–(3)) than to the ability of this model to accurately represent reality. There exists a great deal of scientific evidence that the more complex pollution fate and transport function is required to accurately represent the impact of on-farm actions on ambient pollution levels. This recognition is not by itself new—researchers beginning with Braden et al. (1989), followed by Lintner and Weersink (1999), Khanna et al. (2003), Arabi et al. (2006), and Rabotyagov et al. (2010) more recently have grappled with the issue of nonlinearity (and resulting endogeneity of effectiveness of abatement actions) of water pollution processes. As a result, evaluating efficient pollution control strategies requires either building a mathematical program—and essentially building a model of the pollution process—or using optimization approaches that incorporate the biophysical model in its entirety (simulation-optimization approach). In the former approach, the solution techniques included dynamic programming (Braden et al., 1989; mixed integer programming, Khanna et al., 2003), and evolutionary algorithms (Arabi et al,. 2006; Rabotyagov et al., 2010) were used in the simulation-optimization approach.

In all cases, the solutions obtained do not immediately lend themselves to being replicated in a simple market-based system. At the crux of the market design issue in these cases is the ability to set the right (explicit or implicit) trading ratio and to provide an ambient pollution constraint that ensures the attainment of the water quality goal. In the case of the linear and separable water quality production function, it is straightforward: farms trade according to the ratio of the delivery coefficients and the pre- and post-trading outcome has to satisfy the ambient pollution constraint.[11]

In the case of nonlinear and nonseparable water quality production function, the ability to set the right trading ratio and the effective trading system constraint is not assured. To demonstrate, assume for the moment that *A(r)* is differentiable. Then the first-order Taylor series expansion around some initial vector of on-farm pollution reductions (e.g., baseline r^0) can be written as:

$$A(r) \cong \sum_{i=1}^{N} \frac{\delta A(r)}{\delta r_i}(r_i - r_i^0) \tag{10}$$

In this case, $\frac{\delta A(r)}{\delta r_i} = d_i'$ can potentially serve as the delivery coefficients and provide the basis for forming the trading ratios, but two things need to be observed. First, the "delivery coefficient" is a function of the abatement activities of other farms, and if a trading system is to be set up, some initial vector of abatement actions needs to be used. Second, the approximation above may be quite close to the initial abatement action vector (that is, around the baseline), but may be quite poor at the post-trading vector of on-farm abatements. This may lead to non-attainment (even on average) of the water quality goal.

Similarly to Cases (1)–(3), for Cases (4)–(6), a market-based system could take the following form. Let $\overline{l_i}^0$ be i^{th} farm's abatement requirement and l_i the quantity of credits bought/sold by the farmer:

$\min_{x_j, l_i \in X} C_i^P(x_{i,}) + pl_i \quad \text{s.}t. \quad d_i' r_i(x_j, \theta_i) + l_i \geq \overline{l_i}^0$ and the market clearing condition $\sum_i l_i = 0$.

The main difference from Cases (1)–(3) is that, instead of d_i (assumed to be a true delivery coefficient in Cases (1)–(3)), d_i' is used, where the prime indicates that this is a set of derived delivery coefficients that were obtained from some form of linearization of the nonlinear water quality production function.

A separate, and important, issue is the selection of $\overline{l_i}^0$—that is, the vector of on-farm ambient reduction requirements. Under a linear water quality production function, delivery coefficients are known, so any combination of $\overline{l_i}^{0'}s$ satisfying $\sum_i \overline{l_i^0} = \sum_i d_i \overline{l_{if}^0} = \bar{A}$, (where l_{if}^0

[11] Under cost uncertainty, optimal trading ratios have been shown to be a function of regulator's information on abatement costs (Rabotyagov and Feng, 2010; Yates and Rigby, 2012).

represents the on-farm pollution reduction requirement), is acceptable. This is identical to the issue of defining the cap by choosing the right number of permits to distribute in a cap-and-trade program design.

Under a nonlinear water quality production function, the "permit distribution" issue represents additional difficulty. Unlike the linear case, where an increase in abatement at one farm, when appropriately weighted by the ratio of the delivery coefficients, is equivalent to the decrease in abatement at another farm, "permit allocation" matters for the achievement of ambient water quality in the non-linear case. Below, we demonstrate how this issue can be addressed involving assignment of weights ("point values") for abatement actions, which provide implicit trading ratios, and what the consequences are for water quality standard non-attainment.

Cases (4)–(6) highlight that, unlike in the case of a linear and separable water quality production function, more flexible systems may outperform CAC in terms of abatement costs, but they may also lead to non-attainment of a water quality goal. The magnitude of the inefficiency or the extent of non-attainment is an empirical question.

Designing a nonpoint-source pollution policy based on conservation actions and an approximation to the water quality production function

We seek to evaluate simple, abatement action-based regulatory systems, where we recognize that the true $r_i(x_i)$ function cannot be measured perfectly, and easily observable abatement actions are used as a proxy, with weights created to achieve a reasonable, scientifically justifiable, approximation to $r_i(x_i)$. Specifically, under a point-based trading system agricultural producers would be required to undertake abatement actions that accrue a sufficient number of points per acre for their farms (Kling, 2011).

Under the point accumulation system, each program-specified abatement action is assigned a specific point value. The point values reflect (approximately) both the edge-of-field effectiveness of abatement actions and the impact of edge-of-field reductions on the ambient water quality. Specifically, the regulator utilizes a linear approximation of the effect of abatement actions on both the edge-of-field and ambient water quality: $A(X) \cong \sum_i^N d_i' \; r_i\left(x_j\right) = \sum_i^N \sum_{j=1}^J d_i' w_j x_{ij} = \sum_i^N \sum_{j=1}^J a_{ij} x_{ij}$, where edge-of-field reductions are given by $r_i(x_i) \equiv \sum_{j=1}^J w_j x_{ij}$, and the total number of points earned by the farmer is given by $\sum_{j=1}^J a_{ij} x_{ij}$ where

a_{ij} provides the weight (in terms of abatement "points") given to a conservation practice j at farm i. We refer to a_{ij} as a "points coefficient". The points coefficient has an obvious interpretation of giving a marginal benefit, in terms of water quality abatement, of practice j at location i (expressed as mean annual reductions in kg N). Below, we discuss the approach for estimating the vector of a_{ij}'s for the study watershed.

The command-and-control policy does not require the use of points, as each farmer is assumed to be directly required to undertake abatement actions. For the more flexible approach (on-farm performance standard), the regulator needs to choose the appropriate on-farm (edge-of-field) pollution reduction, where the reduction is specified in terms of "points" that accrue to a farmer for each unit of pollution abatement action.

Under this approach, a farmer is free to solve the on-farm cost-minimization problem: $\min_{x_{ij},b_i \in X} C_i^P(x_{ij}) \quad \text{s.}t. \ \sum_{j=1}^{J} a_{ij}x_{ij} \geq b_i^o$, where the performance requirement is specified by b_i^o.

Under the trading approach, credits generated by abatement actions are freely tradeable, on a one-to-one basis, across the watershed. As a result, a farmer solves:

$$\min_{x_{ij},b_i \in X} C_i^P(x_{ij}) + pb_i \quad \text{s.}t. \ \sum_{j=1}^{J} a_{ij}x_{ij} + b_i \geq b_i^o \tag{11}$$

where b_i^o is the "points requirement" that a farmer can satisfy by undertaking abatement actions on-farm or by buying points in the market, with the point price determined in a points market equilibrium where $\sum_i b_i = 0$.

Conceptually, our proposed trading approach is a combination of an *emission permit system (EPS)*, where rights are defined in terms of what firms can emit, and an *ambient permit system (APS),* where rights are defined in terms of pollution contributions to a receptor point (Montgomery, 1972; Baumol and Oates, 1988). Like in an EPS system, firm permit (points) requirements are specified at the firm level and not at the level of the pollution receptor, and trades in points can occur on a one-to-one basis across the entire watershed. Similar to an APS system, the point values estimate aims to approximate the impact of abatement actions at the (single) pollution receptor (watershed outlet). Trading ratios among abatement actions and across the watershed are specified implicitly by the promulgated point values.

In this work, we consider a relatively simple case where there is a single receptor (watershed outlet). The obvious attraction of considering a market with a single receptor point is its simplicity and a decreased potential for "thin" markets. Permit trading systems with multiple receptor requirements are likely to suffer from the problems of imperfect competition, thin markets, and high transactions costs (Ermoliev et al., 2000). Thus, similar proposals for permit trading involving multiple receptors have introduced the need for some kind of a "smart market" where the burden of optimization and satisfaction of environmental constraints is delegated to the regulator, who solves for appropriate vector of equilibrium prices in all specified markets.[12] Morgan et al. (2000) and Prabodanie et al. (2010) are the most closely related proposals, both proposing a use of a water quality simulation model and a market broker. Our approach can be extended to multiple pollution receptors and can easily accommodate a "smart market." We show, however, that even in the presence of (*a*) multiple abatement actions and (*b*) potentially complicated fate and transport relationships, a simple "thick" market involving all farms in a watershed, and a single freely tradable commodity (point credit) has very attractive properties in terms of reaching environmental goals at the watershed outlet.

Finally, we consider trading between nonpoint sources (which have been transformed into knowable "point sources" by means of a water quality simulation model (an insight apparently due to Morgan et al. (2000)). When expected water quality goals are sought by the regulator, the point system we propose can be extended in an unmodified fashion to include point sources (which SWAT has the ability to simulate). A substantial literature exists discussing choosing the correct trading ratio between point and nonpoint sources when the regulator treats point source and nonpoint source abatement as different in risk (e.g., Horan et al., 2002; Hung and Shaw, 2005). Conceptually, the point values assigned to nonpoint sources could be adjusted in a similar fashion.

Empirical Application

Study area: Boone Watershed River

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.

[12] Proposed "smart" markets appear to promise to implement the original idea of Krupnick et al. (1983) of a *pollution offset (PO)* system where trades are allowed subject to attainment of relevant environmental quality constraints.

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, and as a result, 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 cropland, 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 (CSR) is another characteristic that defines the potential yield.[13] 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 40% of the soils have CSR values higher than 80.

The required data for a modeling system (i.e., SWAT model) was collected at Common Land Unit (CLU) level.[14] More than 16,300 CLUs have been identified in the BWR. As a Hydrological Response Unit (HRU) is the unit required by the SWAT model, the CLUs were regrouped into 2,968 HRUs. 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 (Table 2). The above set is augmented with all feasible combinations of these practices but land retirement (i.e., the combination of no till and cover

[13] 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: (http://www.extension.iastate.edu/Publications/PM1168.pdf)
[14] "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)

crops is considered as an independent conservation practice). The baseline is also considered as a choice alternative. This allows considering the cases where keeping the baseline is optimal.

Conservation practices cost

Costs for each conservation practice were drawn from several sources. All costs are expressed as dollars 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.[15]Cover crop cost estimates were provided by local farmers.[16] The average cost for cover crops is $25.[17]

An implied yield curve for corn-soybean rotation, where yield is estimated as a function of fertilizer applied, was used to derive the cost for reducing the fertilizer application rate. The procedure is similar to the one used by Rabotyagov (2007), Sawyer et al. (2006), Libra, Wolter, and Langel (2004), and Feng, Jha, and Gassman (2008). 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 polynomial function of the fertilizer rate.[18] The cost of reducing fertilization is given by multiplying a 20% percent reduction in the baseline fertilizer rate by the price of corn and by subtracting the cost savings from applying less fertilizer. The price of corn used is $3.08 per bushel.[19]

The 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

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[15] Mulch tillage is an interim type of tillage (between 30% and 60% of residue remaining).
[16] The cover crops cost estimate was provided by Tom Kaspar scientist at USDA-ARS National Laboratory for Agriculture and the Environment.
[17] 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 is applied for cover crop growth
[18] The coefficients of nitrogen response yield curve Y=-3.32904824784026E-09*N^4+8.88402E-06*N^3-0.004459448*N^2+0.822128904200617*N-0.374570292118776
[19] 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

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.

Water quality production function: Soil and Water Assessment Tool (SWAT)

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 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 subbasins. In SWAT, each sub watershed is delineated further into smaller HRUs.[20]

The optimization method

The development of hydrological models like SWAT, calibrated with watershed-specific data, makes it possible to simulate the impact of different watershed scenarios on water quality. A watershed is divided into 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 9 agricultural practices and 2968 fields, there are a total of 9^{2968} possible watershed scenarios. Using SWAT, a water quality level can be estimated for each watershed configuration. With appropriate economic data, the cost 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?

The implementation of an evolutionary algorithm provides one way to deal with the combinatorial nature of the watershed simulation-optimization model. Evolutionary or genetic algorithms (EA) are designed to mimic biological evolution (Deb, 2001). Genetic algorithms are heuristic global search algorithms that are able to find the nearly optimal solution by using principles like "natural selection" and "survival of the fittest." The main terminology used in

[20] An HRU, is a conceptual entity, with no precise spatial location within the sub-watershed. It is identified as a percentage area in the sub-watershed 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.

defining EAs is similar to that used in evolutionary biology, and consists of terms such as population, genome, individual, allele set, offspring, recombination, mutation, etc.

In our case, an individual represents a watershed configuration. The genome is defined by the total number of fields. The fields' properties, or genes, are defined in terms of the agricultural abatement 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 abatement practices. An individual represents a possible solution to the optimal placement of abatement practices, 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 achieves a given level of ambient standard at the lowest cost, or given a budget achieves the lowest ambient pollution level.

We use a simulation optimization system using SWAT and modification of the Strength Pareto Evolutionary Algorithm 2 (Zitzler, Laumanns, and Thiele, 2001, as described in Rabotyagov et al., 2010) to approximate the solution to a two objective minimization problem that simultaneously minimizes the total mean annual nitrogen loadings and the costs of abatement practices for the study watershed. The solution to this multiple objective problem can be interpreted as a set of Pareto-nondominated points in the search space, where each point on the frontier, called individual, is a specific watershed configuration that achieves a particular level of nitrogen loadings in the least-cost way.

Obtaining the point coefficients

We estimate the point coefficients by linearizing both the water quality production function and the edge-of-field pollution reduction in terms of abatement actions.

Specifically, as in Eq. (10), we approximate the nonlinear water quality production function by $A(X) \cong \sum_i^N d_i' \ r_i(x_j) = \sum_i^N \sum_{j=1}^J d_i' w_j x_{ij} = \sum_i^N \sum_{j=1}^J a_{ij} x_{ij} = Xa$, where X is the vector of specific abatement actions, and a is the vector of point coefficients. For the empirical demonstrations, we assume that point coefficients are obtained at the level of a subbasin (although obtaining point coefficients that assign different point values for conservation practices for every farm would follow the same steps). There are 30 subbasins in the watershed, ($N = 30$), and 9 abatement actions are considered ($J = 9$). Thus, we need to estimate the 270×1 vector of a. In order to do that, we generate 3,000 random allocations of abatement actions to the fields in the watershed, and simulate the water quality impacts using SWAT. The resulting 3,000 simulated abatement outcomes of water quality, denoted by A_s, are combined with the 3,000 $\times$ 270 vector of abatement action assignments, denoted by X_s, to estimate the points coefficient vector a by ordinary least squares: $\min_a (A - Xa)'(A - Xa)$. Table 3 presents the estimation results.[21]

Most of the abatement actions (combinations of conservation practices) are highly significant across the subbasins of the watershed. The only somewhat unexpected result is that nitrogen fertilizer reductions alone are not always significant, but they are significant in all subbasins when combined with no-till (and no-till with cover crops), and in all but one (Subbasin 27) when combined with cover crops. For subbasins with non-significant fertilizer reductions, fertilizer reductions are rewarded when combined with other conservation practices. Note that the farmers would not face an additive reward for adopting several conservation practices. In 22 out of 30 subbasins, a farmer gets less than an additive credit for adopting no-till and cover crops jointly, while in the remaining subbasins, a farmer gets an additional points reward for joint adoption. Among nine subbasins where fertilizer reductions receive credit on their own, only one subbasin gets the joint adoption reward for adopting fertilizer reductions with no-till. The overall pattern is of non-additive rewards for adopting multiple conservation practices. Unless the farmers face substantial cost reductions for adopting multiple conservation practices on the same field, this reward system is likely to lead to single-practice adoption in subbasins with sub-additive point credits (with fertilizer reductions adopted jointly in 21 subbasins). In terms of practical implementation, farmers in different subbasins are given one row of the table above, which specifies the credits earned from practice adoption.

Once the regulatory agency has the estimates of point values that are credited to a particular abatement action in a specific subbasin, one can compute the *total points value* associated with any watershed configuration. For both the performance standard and the tradable credit programs, the total points value chosen by the regulator will have a direct implication for the watershed abatement levels achieved.

[21] Feng, Jha, and Gassman (2008) use SWAT to estimate delivery ratios by changing N application rates in each subbasin of a watershed, holding rates constant in other subbasins, obtaining the implied "delivery ratio", and solving for the least-cost allocation of N abatement across subbasins. As discussed above, such approach imposes the linear structure on the water quality production function, and estimated delivery ratios provide a coarse approximation to the modeling capability of SWAT.

We are now in the position to demonstrate the performance of all three regulatory approaches under different assumptions of how the regulator formulates the policy. The benchmark for comparison will be given by the (approximate) Pareto-efficient frontier in N-Cost space, obtained using simulation-optimization approaches described above (Figure 2).

Evaluating CAC, the performance standard, and the trading system for different abatement targets

Setting goals under the three approaches

Under a nonlinear water quality production function, setting the on-farm or watershed-level goals under the CAC, PS, or a fully tradable approach is somewhat challenging. In setting up the CAC program, the regulator wishes to directly dictate the on-farm abatement actions and looks for the desired vector of abatement actions. Since this is the least flexible approach for the farmers, the regulator is in a position to immediately evaluate the water quality impacts of a CAC program using the model representation of the water quality production function—that is, given $X_{program}$, watershed-level abatement is $A(X_{program})$. The regulator's task is to choose $X_{program}$ so that $A\left(X_{program}\right) = \bar{A}$. If the achievement of the water quality goal is the only objective, the regulator can simply evaluate a range of $X_{program}$ scenarios and select one that achieves its goal. We will refer to such an approach (which does not utilize or require any cost information) as the "satisficing" approach (after Simon (1956)), and denote the prescribed vector abatement actions as $X_{program}^{satisfice}(\bar{A})$.[22] Clearly, the satisficing approach is unlikely to be cost-efficient.

An alternative approach for the regulator is to use some information on the costs of abatement actions and to optimize using cost information in the objective function. In fact, we assume that the regulator can do that using the methods described above. This leads to selecting $X_{program}^{optimize}(\bar{A})$ as the target vector of abatement actions. In our example, this means selecting a Pareto-efficient solution from the frontier which achieves $\bar{A}$.

Unlike the CAC approach, where $X_{program}^{satisfice}(\bar{A})$ and $X_{program}^{optimize}(\bar{A})$ can be implemented directly, the on-farm PS and credit trading programs require mapping the abatement actions to

[22] Simon, H. A. (1956). "Rational choice and the structure of the environment". Psychological Review, Vol. 63 No. 2, 129-138. (page 129: "Evidently, organisms adapt well enough to 'satisfice'; they do not, in general, 'optimize'."; page 136: "A 'satisficing' path, a path that will permit satisfaction at some specified level of all its needs.

on-farm or total watershed point requirements. For the PS, this involves using point coefficient estimates and computing $b_i^o = \sum_{j=1}^{J} a_{ij} x_{ij}^{program}$, where a corresponding element of $X_{program}^{satisfice}(\bar{A})$ ($X_{program}^{optimize}(\bar{A})$) is used in place of $x_{ij}^{program}$ under the satisficing (optimizing) approaches.

The same kind of assignment occurs in setting up the trading program, and the resulting on-farm point requirements are summed to obtain the total points for the watershed as follows: $P = \sum_i b_i^o = \sum_i \sum_j a_{ij} x_{ij}^{program}$. Total point values associated with the satisficing (optimizing) approaches are denoted as $P^{satisficing}$ and $P^{optimize}$, respectively. The total points are translated into individual points requirements $b_i^{o,trading}$, so that $P = \sum_i b_i^{o,trading}$ where the initial (pre-trading) point requirements may be different from the requirements imposed under the on-farm performance standard.

Efficiency properties of alternative programs and goal-setting approaches

We now provide an empirical assessment of the proposed policy approaches. First, we compare the simulated program outcomes with the efficient frontier and assess whether the proposed policy approaches result in water quality non-attainment for a range of water quality targets. For these assessments, we keep all the costs of abatement actions constant across scenarios (in order to be able to make comparisons to the approximate efficient frontier).

We present the results for three levels of desired water quality improvements: 20%, 30%, and 40% desired reductions in mean annual loadings of nitrogen relative to the baseline (Table 4). Several observations should be made. Under the CAC approaches, abatement actions are mandated, so non-attainment of the average water quality goal is precluded. However, under the PS and the trading approaches, only point totals (for the farm and the watershed, respectively) are mandated, and the optimization with respect to abatement actions occurs in a decentralized fashion; therefore, the watershed-level water quality may differ from the abatement goal. We find that the PS-satisficing approach leads to slight over-achievement of abatement goals for the range specified, and the PS-optimizing approach yields similar results (with the exception of slight goal non-attainment for the 40% reduction goal).

A clear pattern of non-attainment is found under the trading approaches: whether total watershed point targets are specified using the satisficing or the optimizing approaches, average abatement fell below the target level for the three goal values considered. However, the magnitude of non-attainment is fairly small (never exceeding 3.5 percentage points of abatement). This suggests that, at the watershed level, the total points requirement is somewhat biased downward and a correction may be required. We discuss the potential correction below.

We now turn to the efficiency properties of the approaches. While the actual *level* of abatement is important in terms of evaluating the approaches, we should consider whether they have good cost-efficiency properties, regardless of the actual level of abatement achieved. Conceptually, we would like to see whether the simulated outcomes lie on the theoretical total abatement cost curve (or, equivalently, the efficient frontier specifying cost-pollution tradeoff). We do not have the theoretical frontier available, but we do have a good approximation obtained using simulation-optimization methods previously discussed. We compare the program outcomes to the empirical approximation of the efficient tradeoff frontier (Figure 2).

For this evaluation, we use the same vector of abatement action costs to derive the tradeoff frontier (total abatement cost curve) and to simulate the program outcomes. In reality, such comparisons are going to be challenging, as the regulator is not going to have perfect information on abatement action costs.

For the programs that use the satisficing approach, and do not engage in any kind of optimization with respect to abatement action costs prior to implementing a program, we expect that the least-flexible CAC approach will have the least favorable efficiency properties. We also expect the more flexible approaches will get progressively closer to the efficient frontier as the degree of cost-minimizing flexibility afforded to program participants increases. This is exactly the pattern we observe. The outcomes of the CAC-satisficing approach are extremely inefficient, being dominated by as few as 164 outcomes (for the 20% abatement goal), to as many as 435 outcomes (30% goal) on the (approximate) efficient frontier. The PS-satisficing approach, while still very inefficient, allows for some flexibility on the part of the farmers, and, as a result, the outcomes are more efficient than the CAC outcomes, as evidenced by fewer Pareto-dominating outcomes across the range of abatement goals.

We expect the trading outcome to be very nearly efficient, as a well-functioning trading program is intended to lead to the lowest-cost outcome, given the trading program rules. The trading rules in the proposed trading program are quite simple, with all the potentially complicated relationships between abatement actions and the watershed-level impacts approximated by the regulator by a system of points at the design stage. Given that the point coefficients represent an approximation to the "true" nonlinear pollution process (assuming for the moment that a computer simulation program like SWAT is accurate), we cannot be assured that the outcomes will lie on the efficient frontier. However, we expect the approximation error to be small, and that the simulated trading outcome will be on (or very close to) the empirical efficient frontier.

This is consistent with our findings in the empirical evaluation. The trading outcome, based on a satisficing approach (where a SWAT-evaluated abatement-action allocation satisfying an abatement goal is converted to point values using Eq. (10) and each farm gets an equal initial per-acre point allocation) is found to deviate from the efficient frontier only under the 40% abatement goal.[23] Although the points approximation leads to some degree of goal non-attainment, the trading program, even when constructed around an extremely inefficient satisficing allocation of abatement actions, performs extremely well in terms of efficiency—the dominating allocation outperforms the trading outcome by only 1,826 kg (0.11% of total abatement) in terms of N abatement, and $44,041 (0.67%) in terms of costs.

In Table 4, the direct comparison of optimizing approaches (i.e., the approaches where the regulator engages in a cost-minimization exercise prior to implementing the program) is of limited practical interest. Clearly, as discussed above, if the regulator knows the true costs of abatement, any regulatory approach can be efficient (conceptually, any farm-level optimization is redundant). Any deviation from that result is likely due to approximation or optimization errors.[24] We do see, as in the satisficing approach, the trading outcome again suffers from a non-attainment issue; and, that structuring a trading program around an approximately efficient solution does not address target non-attainment and alternative remedies (discussed later) should be employed.

The more interesting question surrounding optimizing approaches lies in their performance when cost information is imperfect. We expect that the attraction of cost-efficiency of a well-

[23] The equilibrium prices, corresponding to the marginal cost of N reductions implied by the abatement goal, were found to be the following for the satisficing (optimizing) approaches: $2.17 ($2.17) for 20% goal, $4.64 ($5.65) for 30% goal, and $11.92 ($11.92) for 40% goal.

[24] Indeed, we see that the CAC-optimizing approach is Pareto-dominated by PS-optimizing approach. This means that the approximation obtained by optimization heuristics (evolutionary algorithm) is being improved on by linear programming. This kind of result has been noted in operations research literature (Whittaker et al. 2007 EJOR). Although interesting, our main focus is on the performance of optimization-improved approaches when cost information is not perfect and such improvements are to be expected.

structured trading approach (especially when modified to correct the issue of non-attainment) is likely to remain. However, the alternative approaches (especially if improved by optimization) may be found attractive where trading is politically infeasible, or secondary water quality goals (such as subbasin-level loadings) are deemed important.[25] Finally, the degree of program flexibility has an impact in the abatement space, with the trading program, as the most flexible, likely leading to the largest range of possible water quality outcomes depending on actual cost realizations, the CAC outcomes allowing variation only in cost space, and PS outcomes occupying the intermediate ground. We provide an empirical demonstration below.

Cost heterogeneity results

The results above present a clear picture of potential gains in efficiency from using optimization approaches or from using flexible market mechanisms. We now wish to explore how the programs behave in the presence of significant cost heterogeneity, where the regulator may have some information about the costs of conservation practices (unbiased estimate of the mean), but the costs vary widely across the farms in the watershed. To simulate this case, we generate 1,000 sets of costs by randomly drawing from U [-0.8 0.8] and multiplying the mean estimate of costs by $(1+u)$. When generating the cost heterogeneity across watersheds, we assume that for a given farm the cost of each conservation practice receives the same shock, u. Further, we show that the non-attainment of the water quality goal that appears under trading programs can be mitigated by appropriately inflating the watershed points target. In our application, inflating the watershed points target by 7.5% shifts the distributions of simulated trading outcomes where the mean is approximately equal the N reduction goal.

Next, we briefly describe the results and present the results graphically. Table 5, and Figures 3–5 present the simulation results for the three chosen abatement goals.

As mentioned above, the CAC (both the optimizing and the satisficing approaches) do not allow any variation in abatement that would result from variation in costs. Clearly, the satisficing CAC approach is going to be inefficient regardless of the cost draw. This inefficiency is large—for all abatement goals, the lowest simulated cost for the CAC-satisficing approach is higher than

[25] Often, the concern with water quality trading (or other cap-and-trade initiatives) is that trading will lead to emergence of "hot spots" (i.e., areas where environmental quality worsens). We evaluate the proposed trading approach on the field (HRU) level and do not find evidence of "hot spots" (Figures A1-A3 in the Appendix).

the highest simulated cost for the CAC-optimizing approach. Moreover, because the satisficing approach involves selecting inefficiently expensive abatement actions, shocks to the costs of abatement actions result in much greater variability in program costs for the CAC-satisficing approaches. As evidence consider the standard deviations of simulated program costs, which for the CAC-satisficing approach exceed the CAC-optimizing approach by at least a factor of five across the abatement goals. The only attractive feature of a CAC-satisficing approach (the approach that often echoes in policy questions like "what would it take to achieve the water quality goal?") is low variability in abatement. However, in the case that CAC approach is being considered, the results suggest that the regulator can do much better by investing in obtaining estimates of abatement action costs, and using those estimates to try to direct abatement actions in a more cost-effective fashion.

In terms of PS approaches, as expected, the limited flexibility provided to farmers results in limited variation in abatement as a result of different cost draws, but this variation is larger under the satisficing approach than under the optimizing approach (although the mean of abatement is somewhat larger under the satisficing approach). In terms of costs, once again the optimizing approach outperforms the satisficing approach dramatically. Should a regulator possess good information on the costs of abatement actions, on-farm performance standard appears to be an attractive approach.

Under the trading approaches, the requirement to possess good cost information, and to use that information in cost-minimization prior to implementing the program in order to obtain desirable cost-efficiency properties, is no longer needed. Trading programs, whether structured using a simple "what does it take" (satisficing) approach or a more complex optimization approach involving using cost estimates, perform equally well in terms of cost efficiency and in terms of simulated variability in program costs and abatement outcomes.[26] Once the nonlinear water-quality production process has been linearized using our approach, the private optimization involved in a well-functioning points market makes any optimization on the part of the regulator redundant.

The only two potential drawbacks to the trading approach are the issue of non-attainment of the abatement goal and the higher cost-induced variability in abatement as compared to the CAC

[26] Note that the outcomes are not identical because the abatement action allocations used to construct the trading programs under the two approaches involve somewhat different total point values (presented in Table 4). Under the same total point values, the simulated outcomes would be identical.

and the PS approaches. The cost-induced variability in abatement outcomes is clearly higher under trading approaches, as can be seen from the charts and by comparing standard deviations of abatement in Table 5. However, under all the abatement goals, the standard deviation of abatement outcomes does not exceed 0.3 percentage points.

In terms of non-attainment, the results indicate that the mean simulated trading outcomes underachieve the specified abatement goals by 2.5–3.4 percentage points. In our simulations, we find that if we inflate the total points value by 7.5%, we are able to shift the distribution of trading outcomes so that the mean outcome is quite close to the desired targets. A higher coefficient of inflation would shift the distribution further to the right in abatement space. Clearly, without some knowledge of abatement costs (so that trading outcomes can be simulated), such inflation coefficients cannot be obtained by the regulator (and if unbiased estimates of costs are available, PS with optimization would be preferred!), and these correction factors are likely to be watershed-specific. However, if the regulator has some cost information, trading outcomes and consequent non-attainment can be simulated. Theoretically, trading outcomes are a function of private costs, and water quality outcomes will differ for each possible vector of abatement action costs (i.e., the total point inflation coefficient is not invariant to abatement costs in theory). The range of variation in water quality outcomes is an empirical question, and the inflation coefficient may not vary much with abatement costs in practice.

We ask, "Can a regulator (who has some, but potentially not very accurate) cost information get close in terms of selecting the right point inflation coefficient for this watershed?" In other words, we investigate how sensitive the empirically derived 1.075 coefficient is to a range of trading outcomes. To do so, we model a regulator who has biased information regarding abatement action costs (underestimates on-farm abatement costs by as little as 10% and as much as 110%). Simulating trading outcomes using biased cost information, we find that the unmodified total point value yields, on average, 36.86% nitrogen abatement for the 40% abatement target, which is similar to the 37.02% average reduction predicted when the regulator has unbiased information on costs. The inflation coefficient of 1.075 selected by the regulator using biased cost information would lead to an expected abatement of 39.49% (just below the 39.89% expected abatement under unbiased cost information). Thus, the inflation coefficient of 1.075 appears to be reasonably invariant both to the target abatement and to the quality of cost information available to the regulator.

Using a similar approach, a regulator who can simulate trading outcomes and choose to evaluate the likely range of non-attainment from a trading program, and can empirically select the total points inflation coefficient, can (at least approximately) correct the bias. Of course, we do have to keep in mind that the actual abatement realization is going to be subject to the stochastic influences of weather, climate, and possibly other factors, and that those influences may swamp the small non-attainment bias of the trading program. The attractive feature of the trading program however, is that regardless of the actual ex-post abatement observed, that level of abatement was carried out at the lowest possible cost.

Policy Implications, Extensions, and Conclusions

We evaluated three simple regulatory approaches to agricultural nonpoint-source water pollution control: the CAC, the on-farm performance standard (PS), and a trading system based on abatement action credits. We consider these approaches under three scenarios regarding regulator's information on the true costs of abatement actions. As a benchmark and a completely unrealistic scenario, we consider the case of perfect information on costs. The unsurprising message is that in this situation, the regulator should use that information to her advantage and, as a result, can formulate cost-efficient policies regardless of the approach adopted. For the more realistic scenario of the regulator having some, but imperfect, cost information, we argue that the regulator can do well by utilizing this information prior to implementing a CAC or a PS program, but the regulator does not benefit from such information under a trading program.[27] From a different angle the interpretation is, when political or secondary environmental considerations preclude a trading program from being implemented, it may very well be worth it for the regulator to engage in an effort to inform herself about the likely costs of abatement actions, and to use that information in designing the program.[28]

[27] Except to use this information to simulate likely outcomes of the trading program to find a good empirical approximation to the inflation factor k.

[28] There exists a set of theoretical results that suggest that an optimal trading ratio in a trading program under uncertainty depends on the quantities evaluated at the optimal solution (Shortle and Horan, 2008; Rabotyagov and Feng, 2010; Yates and Rigby, 2012). These are discouraging results for the proponents of water quality trading, since if costs are known (to solve for the optimum), no trading is necessary. We originally expected that such results may find empirical support in this application (e.g., via the trading program structured around point coefficients estimated from the optimal frontier performing better than a trading program utilizing approximations from random SWAT model draws). We do not find it to be the case.

In the proposed PS and trading programs, we consider a procedure to approximate a complex and nonlinear water quality production function in order to linearize the process, and to make abatement actions across farms independent of each other in order to capitalize on individual optimizing behavior. We affirm the good cost-efficiency properties of a trading program, although we find that setting the total points value (akin to choosing a cap in a cap-and-trade program) may require correcting the approximation bias. However, we argue that by employing the abatement action tradable credit system described in this work, we can transform the complex nonpoint-source pollution problem into one where a simple market in one freely tradable commodity (abatement point credit) can be implemented, with all the attractive cost-efficiency properties known since Montgomery (1972).

The point-credit approximation procedure can also be adapted to (*a*) extend the market to multiple pollutants (using either a single point system where the regulator seeks to achieve a specific point in abatement space, or a system with separate point markets for different pollutants), (*b*) to bring cropping choices into the point credit system (Collentine and Johnsson, 2012), (*c*) to create sub-watershed-scale markets, or (*d*) to modify the market for stochastic weather and climate factors to try to build in some kind of "margin of safety," or "safety-first," considerations. For example, echoing the approach suggested by Shortle and Horan (2006), where trading in nonpoint-source pollution happens in multiple markets, and where one market focuses on the mean and other markets focus on higher moments of pollution distribution, we can envision a related "safety-first" points market. To estimate those points, one would simulate a large number of possible watershed configurations for a sufficiently long simulation period, encompassing most of the likely weather realizations. Then, the share of simulation years where water quality target is reached would serve as an estimate of reliability of reductions, and would subsequently be used in constructing the "risk-modified" set of points. We leave these extensions to future work.

Many caveats regarding the water quality modeling process, data availability, uncertainty over the changing climate and hydrologic regimes, and monitoring and compliance issues apply. The approaches presented are necessarily simplified compared to any actual watershed programs. We believe, however, that these should not serve as an impediment to more thorough consideration of the proposed flexible approaches by the research community, and perhaps warrant a serious look for possible implementation by watershed managers.

TABLES

Table 1. Summary of cases considered.

	Familiar and convenient theoretical territory, but not the best representation of water quality production function	More realistic, but more difficult, water quality production function, and possible "workarounds" to create an incentive-based system:
Pollution process / Availability of cost information	**Linear, separable:** $$A(r) = \sum_{i}^{N} d_i r_i(x_i)$$ Environmental goal reached by construction in any regulatory system	**Nonlinear, nonseparable:** $$A(r) = A(r_1(x_1), r_2(x_2), \dots, r_N(x_N))$$ Environmental goal is not guaranteed to be reached in all cases
Form of market trading system	$\min_{x_j, l_i \in X} C_i^P(x_{i,}) + pl_i$ s.$t.$ $d_i\, r_i(x_j, \theta_i) + l_i \geq \overline{l_i}^0$ and the market clearing condition $\sum_i l_i = 0$	$\min_{x_j, l_i \in X} C_i^P(x_{i,}) + pl_i$ s.$t.$ $d_i' r_i(x_j, \theta_i) + l_i \geq \overline{l_i}^0$ and the market clearing condition $\sum_i l_i = 0$ Where d_i' and $\overline{l_i}^0$ vectors are created using the water quality model simulation and/or optimization results
Perfect information	CASE 1: Ease of solution: Easily solve for the optimal allocation of abatement effort CAC at the farm level: first-best Performance standard: first-best Market: **first-best**	CASE 4: Ease of solution: Not easy, but can (using OR techniques, evolutionary algorithms, etc.) solve for first-best CAC at the farm level: On-farm target: first-best Water quality goal: attained Performance standard: second-best (but may be close to first-best) if in the form of $d_i^* r_i^*$, where d_i^*'s are based on the linearization of A(r) Water quality goal: attained Market: second-best (even if based on d_i^*'s at the optimum), water quality goal may not be attained

Some information (e.g., unbiased estimate of the mean)	CASE 2: Ease of solution: easy, but second-best CAC at the farm level: On-farm: second-best Ambient: second-best Market: first-best	CASE 5: Can solve the cost-minimization problem (second-best) CAC at the farm level: On-farm: second-best Water quality goal: attained Ambient: second-best Water quality goal: may not be attained Market: second-best (but cost savings may be possible), water quality goal may not be attained
No information	CASE 3: Ease of solution: no solution on cost-efficient allocation of effort CAC ("satisficing approach"): "third-best" for both on-farm and ambient targets (any allocation r_p s.t. $A(r_p) = \sum_i d_i r_{pi} = \bar{A}$) PS-satisficing approach (require $d_i r_{pi}$ on-farm) : second-best—more efficient than CAC Trading program: first-best (Montgomery)	CASE 6: Cannot solve the cost-minimization problem. CAC: "third-best", water quality goal reached (any allocation r_p s.t. $A(r_p) = \bar{A}$) Performance standard cannot be specified Trading program: delivery coefficients derived at the arbitrary (e.g., baseline), r: $A(r) \cong \sum_{i=1}^{N} d_i'(r_i^0) r_i$. second-best, water quality goal may not be reached

Table 2. Mutually exclusive conservation practice combinations.

	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 is removed.
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 is removed.
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 N application rate and cover crops.

Table 3. Estimated point values coefficients by subbasin (with standard errors from estimation and the overall fit statistic)

		Abatement practices														
Location		**No till**		**Cover crops**		**No till, Cover Crops**		**Red.fertilizer**		**Red.Fert, No till**		**Red.Fert., Cover Crops**		**Red.Fert., No till, CC**		**CRP**
Subbasin1	3.441	(7.295)***	1.872	(3.918)***	5.355	(11.153)***	0.213	(0.449)	4.507	(9.630)***	2.692	(5.730)***	6.153	(13.285)***	10.263	(21.263)***
Subbasin2	3.959	(8.813)***	2.419	(5.259)***	5.342	(11.956)***	0.73	(1.619)	4.489	(9.914)***	2.481	(5.362)***	5.918	(13.106)***	9.561	(20.586)***
Subbasin3	3.541	(7.496)***	1.897	(4.071)***	4.585	(10.022)***	0.318	(0.682)	3.867	(8.486)***	2.56	(5.565)***	4.845	(10.455)***	7.498	(16.072)***
Subbasin4	2.501	(2.780)**	2.818	(3.130)**	4.522	(5.024)***	0.328	(0.352)	3.834	(4.208)***	2.065	(2.268)**	4.161	(4.547)***	5.842	(6.336)***
Subbasin5	2.036	(7.289)***	1.985	(7.116)***	3.976	(14.305)***	0.621	(2.194)**	2.612	(9.515)***	2.499	(9.139)***	4.709	(16.638)***	6.428	(22.779)***
Subbasin6	2.238	(6.187)***	2.153	(5.972)***	4.441	(12.421)***	0.734	(2.024)**	2.449	(6.813)***	2.91	(7.924)***	5.048	(13.968)***	7.007	(19.372)***
Subbasin7	6.339	(6.617)***	3.315	(3.370)**	6.514	(6.737)***	1.285	(1.3)	6.596	(6.757)***	3.265	(3.347)**	7.798	(8.135)***	10.125	(10.451)***
Subbasin8	2.838	(5.292)***	3.144	(5.835)***	5.198	(9.623)***	0.759	(1.368)	3.866	(7.228)***	3.185	(5.835)***	5.161	(9.724)***	7.459	(13.648)***
Subbasin9	0.872	(3.303)**	1.037	(3.951)***	2.005	(7.41)***	0.344	(1.297)	1.071	(4.021)***	1.78	(6.732)***	2.339	(8.706)***	4.331	(15.977)***
Subbasin10	1.678	(4.679)***	2.316	(6.439)***	2.992	(8.397)***	0.504	(1.439)	2.233	(6.492)***	2.701	(7.554)***	4.481	(12.732)***	5.911	(16.445)***
Subbasin11	2.092	(4.472)***	1.819	(3.799)***	3.412	(7.083)***	0.144	(0.302)	3.219	(6.780)***	2.847	(6.004)***	5.344	(11.233)***	7.314	(15.442)***
Subbasin12	2.927	(7.471)***	2.312	(5.876)***	4.027	(10.065)***	0.02	(0.051)	3.225	(8.365)***	2.953	(7.458)***	5.115	(12.953)***	6.957	(17.994)***
Subbasin13	2.166	(7.249)***	2.472	(8.439)***	3.53	(11.838)***	0.276	(0.934)	2.336	(7.779)***	2.455	(8.266)***	3.413	(11.513)***	5.83	(19.509)***
Subbasin14	2.041	(4.397)***	2.043	(4.361)***	3.239	(7.126)***	1.003	(2.134)**	2.529	(5.377)***	3.188	(6.764)***	3.976	(8.543)***	5.656	(12.015)***
Subbasin15	2.368	(6.689)***	1.687	(4.769)***	3.96	(11.097)***	0.097	(0.276)	2.683	(7.643)***	1.73	(4.998)***	3.847	(10.633)***	5.101	(14.538)***
Subbasin16	1.056	(3.370)**	1.125	(3.586)***	2.458	(8.122)***	0.242	(0.783)	1.559	(5.055)***	1.525	(5.003)***	2.763	(8.966)***	3.886	(12.581)***
Subbasin17	1.765	(4.370)***	1.897	(4.679)***	3.242	(7.874)***	1.021	(2.505)**	2.064	(5.108)***	2.46	(6.033)***	3.577	(8.742)***	4.443	(10.905)***
Subbasin18	2.905	(6.200)***	3.097	(6.473)***	4.099	(8.881)***	1.507	(3.177)**	3.443	(7.503)***	3.447	(7.562)***	4.831	(10.251)***	7.148	(15.57)***
Subbasin19	3.355	(4.789)***	1.962	(2.819)**	4.821	(6.883)***	0.001	(0.001)	3.026	(4.267)***	2.766	(3.987)***	4.775	(6.775)***	7.451	(10.655)***
Subbasin20	1.909	(5.176)***	2.593	(7.095)***	4.279	(11.825)***	0.859	(2.301)**	2.738	(7.339)***	2.513	(6.716)***	4.493	(11.997)***	6.594	(17.705)***
Subbasin21	4.133	(15.85)***	2.834	(10.529)***	6.714	(25.702)***	0.922	(3.450)**	4.927	(18.418)***	3.587	(13.565)***	7.007	(26.46)***	12.188	(45.724)***
Subbasin22	2.321	(4.348)***	3.114	(5.943)***	4.386	(8.145)***	0.597	(1.145)	3.682	(6.990)***	3.5	(6.770)***	5.35	(10.086)***	8.49	(15.875)***
Subbasin23	2.59	(4.181)***	3.07	(4.942)***	4.422	(7.020)***	0.434	(0.706)	3.647	(5.857)***	3.493	(5.564)***	5.768	(8.989)***	7.894	(12.489)***
Subbasin24	2.151	(4.659)***	2.057	(4.588)***	4.361	(9.587)***	0.842	(1.878)*	3.468	(7.611)***	3.07	(6.809)***	4.742	(10.263)***	7.772	(17.112)***
Subbasin25	1.534	(2.688)**	1.663	(2.936)**	4.519	(7.993)***	0.169	(0.295)	2.515	(4.446)***	1.862	(3.248)**	4.194	(7.526)***	6.651	(11.771)***
Subbasin26	3.33	(4.594)***	3.737	(5.057)***	8.12	(11.185)***	0.66	(0.874)	5.569	(7.636)***	4.77	(6.579)***	7.337	(9.927)***	12.689	(17.399)***
Subbasin27	5.527	(2.490)**	5.055	(2.286)**	9.192	(4.147)***	1.468	(0.642)	3.934	(1.769)*	3.186	(1.41)	9.116	(4.132)***	12.18	(5.481)***
Subbasin28	2.032	(4.108)***	2.105	(4.313)***	4.364	(8.639)***	0.001	(0.002)	2.638	(5.351)***	1.879	(3.874)***	3.886	(7.888)***	5.509	(11.311)***
Subbasin29	3.482	(4.651)***	2.692	(3.503)***	4.546	(5.946)***	0.501	(0.659)	3.72	(4.98)***	4.116	(5.564)***	5.229	(6.804)***	9.28	(12.465)***
Subbasin30	3.757	(6.583)***	2.198	(3.947)***	5.367	(9.377)***	1.241	(2.175)**	3.619	(6.492)***	3.403	(6.062)***	5.508	(9.535)***	8.269	(14.585)***

* p<=0.1 　 ** p<.=001 　 ** p <=0.05 　 * p<=0.1 　 R_square 　 0.993

Table 4. Simulated program performance under varying N abatement goals.

Target N reduction, % from baseline	Approximately optimal solution (AC optimizing approach)		CAC, satisficing approach			PS, satisficing approach			PS, optimizing approach			Trading, satisficing approach Total point values 20%--974,626 30%--1,419,642 40%--1,864,908			Trading, optimizing approach Total point values 20%--963,658 30%--1,401,848 40%--1,868,107		
	N red.	**$**	**N red.**	**$, million**	**Dominated by**	**N red.**	**$, million**	**Dominated by**	**N red.**	**$, million**	**Dominated by**	**N red.**	**$, million**	**Dominated by**	**N red.**	**$, million**	**Dominated by**
20	20.73	1.8	20.86	7.2	164	22.19	5.0	95	20.85	1.7	0	17.29	1.2	0	17.03	1.2	0
30	30.12	3.2	30.12	19.8	435	31.23	17.8	379	30.18	3.1	0	27.80	2.3	0	28.58	2.4	0
40	40.00	9.0	40.00	29.6	323	40.83	28.0	305	39.67	8.7	0	36.13	6.7	1	36.21	6.7	2

Table 5. Simulated outcomes under cost heterogeneity.

Command and Control and Performance Standard Outcomes, 20% goal

	PS, optimizing		CAC, optimizing (20.73% N red.)	PS, satisficing		CAC, satisficing (20.86% N red.)
	Cost, $/yr	N, % red.	Cost, $/yr	Cost, $/yr	N, % red.	Cost, $/yr
Mean	1,665,199	20.85	1,793,057	4,950,564	22.30	7,231,175
Max	1,820,648	20.86	1,955,425	5,483,399	22.52	7,828,026
Min	1,540,891	20.83	1,663,784	4,392,286	22.07	6,665,245
StdDev	38,090	0.01	38,705	184,403	0.07	200,556

Trading Outcomes, 20% goal

	Optimizing P		Satisficing P		$P_{satisficing}$*(K =1.075)	
	Cost, $/yr	N, % red.	Cost, $/yr	N, % red.	Cost, $/yr	N, % red.
Mean	927,373	17.68	950,499	17.92	1,113,597	19.45
Max	1,026,921	18.91	1,051,417	19.05	1,222,170	20.72
Min	839,141	16.65	861,319	16.97	1,012,692	18.43
StdDev	29,253	0.30	29,583	0.30	31,850	0.28

Command and Control and Performance Standard Outcomes, 30% goal

	PS, optimizing		CAC, optimizing (30.12% N red.)	PS, satisficing		CAC, satisficing (30.12% N red.)
	Cost, $/yr	N, % red.	Cost, $/yr	Cost, $/yr	N, % red.	Cost, $/yr
Mean	3,081,106	30.32	3,232,261	17,814,415	30.32	19,804,107
Min	3,240,390	30.60	3,002,472	15,857,322	30.60	21,643,385
Max	2,863,244	30.14	3,386,230	19,640,986	30.14	17,831,074
StdDev	60,465	0.07	59,303	644,392	0.07	645,923

Trading Outcomes, 30% goal

	Optimizing P		Satisficing P		$P_{satisficing}$*(K =1.075)	
	Cost, $/yr	N, % red.	Cost, $/yr	N, % red.	Cost, $/yr	N, % red.
Mean	2,260,722	27.92	2,188,889	27.51	2,653,474	29.89
Max	2,422,324	28.50	2,347,530	28.15	2,846,200	30.38
Min	2,103,920	27.42	2,035,468	26.97	2,468,987	29.39
StdDev	48,061	0.18	46,943	0.19	56,049	0.16

Table 5. Continued

Command and Control and Performance Standard Outcomes, 40% goal

	PS, optimizing		**CAC, optimizing (40.00% N red.)**	**PS, satisficing**		**CAC, satisficing (40.00% N red.)**
	Cost, $/yr	**N, % red.**	**Cost, $/yr**	**Cost, $/yr**	**N, % red.**	**Cost, $/yr**
Mean	8,654,175	39.93	9,010,815	27,910,009	40.92	29,573,330
Max	9,212,053	40.18	9,572,124	30,669,551	41.14	32,318,543
Min	8,139,097	39.74	8,507,064	24,773,870	40.74	26,419,302
StdDev	163,169	0.07	162,446	897,480	1.30	900,772

Trading Outcomes, 40% goal

	Optimizing P		**Satisficing P**		**$P_{satisficing}$*(K =1.075)**	
	Cost, $/yr	**N, % red.**	**Cost, $/yr**	**N, % red.**	**Cost, $/yr**	**N, % red.**
Mean	5,382,613	37.09	5,350,838	37.02	6,907,911	39.89
Max	5,859,830	37.80	5,823,730	37.79	7,554,883	40.62
Min	5,004,844	36.51	4,975,517	36.46	6,372,985	39.19
StdDev	123,255	0.20	122,218	0.20	166,865	0.22

FIGURES

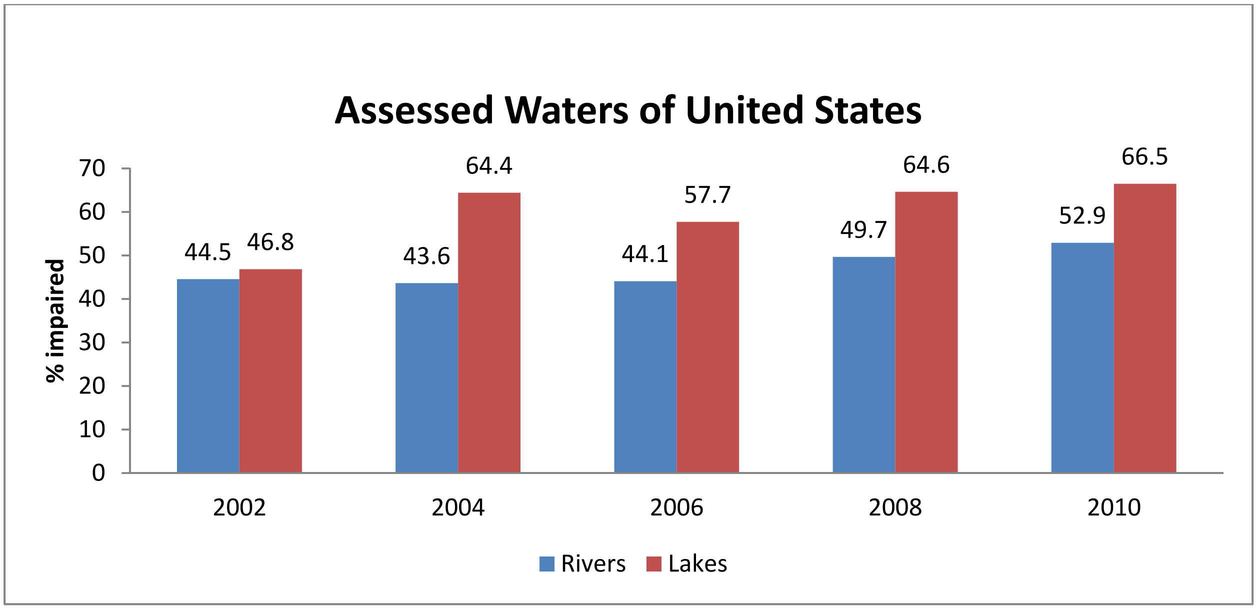

Figure 1. US waters assessed as impaired
Source: EPA National Summary of Assessed Waters Report 2002,2004,2006,2008,2010

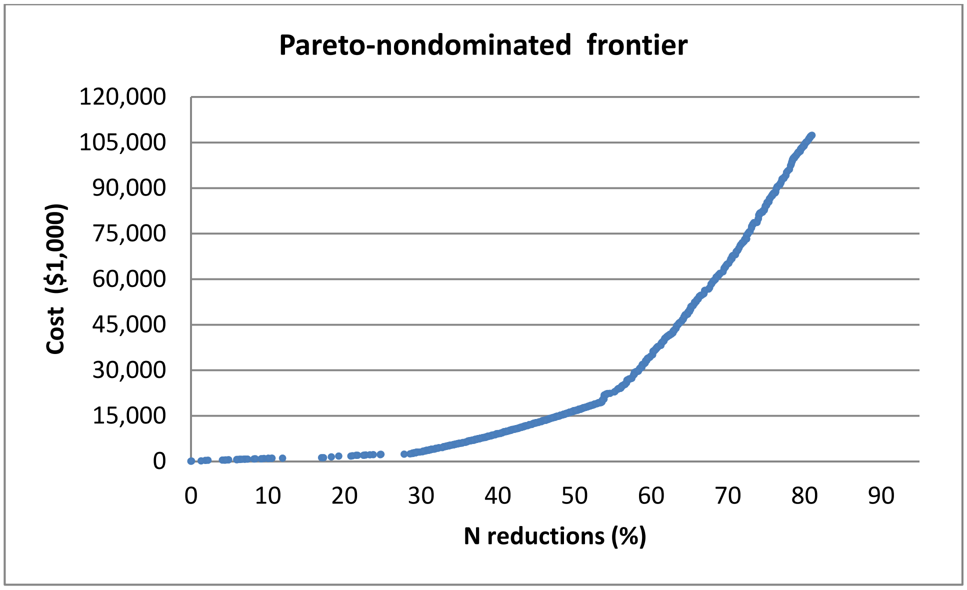

Figure 2. Total abatement cost curve (tradeoff frontier)

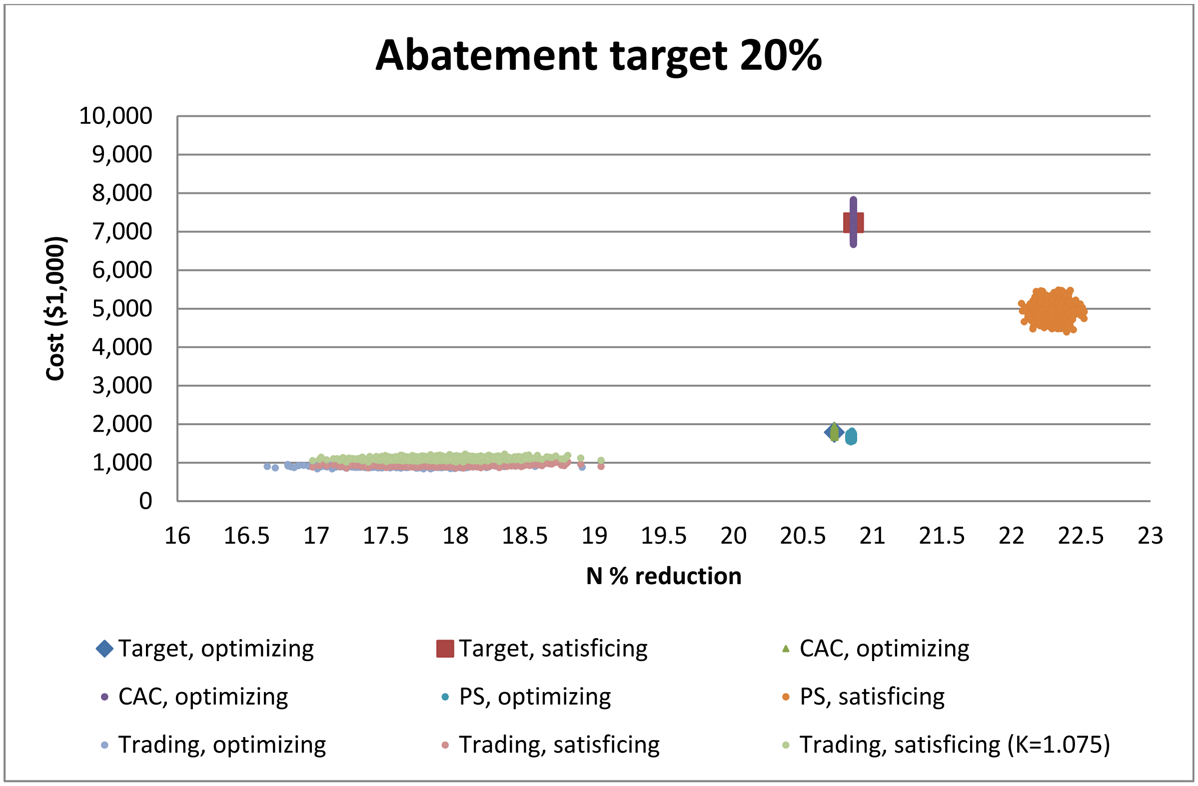

Figure 3. Simulated program outcomes under cost heterogeneity, 20% N abatement goal

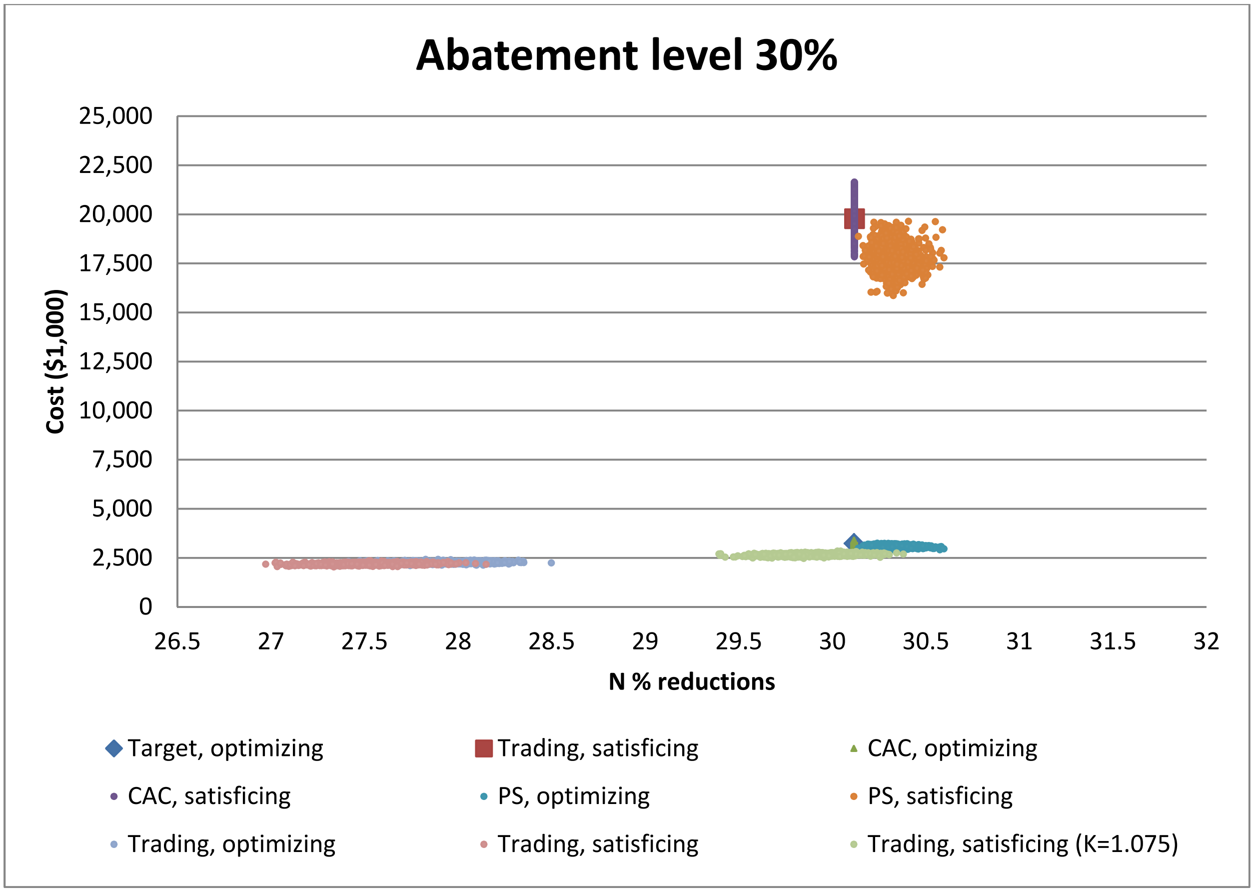

Figure 4. Simulated program outcomes under cost heterogeneity, 30% N abatement goal

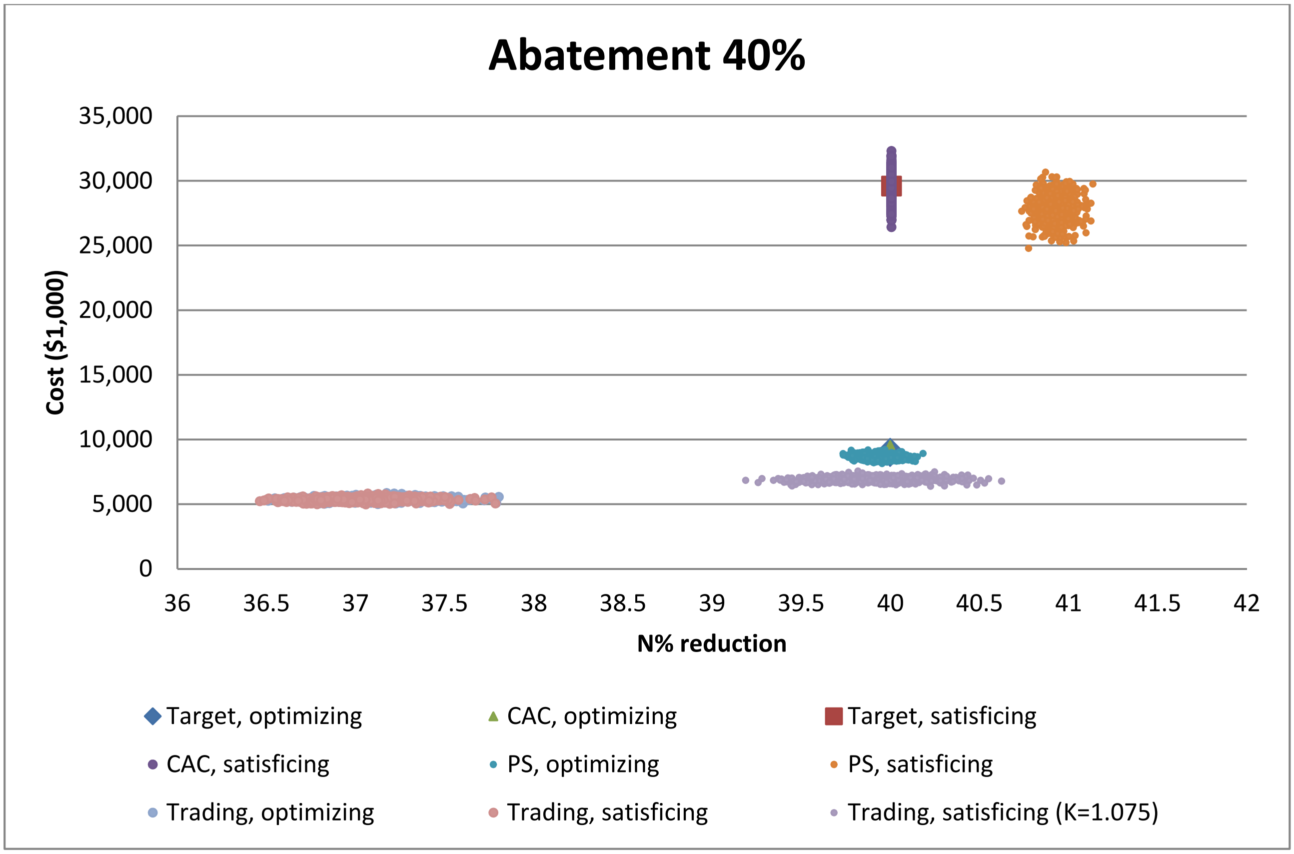

Figure 5. Simulated program outcomes under cost heterogeneity, 40% N abatement goal

APPENDIX

1. Equivalence of the trading program outcome to the social planner's cost-minimization outcome.

Social planner's problem:

$$\mathrm{TC} = \min_{x_{ij},} \sum_{i}^{N} \sum_{j}^{J} c_{ij} x_{ij}$$

s.t

$$\sum_{i}^{N} \sum_{j}^{J} a_{ij} * x_{ij} \geq \sum_{i}^{N} \overline{a_i} * s_i$$

$$L = \sum_{i}^{N} \sum_{j}^{J} c_{ij} x_{ij} - \lambda(\sum_{i}^{N} \sum_{j}^{J} a_{ij} * x_{ij} - \sum_{i}^{N} \overline{a_i} * s_i)$$

First order conditions

$$x_{ij} \ : \qquad c_{ij} - \lambda a_{ij} \geq 0 \qquad x_{ij} \geq 0 \quad x_{ij}\left(c_{ij} - \lambda a_{ij}\right) = 0$$

Trading program: cost minimization at farm level. Farmers minimize the abatement costs by choosing the amount of land allocated to each abatement practice, and by buying or selling abatement points such that to satisfy the field constraint.

$$\mathrm{TC_i} = \min_{x_{ij}, b_i} \sum_{j}^{J} c_{ij} x_{ij} \ + p b_i$$

s.t

$$\sum_{j}^{J} a_{ij} * x_{ij} + b_i \geq \bar{a_\iota} s_i$$

$$L = \sum_{j}^{J} c_{ij} x_{ij} - p b_i - \mu_i (\sum_{j}^{J} a_{ij} * x_{ij} + b_i - \bar{a_\iota} s_i)$$

$$x_{ij} : \quad c_{ij} - \mu_i a_{ij} \geq 0 \quad x_{ij} \geq 0 \quad x_{ij}\left(c_{ij} - \mu_i a_{ij}\right) = 0$$

$$b_i : \quad p - \mu_i \geq 0 \quad b_i \geq 0 \quad b_i(p - \mu_i) = 0$$

Second equation implies $p = \mu_i$

Replacing in the first equation $c_{ij} - p\, a_{ij} \geq 0$ and comparing with the problem above we obtain $p = \lambda$.

Under trading, the market clearing condition is $\sum b_i = 0$ but $b_i = \bar{a_\iota} s_i - \sum_j^J a_{ij} * x_{ij}$

$$\sum_{i} \overline{\{a_\iota} s_i - \sum_{j}^{J} a_{ij} * x_{ij} \} = 0$$

$$\sum_{i} \bar{a_\iota} s_i - \sum_{i} \sum_{j}^{J} a_{ij} * x_{ij} = 0$$

$$\sum_{i} \sum_{j}^{J} a_{ij} * x_{ij} = \sum_{i} \bar{a_\iota} s_i = A$$

Hence the equivalence of the two problems.

Distribution of abatement effort corresponding to outcomes presented in Table 4

Figure A1. Distribution of reductions, 20% N abatement goal.

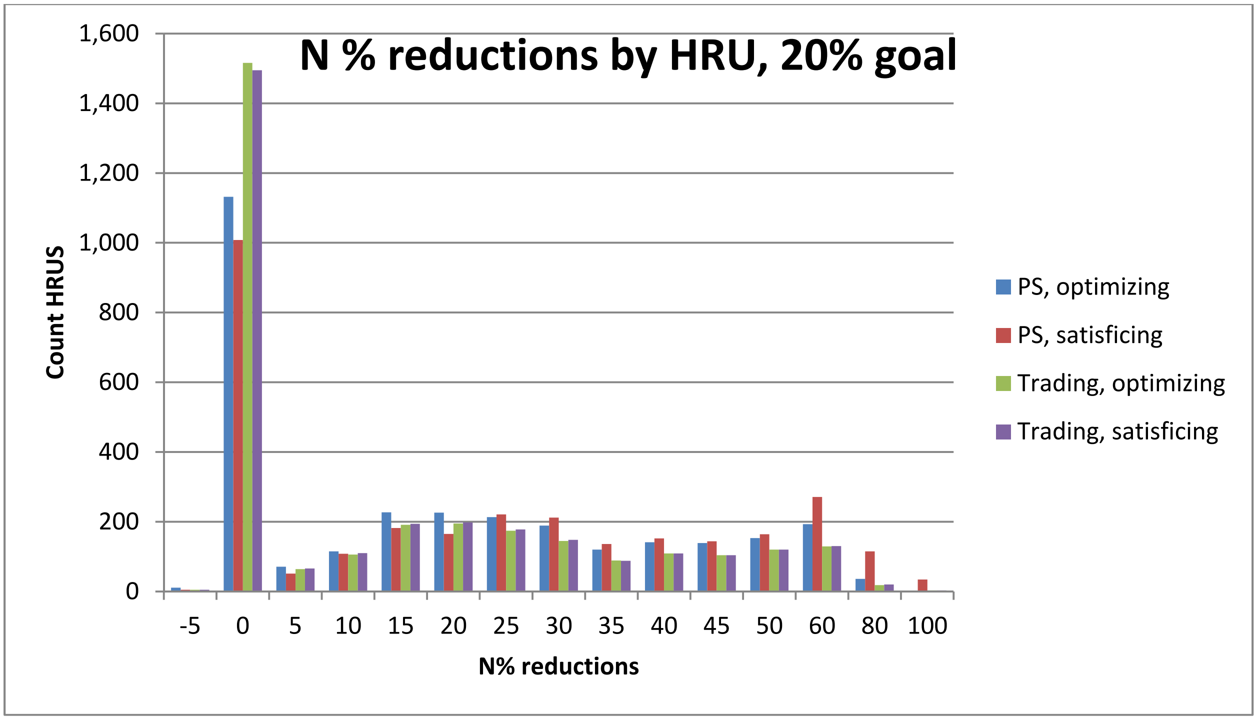

Figure A1. Distribution of reductions, 20% N abatement goal.

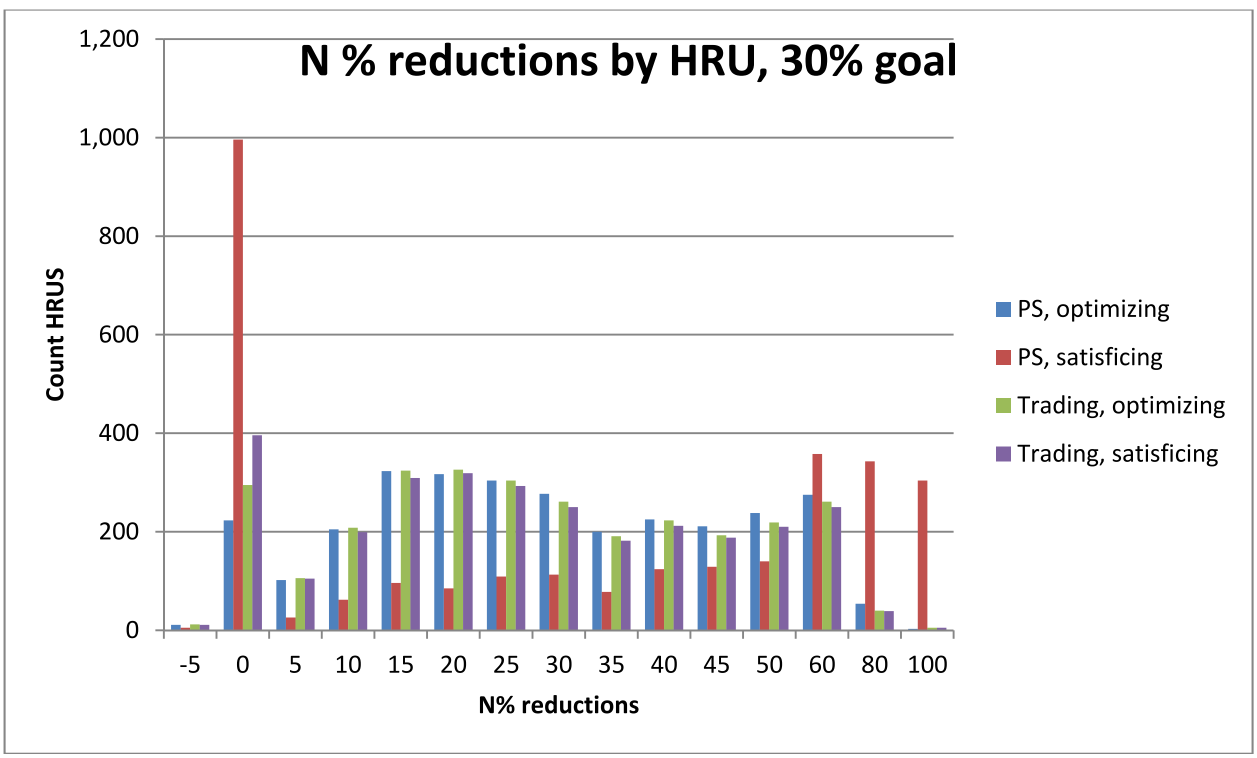

Figure A2. Distribution of reductions, 30% N abatement goal.

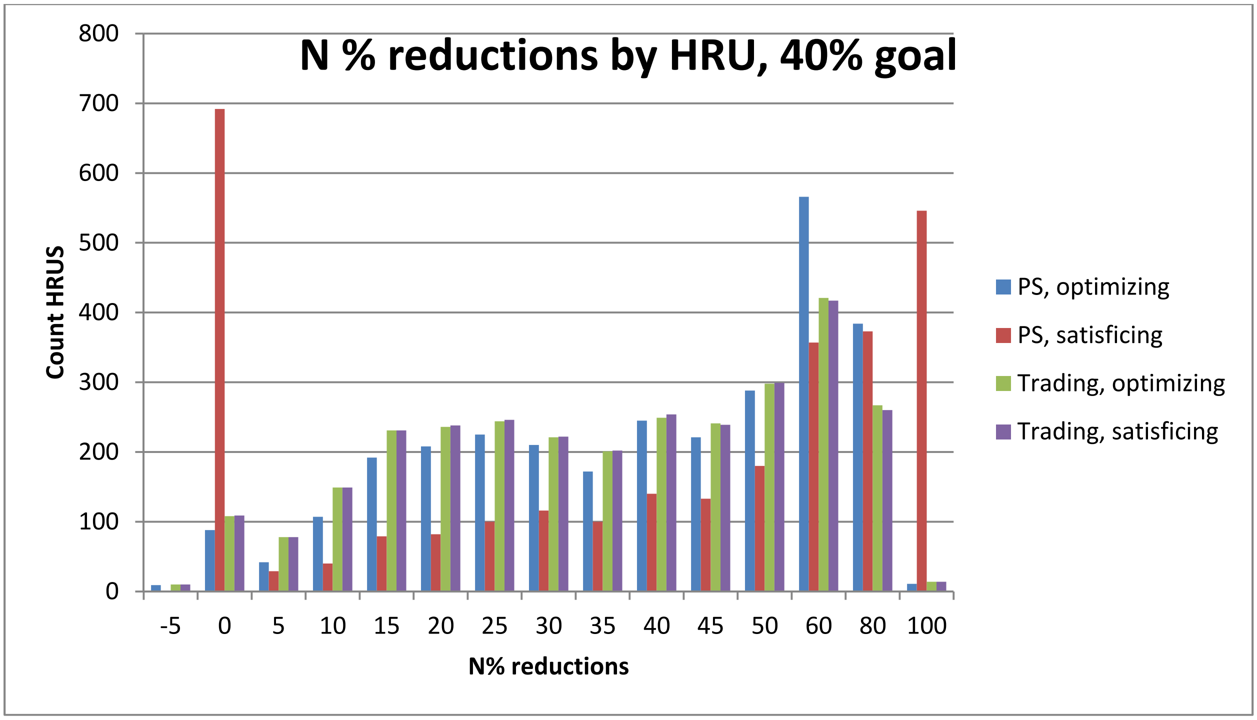

Figure A3. Distribution of reductions, 40% N abatement goal.

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